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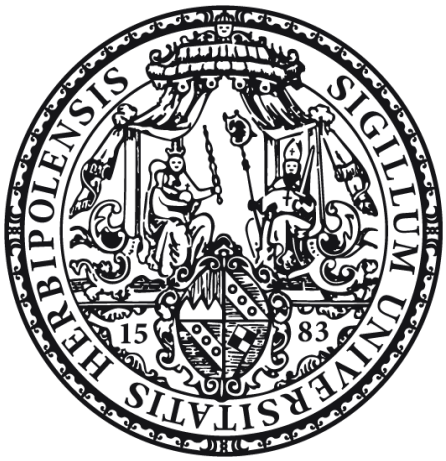

Artificial Intelligence for Human Decision-Makers: Systematization, Perception, and Adoption of Intelligent Decision Support Systems in Industry 4.0

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Würzburg, den 20. Oktober 2021

Jonas Paul Wanner

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Abstract

The Fourth Industrial Revolution has already begun. It is assumed that this will lead to significant changes. As a new production factor, information plays a particularly important role. Innovative possibilities for data collection, networking, and evaluation are unleashing previously untapped potential. However, harnessing this potential also requires a change in the way we work. In addition to expanded automation, human-machine cooperation is becoming more important: The machine achieves a reduction in complexity for humans through artificial intelligence. In fractions of a second large amounts of data of high decision quality are analyzed and suggestions are offered. The human being, for this part, usually makes the ultimate decision. He validates the machine's suggestions and, if necessary, (physically) executes them.

Both entities are highly dependent on each other to accomplish the task in the best possible way. Therefore, it seems particularly important to understand to what extent such cooperation can be effective. Current developments in the field of artificial intelligence show that research in this area is particularly focused on neural network approaches. These are considered to be highly powerful but have the disadvantage of lacking transparency. Their inherent computational processes and the respective result reasoning remain opaque to humans. Some researchers assume that human users might therefore reject the system's suggestions. The research domain of explainable artificial intelligence (XAI) addresses this problem and tries to develop methods to realize systems that are highly efficient and explainable.

This work is intended to provide further insights relevant to the defined goal of XAI. For this purpose, artifacts are developed that represent research achievements regarding the systematization, perception, and adoption of artificially intelligent decision support systems from a user perspective. The focus is on socio-technical insights with the aim to better understand which factors are important for effective human-machine cooperation. The elaborations predominantly represent extended grounded research. Thus, the artifacts imply an extension of knowledge in order to develop and/ or test effective XAI methods and techniques based on this knowledge. Industry 4.0, with a focus on maintenance, is used as the context for this development.

The area of systematization of the research field includes the review of existing research in the area of Industry 4.0 as well as a basic understanding of potential obstacles to effective human-machine cooperation. The first step was a review of business analytics applications and trends in this environment. This showed that many innovative approaches are being developed, particularly for industrial maintenance. Increasingly, data evaluation is being technically implemented using approaches from the field of deep learning. Since this leads to the aforementioned problem of such systems lacking explainability, a reappraisal of XAI transfer techniques was undertaken. Hereby, the inadequate transparency of such approaches is remedied by transferring them into per se explainable approaches. It was found that techniques for visualization and rule-based target models are particularly widely used. Nevertheless, due to the associated criticisms of loss of accuracy and increased complexity of applied XAI transfers, an application-based implementation was extended. It was shown that the complexity of the translations does not provide a user-adequate solution to allow effective human-machine cooperation.

The area of perception of (X)AI decision support systems deals with insights into users' perceptions. In the first applied study, factors influencing the perception of the objective truth of results of advanced

data analysis were investigated. It was found that the accuracy and completeness of the information presented were particularly strong influences on the perception from a user perspective. The timeliness of information appears to be less significant. In study two, these findings were applied to the XAI context. Different types of AI models were examined with respect to the theoretically assumed trade-off between system performance (=accuracy) and system explainability (=completeness). The trade-off was confirmed. The ML type decision tree yielded the best trade-off solution, whereas the neural network had the best performance with the lowest perceived explainability. In the third study, a link between perceived explainability and user understanding was investigated. A positive correlation between the two dimensions was proven. Here, the decision tree again performed particularly well. The best result, however, was achieved by the modified neural network, which was made explainable ex-post via an XAI framework.

Investigation into the area of adoption of (X)AI decision support systems provide extended insights into the importance of individual influencing factors on users' willingness to consider such a system in their decision-making. First, we have determined which factors are particularly important for users in the selection of an intelligent decision support system. Using a hierarchical analysis method, we have shown that the performance of the system is the most important factor. Effort and explainability were secondary. Due to the perceived contradiction of this finding to previous assumptions, a further study was undertaken. Using a separate adoption model, the importance of individual factors could be explored in a broader context. The great significance of system performance was confirmed. In addition, system transparency in terms of perceived explainability was shown to have a strong indirect influence on users' willingness to adopt. Finally, the extent to which such (X)AI systems influence human decision-making was investigated. In this context, it was shown that the decision-maker becomes more confident in his decision due to the recommendation given by the machine. This is significantly positively related to the final decision quality. The combination of human and machine achieved the best result. A difference between different levels of explanation of the decision support system, however, could not be proven.

A structured research design is used to present the artifacts of this work. Each subdomain of systematization, perception, and adoption is defined using individual research objectives. The design and results represent individual scientific publications. These, in turn, are related to each other and contribute to the overarching research objective. In addition to a critical reflection on these findings, their connection with existing research is also shown. Furthermore, suggestions are made regarding potential directions for future work and how a practical implementation can be designed.

Kurzfassung

Die vierte industrielle Revolution ist bereits eingeleitet. Es wird davon ausgegangen, dass diese zu weitreichenden Veränderungen führt. Als neuer Produktionsfaktor kommt der Information hierbei eine besonders große Bedeutung zu. Durch innovative Möglichkeiten der Datenerhebung, Vernetzung und Auswertung werden Potenziale freigesetzt, die bisher ungenutzt sind. Die Nutzenmachung der Potenziale bedingt jedoch auch eine Veränderung der Arbeitsweise. Neben einer erweiterten Automatisierung wird die Mensch-Maschinen-Kooperation wichtiger: Die Maschine erreicht durch künstliche Intelligenz eine Komplexitätsreduktion für den Menschen. In Sekundenbruchteilen werden Vorschläge aus großen Datenmengen von hoher Entscheidungsqualität geboten, während der Mensch i.d.R. final die Entscheidung trifft. Er validiert die Vorschläge der Maschine und führt diese ggf. (physisch) aus.

Beide Instanzen sind stark voneinander abhängig, um eine bestmögliche Aufgabenbewältigung zu erreichen. Es scheint daher insbesondere wichtig zu verstehen, inwiefern eine solche Kooperation effektiv werden kann. Aktuelle Entwicklungen auf dem Gebiet der Künstlichen Intelligenz zeigen, dass die Forschung hierzu insbesondere auf Ansätze Neuronaler Netze fokussiert ist. Diese gelten als hoch leistungsfähig, haben aber den Nachteil einer fehlenden Nachvollziehbarkeit. Ihre inhärenten Berechnungsvorgänge und die jeweilige Ergebnisfindung bleiben für den Menschen undurchsichtig. Einige Forscher gehen davon aus, dass menschliche Nutzer daher die Systemvorschläge ablehnen könnten. Die Forschungsdomäne erklärbare Künstlichen Intelligenz (XAI) nimmt sich der Problemstellung an und versucht Methoden zu entwickeln, um Systeme zu realisieren die hoch-leistungsfähig und erklärbar sind.

Diese Arbeit soll weitere Erkenntnisse für das definierte Ziel der XAI liefern. Dafür werden Artefakte entwickelt, welche Forschungsleistungen hinsichtlich der Systematisierung, Wahrnehmung und Adoption künstlich intelligenter Entscheidungsunterstützungssysteme aus Anwendersicht darstellen. Der Fokus liegt auf sozio-technischen Erkenntnissen. Es soll besser verstanden werden, welche Faktoren für eine effektive Mensch-Maschinen-Kooperation wichtig sind. Die Erarbeitungen repräsentieren überwiegend erweiterte Grundlagenforschung. Damit implizieren die Artefakte eine Erweiterung des Wissens, um darauf aufbauend effektive XAI-Methoden und -Techniken zu entwickeln und/ oder zu erproben. Als Kontext der eigenen Erarbeitung wird die Industrie 4.0 mit Schwerpunkt Instandhaltung genutzt.

Der Bereich der Systematisierung des Forschungsfeld umfasst die Aufarbeitung der bestehenden Forschung im Umfeld Industrie 4.0 sowie das Grundverständnis über potenzielle Hindernisse für eine effektive Mensch-Maschinen-Kooperation. Als erstes erfolgte eine Aufarbeitung von Business Analytics Anwendungen und Trends im genannten Umfeld. Hier zeigte sich, dass insbesondere für die industrielle Instandhaltung viele innovative Vorgehensweisen entwickelt werden. Die Datenauswertung wird dabei verstärkt durch Ansätze aus dem Bereich des Deep Learning technisch umgesetzt. Da dies die genannte Problematik der fehlenden Erklärbarkeit solcher Systeme bedingt, wurde eine Aufarbeitung von XAI-Transfertechniken unternommen. Hierdurch wird die fehlende Transparenz solcher Ansätze durch die Überführung in per-se erklärbare Ansätze erreicht. Es zeigte sich, dass Techniken zur Visualisierung und Regel-basierte Zielmodelle besonders verbreitet sind. Aufgrund der verbundenen Kritiken von Genauigkeitsverlust und erhöhter Komplexität wurde erweitert eine anwendungsbezogene Umsetzung realisiert. Es zeigte sich, dass die Komplexität der Übersetzungen keine Nutzer-adäquate Lösung darstellt, um eine effektive Mensch-Maschinen-Kooperation zu erlauben.

Der Bereich der Wahrnehmung von (X)AI Entscheidungsunterstützungssystemen befasst sich mit der Erarbeitung von Erkenntnissen über die Auffassungen von Nutzern. In der ersten Studie wurden Einflussfaktoren auf die Wahrnehmung der objektiven Wahrheit von Ergebnissen einer fortgeschrittenen Datenanalyse untersucht. Die Genauigkeit und Vollständigkeit der dargestellten Informationen hatte besonders starken Einfluss. Die Informationsaktualität war hingegen weniger bedeutend. In der zweiten Studie wurden diese Erkenntnisse auf den XAI Kontext übertragen. Untersucht wurden verschiedene KI-Modellarten hinsichtlich des theoretisch angenommenen Trade-offs zwischen der Systemperformance (=Genauigkeit) und Systemerklärbarkeit (=Vollständigkeit). Der Trade-off konnte bestätigt werden. Der Entscheidungsbaum zeigte die beste Trade-off Lösung, wohingegen das Neuronale Netze die beste Performanceleistung bei der geringsten wahrgenommenen Erklärbarkeit hatte. In der dritten Studie wurde eine Verbindung aus wahrgenommener Erklärbarkeit und Nutzerverständnis untersucht. Es konnte eine positive Korrelation zwischen den beiden Dimensionen bewiesen werden. Der Entscheidungsbaum schnitt erneut besonders gut ab. Das beste Ergebnis erreichte hingegen das über ein XAI-Framework ex-post erklärbar gemachte Neuronale Netz.

Der Bereich der Adoption von (X)AI Entscheidungsunterstützungssystemen bietet erweiterte Erkenntnisse über die Bedeutung von einzelnen Einflussfaktoren auf die Bereitschaft von Nutzern, ein solches System in ihrer Entscheidungsfindung zu berücksichtigen. Zunächst wurde untersucht, welche Faktoren bei der Systemauswahl eines intelligenten Entscheidungsunterstützungssystems für Nutzer besonders wichtig sind. Durch eine hierarchische Analysemethode zeigte sich, dass die Leistungsfähigkeit des Systems den wichtigsten Faktor darstellt. Der Aufwand und die Erklärbarkeit waren sekundär. Aufgrund des vermeintlichen Widerspruchs zu vorausgehenden Annahmen wurde eine weitere Studie unternommen. Über ein eigenes Adoptionsmodell konnten die Bedeutungen einzelner Faktoren in einem größeren Zusammenhang erforscht werden. Die hohe Bedeutung der Systemperformance bestätigte sich. Darüber hinaus zeigte sich, dass die Systemtransparenz i.S.d. wahrgenommenen Erklärbarkeit einen starken indirekten Einfluss auf die Adoptionsbereitschaft von Nutzern nimmt. Abschließend wurde untersucht, inwiefern solche (X)AI-Systeme Einfluss auf die menschliche Entscheidungsfindung nehmen. Es zeigte sich, dass der Entscheidungsträger durch die Maschine sicherer in seiner Entscheidung wird. Ebendies steht in einem signifikant positiven Zusammenhang zur finalen Entscheidungsqualität, wobei die Kombination aus Mensch und Maschine das beste Ergebnis erzielte. Ein Unterschied zwischen verschiedenen Erklärungsstufen des Entscheidungsunterstützungssystems konnte nicht nachgewiesen werden.

Die Präsentation der Artefakte dieser Arbeit erfolgt anhand eines strukturierten Forschungsdesigns. Jeder Teilbereich von Systematisierung, Wahrnehmung und Adoption wird anhand einzelner Forschungsziele definiert. Die Ausgestaltung und Ergebnisse repräsentieren einzelne wissenschaftliche Publikationen. Diese stehen wiederum in Verbindung zueinander und leisten einen Beitrag zum jeweiligen Forschungsziel. Neben einer kritischen Reflektion der eigenen Erkenntnisse wird deren Verbindung mit der bestehenden Forschung aufgezeigt. Darüber hinaus wird erläutert, an welchen Stellen zukünftige Arbeiten anknüpfen können und wie eine jeweilige Umsetzung aussehen kann.

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List of Abbreviations

AGV	Automated Guided Vehicles
AHP	Analytical Hierarchical Process
AI	Artificial Intelligence
AI DSS	AI-based decision support systems
ANN	Artificial Neural Network
ANP	Analytical Networking Process
AR	Augmented Reality
ATT	Attitude Towards Technology
AVE	Average Variance Extracted
BA	Business Analytics
BI	Behavioral Intention
BR	Behavioral Research
C	Chapter
CA	Cronbach's Alpha
CaseID	Events zur Prozessinstanz
CBM	Condition-Based Maintenance
CE	Causal Explanation
C-MAPSS	Modular Aero Propulsion System Simulation
CNN	Convolutional Neural Network
CPS	Cyber-physical Systems
CQ	Control Question
CR	Composite Reliability
CSR	Corporate Social Responsibility
DARPA	Defense Advanced Research Projects Agency
DGIQ	Deutschen Gesellschaft für Informations- und Datenqualität
DL	Deep Learning
DSR	Design Science Research
DSS	Decision Support System
DT	Decision Tree
EBESCO	Business Source Premier
EC	Ending Condition
EE	Effort Expectancy
EIS	Executive Information System
ERP	Enterprise Resource Planning
FL	Fornell-Larcker

GDPR	General Data Protection Regulation
GRI	Global Reporting Initiative
H	Hypothesis
HI	Health Index
I4.0	Industry 4.0
IFT	Inference Time
IMT	Implementation Time
IoS	Internet of Services
IoT	Internet of Things
IS	Information System
ISR	Information Systems Research
IT	Information Technology
LIME	Local Interpretable Model-agnostic Explanations
LSTM	Long-Short-Term Memory
MAS	Multi-Agent Systems
MIS	Management Information System
ML	Machine Learning
MRO	Maintenance, Repair and Operations
MSE	Mean Squared Error
NGO	Non-Governmental Organization
OLAP	On-line Analytical Processing
P	Publication
PE	Performance Expectancy
PLS	Partial Least Squares
PV	Prediction Value
RF	Random Forest
RFID	Radio-Frequency Identification
RMSE	Root Mean Square Error
RO	Research Objective
RSL	Required Skill Level
RUL	Remaining Useful Life
SEM	Structural Equation Model
SHAP	SHapley Additive exPlanations
ST	System Transparency
SVM	Support-Vector Machine
TA	Trust Ability
TAM	Technology Acceptance Model

TB	Trusting Beliefs
TT	Training Time
UTAUT	Unified Theory of Acceptance and Use of Technology
VE	Visual Explanation
XAI	Explainable Artificial Intelligence
XANN	XAI-transferred ANN

1 Introduction

"In God we trust. All others must bring data."

W. Edwards Deming – physicist, statistician, and pioneer in the field of quality management

1.1 Research Motivation

Today's society and economy are strongly influenced by digitalization. Data is generated everywhere, is omnipresent, and offers a multitude of opportunities (Guidotti et al. 2018b). This change is likewise evident in the industrial sector. Here, a change from its third evolutionary phase to its fourth evolutionary phase is already in progress. While the third phase saw the use of electronics and Information Technology (IT) to further automate production, the fourth phase explores the purpose and potential ubiquitous connectivity (Bauer et al. 2014). The vision behind this effort is to connect the physical world with digital entities, whereby smart objects can communicate with each other and with humans in real-time (Hermann et al. 2016). The related increase in data, computing power, and connectivity enables novel applications for business analytics (BA). This includes a wide range of techniques that allow data to be processed by machines to extract valuable information. Successful applications yield cost benefits, increased customer satisfaction, and improvements in production effectiveness and quality (Fay and Kazantsev 2018).

In conjunction with BA techniques, maintenance is the most researched segment of the Fourth Industrial Revolution (Wanner et al. 2021b). It describes the task of preserving or restoring the operational readiness of a product or production process, with the aim of keeping opportunity costs to a minimum. Maintenance has the potential to benefit greatly from modern BA techniques of exploiting data, as unplanned downtime can be costly at up to $250,000 per hour (Koochaki et al. 2011). Ensuring proper functioning can even be critical to the preservation of human life, as in aircraft turbine maintenance. This highlights the importance of determining the right time to implement relevant maintenance procedures (Civerchia et al. 2017). Due to the increasing complexity and dynamics of modern production plants, however, ensuring the reliability of such systems is likewise becoming more challenging (Lee et al. 2011). Nevertheless, today's service employees still seem to inspect, repair, and improve manufacturing machinery predominantly based on their experience and intuition (Wanner et al. 2019a). Thus, to ensure human safety, high reliability, and low environmental risks, advanced maintenance systems are needed (Muchiri et al. 2011).

Developments and assessment from research have shown that artificial intelligence (AI) is particularly promising for this purpose. AI in this context refers to the concept of machine learning (ML), whereby algorithms are used to find relevant relationships and patterns in data based on mathematical models and statistical methods (Alpaydin 2020), without the need of being explicitly programmed for a specific task (Bishop 2006). Today, ML-based approaches often outperform other analysis methods and even humans in many use cases (e.g., Akay 2009; Kourou et al. 2015; Silver et al. 2016). Additionally, modern maintenance approaches include AI-based decision support systems (DSSs) (Zschech et al. 2019). These systems are designed to provide data-driven support to employees in their decision-making. This reduces unnecessary manual work and related issues during maintenance tasks, achieving an efficient

utilization of given resources (Elattar et al. 2016; Peng et al. 2010). On the downside, such systems have the disadvantage that the processing mechanisms and their results are often difficult to reproduce as the ML algorithms are, in many cases, not comprehensible to humans.

As a consequence, the adoption of AI-based systems has been lacking in practice. Organizational or technical issues notwithstanding, this seems to be largely the result of a psychological barrier (Chui et al. 2018; Milojevic and Nassah 2018). The 'real problem' behind this is assumed to be the dilemma between ML model performance and ML model explainability (Gilpin et al. 2018; Gunning and Aha 2019). In the example of industrial maintenance, high complexity and a large amount of input data must to be processed by today's maintenance experts, which requires the support of high-performance, AI-based DSSs (Raouf et al. 2006b). In turn, a high-performance system will only be effective if the user has sufficient confidence in its calculations and results. Otherwise the user will not include the input of the system in his subconscious decision-making (Adadi and Berrada 2018; Sheridan and Hennessy 1984). This requires the presence of explainability and trustworthy explanations (Hayes and Shah 2017; Hoff and Bashir 2015; Mercado et al. 2016). Nevertheless, the focus within AI research is on improving performance with little regard for explainability. This is especially evident by the successes of Deep Learning (DL) (La Cava et al. 2021; Wang et al. 2018a). These algorithms are characterized by a complex, multi-layered architecture yielding high performance, but lacking of transparency and thus explainability (LeCun et al. 2015; Siau and Wang 2018).

Research in the domain of explainable AI (XAI) attempts to address this issue by trying to formulate models that offer both performance and explainability (Gunning and Aha 2019). Therefore, methods are developed with the goal of making black-box ML models explainable. The term 'explainable' refers to the aim of achieving interpretability for human users. Essentially, two XAI approaches can be distinguished: the transformation of black-box models into per se explainable white-box models (Wanner et al. 2020c); and an ex-post model extension to reveal the internal computational logic (Rudin 2019) or its reasoning for a particular recommendation (Dam et al. 2018; Lipton 2018). Still, both approaches are criticized for lacking user focus (Arrieta et al. 2020). That is, provided explanations are neither consistent with the original ML model nor intuitive to a human decision-maker (Rudin 2019). In response, researchers have called for further socio-technical studies in (X)AI (among others, Lu et al. 2020; Saha et al. 2019; Springer and Whittaker 2019; Weitz et al. 2019; Zahedi et al. 2019). Especially the lack of user understanding regarding the perception of explanations and general acceptance criteria of such systems needs to be better understood.

With this in mind, this thesis attempts to conduct appropriate basic research in the area of socio-technical (X)AI and to focus specifically on the user. This should contribute artifacts that assist in the structuring of such techniques and systems and in a better understanding of the perception of explanations as well as adoption preferences from a user perspective. Therefore, Industry 4.0 was chosen as the study context. Both practitioners and researchers can benefit from this. On the one hand, the results allow for a better understanding of the requirements for future development of effective XAI methods. On the other hand, the results support the evaluation of relevant adoption barriers hindering the introduction and selection of such AI-based DSS for practical use.

The thesis is divided into six chapters (C). C1, 'Introduction', gives an overview of the theoretical and methodological foundations, the related work, the research design, and the thesis structure. C2 to C4 contain the three main areas of 'Systematization of the Field' (C2), '(X)AI DSS User Perception' (C3),

and ‘(X)AI User Adoption’ (C4). In ‘Discussion of the Results’ (C5) the connections among the publications and related work are shown. Finally, ‘Concluding Remarks and Future Research’ follows in C6.

1.2 Theoretical Foundation

This chapter serves to provide a better understanding of the overall context of this thesis and the related theoretical foundations. In addition, it aims to clarify how technical aspects meet social aspects in these social-technical investigations.

A graphic illustration of the most important topics and their interrelation is provided in Figure 1. It is subdivided into three sections: *TECHNICAL*, *CONNECTION*, and *SOCIAL*.

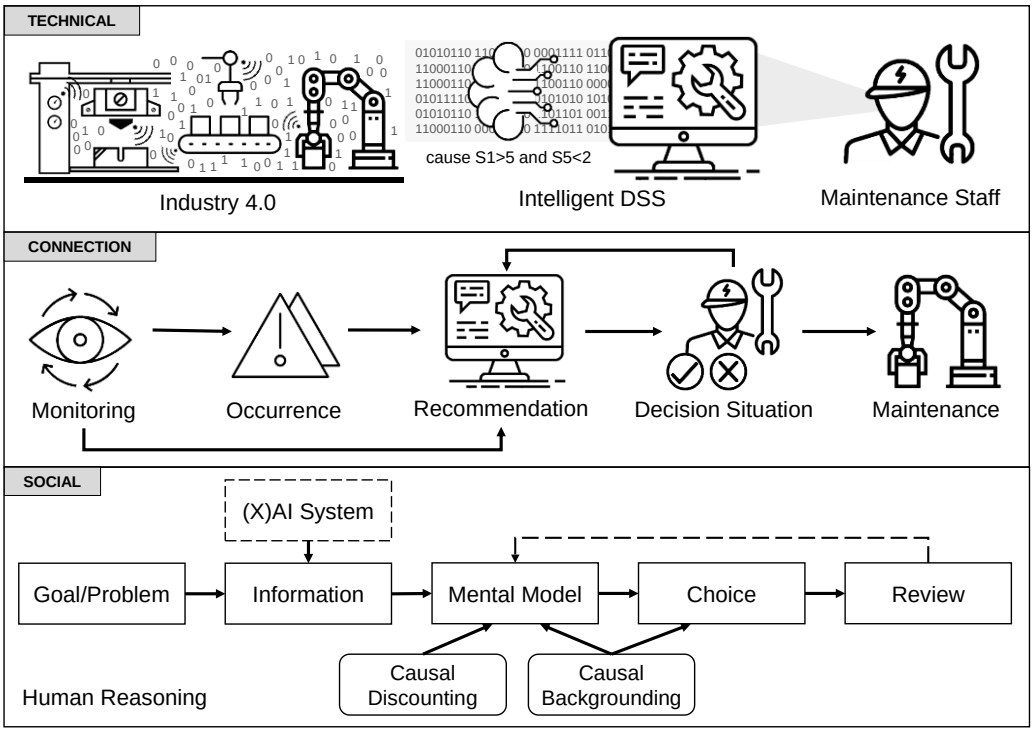


Figure 1: Big Picture of the Interrelated Thesis Topics

The first part of Figure 1, TECHNICAL, shows the main topics of interest and their interrelations from a technical point of view (cf. Section 1.2.1). The CONNECTION part outlines the link between technical and social issues by describing the I4.0 data-based maintenance process. Finally, the SOCIAL part of Figure 1 demonstrates the decision-making reasoning of the employee that determines the effectiveness of the (X)AI-based DSS and the resulting decision quality (both cf. Section 1.2.2).

1.2.1 Technical Foundation

This section defines the most important technical topics of this thesis: Industry 4.0, maintenance, decision support systems, artificial intelligence, and explainable AI (technical). First, a brief summary of the interrelations is provided (cf. Figure 1, top). This is followed by a more detailed explanation of the individual topics.

Summary. In short (from left to right), there is extensive networking and data exchange within so-called ‘smart factories’. This name is given to factories that apply the principles and techniques of I4.0. The provided data variety, volume, and velocity can be used by algorithms from the field of AI to identify data patterns that indicate anomalies of interest. This information is valuable for maintenance tasks, and thus for maintenance staff. However, to benefit from these opportunities, a suitable human-machine collaboration is needed. Such information is therefore often provided by an AI-based DSS. This system attempts to prepare the information in an appropriate manner for its user. One possibility to support this in the context of black-box DL algorithms is offered by methods from the field of explainable AI.

Industry 4.0. The Fourth Industrial Revolution is about an overall connection and interaction between objects within ‘smart factories’. Here, cyber-physical systems (CPSs), as each intelligent self-acting object connected is, monitor physical processes, create virtual copies of the physical world, and make decentralized decisions. Through the use of the Internet of Things (IoT) technology, CPSs communicate and cooperate with each other and with humans in real time. Via the Internet of Services (IoS), both internal and cross-organizational services are offered and used by the participants of the value chain (Hermann et al. 2016). The term ‘Industry 4.0’ itself refers to a specific concept put forth by the German federal government (Kagermann et al. 2013). In English-language literature, however, the term ‘smart manufacturing’ is more frequently used (e.g., He and Wang 2018; Kang et al. 2016; Kusiak 2018; Mittal et al. 2017). This variety of names notwithstanding, the concept is rather multifaceted as the ideas behind it are fulfilled by diverse technological innovations (Hermann et al. 2016). So, for many experts the focus of I4.0 is on the technological advances that are responsible for the changes in the value chain (among others, Kagermann et al. 2013; Lu 2017; Zhou et al. 2015b).

An important sub-sector of manufacturing that can benefit greatly from the new principles and techniques of I4.0 is industrial maintenance (Wanner et al. 2021b). According to the European standardization of terms (CEN/TC 319), maintenance is understood as the combination of all technical, administrative, and managerial measures that are necessary during the life-cycle of an item in order to keep it in a condition or restore it to a condition in which it can fulfill its intended functions. Here, an item is a part, component, device, subsystem, functional unit, equipment, or system, which can be described and considered individually. It can be either a piece of hardware, software, or both (Committee 2010). The need for maintenance to keep an item in its working condition is due to the problem of wear. This is caused by chemical and/or physical processes, such as corrosion or breakage. Upon reaching a certain degree of wear, the individual wear limit of the item, a failure of the functional capability occurs. This undesirable condition can be remedied or even prevented through maintenance measures (Committee 2010).

Maintenance measures are part of a maintenance strategy. A maintenance strategy is a defined and time-based combination of measures for machinery and/or related components based on a target function (Biedermann 1990; Sturm 1996). This is the most common approach in order to minimize opportunity costs (Liu and Xu 2017). The activities included can be both reactive, after the occurrence of a fault, and preventive, with regard to anticipatory countermeasures (Delen 2014). The implementation of I4.0 paradigms expands the set of possible measurement options for manufacturers. This new data infrastructure allows for modern data-based evaluations and use cases. On the one hand, existing maintenance strategies and measures can be improved. On the other hand, modern procedures, such as real-time data monitoring for condition-based maintenance, become possible (e.g., Wanner et al. 2019a). In conclu-

sion, modern data evaluation procedures should minimize unplanned downtime (Mungani and Visser 2013; Pawellek 2016).

Decision Support Systems. The increasing complexity and amount of information in modern manufacturing cannot be fully processed by maintenance employees (Belciug and Gorunescu 2020). Research in DSS attempts to address this problem by supporting the decision-maker with modern techniques and optimization theory. Such systems are designed to encapsulate the complexity of the respective process (Wanner et al. 2020a). While management information systems (MIS) offer decision support for structured decisions, modern DSSs provide support for semi-structured and unstructured decisions as well (Belciug and Gorunescu 2020; Gorry and Morton 1971). In this capacity, they are able to process a wide variety and volume of data, e.g., from different sensors, to gain insights (Belciug and Gorunescu 2020; Kasie et al. 2017). Combined with domain-specific knowledge and analytical decision models, these systems assist their users in selecting logical actions for given problems in a limited timeframe (Hamouda 2011; Wang 1997). Through a human-machine interface, the computations are presented. This allows the user to extract meaningful information to support his decision-making (Simonovic 1999). Especially in complex situations, more efficient and effective decisions become possible (Yam et al. 2001).

According to Power, there are five types of DSSs. Model-driven DSSs allow one to access and manipulate specific models (1). These can represent, for example, a financial, simulation, optimization, or statistical model. Based on limited data, parameters, and quantitative methods, decision-makers are assisted in analyzing a situation without the need for large databases (Power 2002). Data-driven DSSs allow one to analyze time series data from various internal and external systems, and even real-time data (2). Typical examples with different levels of functionality and decision support are data warehouses, on-line analytical processing (OLAP), and executive information systems (EIS) (Power 2008). Communication-driven DSSs process data from networks and communication technologies to accelerate decision-relevant collaboration and communication (3). So, these DSSs include, for example, the data of e-mail programs or meeting software (Power 2002). Document-driven DSSs retrieve and manage data from structured and unstructured documents from a variety of origins, such as catalog data or product specifications (4). An example of a decision-support tool associated with a document-driven DSS is a search engine (Power 2002). Knowledge-driven DSSs recommend suitable actions to their users (5). These systems have specialized problem-solving expertise for (a) particular domain(s) or task(s) (Power 2002). An example is a decision support system for ‘smart maintenance’. The system could monitor the operating conditions of the machine and give a feedback about the wear status of a machine (part) to tell the employee, for example, the optimal time for maintenance (Yam et al. 2001).

Over the years, DSSs have been enhanced with AI logic, making them intelligent DSSs (Bonczek et al. 2014). This is especially found in the case of knowledge-driven DSSs (Power 2001). Such systems are intended, for example, to detect fraud and expedite financial transactions, to serve as a web-based advisory system, or to improve scheduling in manufacturing operation (Power 2008).

Artificial Intelligence. AI in the field of Information Systems (IS) research is a generic term for ‘intelligent agents’. These agents pursue a specific goal, which they try to maximize by perceiving and interacting with the environment (Poole et al. 1998). Therefore, they need cognitive abilities of learning and problem solving, which can be compared with intelligent abilities that resemble those of a human being (Nilsson 2014). ML is a subfield of AI. It is the science of mathematical models and algorithms that use

machines to solve tasks (Alpaydin 2020). ML algorithms are able to learn iteratively from empirical data, which enables them to find non-linear relationships and complex patterns without being explicitly programmed to do so (Bishop 2006). Their implementation is divided into training and testing phases. During training, the algorithm is trying to learn how to solve the data problem at hand most accurate. Its performance is then tested and evaluated on new data unknown to it (Alpaydin 2020).

In general, there is a distinction between three forms of ML. Supervised ML describes a learning paradigm in which inputs are consciously assigned to predefined outputs. By transferring input-output pairs for training purposes, the machine can automatically assign (unknown) future cases (Marsland 2015; Shalev-Shwartz and Ben-David 2014; Wang et al. 2012). In unsupervised ML, the input-output pairs are not known, and the machines receive only inputs. The aim is to uncover previously undiscovered patterns within the transferred input data by the use of the algorithm (Ghahramani 2003; Kubat 2017; Shalev-Shwartz and Ben-David 2014). Reinforcement ML is a paradigm that automates learning and decision-making processes. Here, a learning agent acts based on a predefined number of actions in a defined digital environment and is trained by trial and error in combination with rewards. The overall aim is to maximize the cumulative rewards, whereby the learner maximizes task-optimal behavior with respect to conditions and actions (Alpaydin 2020; Sutton and Barto 2018; Tokic 2013; Wang et al. 2012).

In addition to the different forms of ML, different algorithms exist. Each of these has different strengths and weaknesses. For example, algorithms of decision trees require manual feature selection to ensure an efficient and effective training but are easier to interpret for a human user. However, the feature selection task can be time-consuming. This is especially evident when the dataset is high-dimensional or when the application context is not known to the ML engineer (Bini 2018). Artificial neural networks (ANNs) attempt to alleviate these problems. Through different computational layers and the use of perceptron, data inputs are processed through a variety of mathematical operations (Bini 2018). Due to the large increase in data and complexity, algorithms with a high number of computational layers also referred to as ‘deep’ show particularly useful results (Schmidhuber 2015). Thus, DL algorithms often outperform other ML algorithms as well as humans (e.g., Wang et al. 2018a). However, due to their nested non-linear structure, they are not per se interpretable by a human user and are called ‘black boxes’ (Adadi and Berrada 2018; Samek et al. 2017).

Explainable AI (technical). The research area of explainable AI addresses the problems that arise from the black-box properties of such models. XAI thus seeks to provide more transparent ML models that simultaneously offer high model performance and high explanatory power (Gunning and Aha 2019). This is accomplished by using algorithms and mathematical methods to explain the internal computational processes of the models (Abdul et al. 2018). In other words, it is about a better understanding of how and why the ML model offers its recommendations. Answering the question of *how* is referred to as ‘global explainability’. Here, the internal computational process should be made transparent (Dam et al. 2018; Rudin 2019). The *why* question is addressed by so-called ‘local explainability’ of the model. Here, it is about providing ex-post justifications for the AI’s recommendation in any particular case (Dam et al. 2018; Lipton 2018). However, purposeful explanations are difficult to achieve. Highly accurate explanations, such as a mathematical expression for ML model decision-making, are difficult for humans to comprehend. Conversely, when an explanation is more abstract and thus easier to understand, it often lacks predictive power (Gilpin et al. 2018; Guidotti et al. 2018a). Attempts such as those by

Ribeiro et al. (2016b) therefore seek to find an XAI approach that abstracts real-world complexity, and thus model accuracy, in favor of better perception and increased human understanding.

Today, three technical branches of XAI research exist, which are not necessarily mutually exclusive. First, there are XAI transfer techniques (Wanner et al. 2020c) (1). A black-box model is transferred into a per se transparent 'glass box' model to explain its internal computational process (Holzinger et al. 2019). This can be done through the use of a second, more explainable ML model and/ or mathematical methods (Abdul et al. 2018). An example is to convert a convolutional neural network (CNN) into a human-readable ruleset (e.g., Oviedo et al. 2019; Xi and Panoutsos 2018). Nevertheless, the transfer process reduces the accuracy of the resulting model in favor of greater explanatory power (Došilović et al. 2018; Guidotti et al. 2018b). In addition, there is criticism of the procedures themselves for explaining something that is per se not self-explanatory (Rudin 2019). In parallel, there is the technical possibility of ex-post explanation frameworks such as Local Interpretable Model-Agnostic Explanations (LIME) (Ribeiro et al. 2016b) and SHapley Additive exPlanations (SHAP) (Lundberg and Lee 2017) (2). These allow particularly local explanations for recommendations of black-box ML models. An example would be how strongly individual features contributed to a classification decision. Alternatively, there is also the possibility to avoid black-box algorithms and focus on per se explainable white-box algorithms and improve them iteratively (Rudin 2019) (3). By their design, these are already explainable to a human user and provide an internal explanation, as in the case of decision trees (Herm et al. 2021b; Rudin 2019).

1.2.2 Social Foundation

This section defines the most important social topics of this thesis: human reasoning, explanation theory, explainable AI (social), and implications for (X)AI models. First, the social-technical connection in the use case of industrial maintenance is explained to shed light on the interrelation between human and (intelligent) DSS (cf. Figure 1, middle). This is followed by a more detailed explanation of the topics involved (cf. Figure 1, bottom).

Social-technical connection. In short (from left to right), there is a growing (partially) automated monitoring of the production process or critical sub-components. By evaluating data from sensors, actuators, and/or other data suppliers, the system can detect events of importance via the analysis of data patterns. An example would be an unusually strong temperature rise with a sudden drop in valve pressure, indicating a burst valve. The DSS provides the user with a notification of the potentially detected event via the dashboard. In many AI-based systems, this includes a direct recommended action for the user. This forces the decision-maker to decide. He can either agree/ trust the recommendation of the system or reject it. In the first case he will act (maintain). In the rejection case, he will not do so. In case of uncertainty, the human user will request further information from the system.

Due to the remaining error term of AI-based systems, a socio-technical dilemma arises. This is caused in particular by the lack of traceability. It often remains unclear to the human user why the system has issued its recommendation. A decision-maker may therefore elect not to consider the system's recommendation. It is not yet clear what information the human user needs and how it must be prepared to counteract this issue. Furthermore, it remains unclear what other factors influence the decision-making process. Conversely, the intelligent assistance system remains ineffective despite its improved per-

formance. Therefore, besides the technical feasibility of intelligent, data-based maintenance approaches, addressing certain social/ psychological aspects via XAI research is crucial and requires further investigation to ensure an effective hybrid intelligence (Dellermann et al. 2019; Wanner 2021).

Human Decision-Making. Human decision-making describes a logical sequence of mental activities (Lunenburg 2010). Behind this is the ultimate goal of choosing the best possible course of action to achieve one's intentions (Eisenfuhr 2011). During the decision-making process, possible causal inferences are drawn from given premises based on known causal relationships. Examples are theoretical inferences or empirical arguments. In addition, the process is influenced by individual differences (Bruine de Bruin et al. 2007), past experiences (Juliusson et al. 2005), personal relevance (Acevedo and Krueger 2004), cognitive biases (Evans et al. 1983), and anchor effects (Tversky and Kahneman 1974). Simon (1977) published a seminal work in which he divided the subconsciously occurring process into several phases. This is the original backbone for many extensions and modifications by numerous researchers (e.g., Mazzolini 1981; Mintzberg et al. 1976; Schwenk 1984; Vari and Vecsenyi 1988). Drawing on these preliminary works, a five-part sequence can be derived, which is graphically illustrated in Figure 1 (bottom): *Goal/Problem* (1), *Information* (2), *Mental Model* (3), *Choice* (4), and *Review* (5).

First, the decision *goal* or *problem* must be identified and defined (Pounds 1969; Vari and Vecsenyi 1988). This implies the recognition and diagnosis of the problem and possible causes (Mintzberg et al. 1976). Then, the decision-maker tries to obtain the appropriate *information*. This serves as input for the generation of the *mental model* to weigh alternatives (Newstead et al. 2002; Schwenk 1984). In this phase, a simplified model of reality is generated based on the problem descriptions and the given knowledge (Johnson-Laird 1983; Jones et al. 2011). One part of this is *causal discounting*. It describes the process by which the assumed probability of an option decreases due to the attribution of a causal relationship of information with respect to a (better) alternative option (Hilton 1996). Another part is *causal backgrounding*. Here, irrelevant causes are discarded (Miller 2019), which thus corresponds to a selection process (Hilton 1996). Ultimately, alternatives are prioritized (Schwenk 1984) to select the most relevant or best solution (Hilton 1996). After the decision is made, a critical *review* of one's *choice* takes place (Dietrich 2010; Schwenk 1984). The experiences and insights are incorporated into one's mental model and can influence future decision-making (Miller 2019; Vari and Vecsenyi 1988).

Explanation Theory. Corresponding information is collected for the mental model and the included selection process. In its own context, this information often equates to rationalizations for or against a recommendation provided by an (X)AI-based DSS. An explanation is considered cognitively. Thus, it is always associated with causality (e.g., Salmon 1984). Extending this, context is crucial. For Miller (2019) this implies the properties of *contrastive*, *selective*, and *social*. *Contrastive* circumscribes the consideration of counterfactual cases, *selective* the possible cognitive biases, and *social* the transfer of knowledge through social interaction (Miller 2019). In addition, an explanation can have different forms. It is specified by its format, i.e., how it is expressed. This might be visualizations, text, or formal expressions. Further, it is specified by its form, i.e., what the explanation is about. These can be examples, patterns, features, decisions, or simplifications (Mueller et al. 2019). The act of considering an explanation or information is therefore a socially cognitive process in which knowledge is transferred in a specific form from the explainer to the recipient (Lombrozo 2006). Explanations allow recipients to revise their beliefs, but only if the explanation helps construct an alternative mental model (Einhorn and Hogarth 1986; Hilton 1996).

It is therefore important to understand what constitutes a good explanation. A variety of conceptual models exist in explanation theory. Traditional concepts argue that an explanation is good if it expresses cause-effect covariation. The same is true for the correct answer to a *why* question (Einhorn and Hogarth 1986; Hilton 1996; Lu et al. 2020; Van Bouwel and Weber 2002). However, it seems problematic that recipients may differ in their characteristics, knowledge, and intentions. Therefore, an explanation is highly dependent on the user group (Hilton 1996; Kulesza et al. 2013; Lu et al. 2020). Other approaches argue that coherence is a main criterion for a good explanation. One example of this is the 'Theory of Explanatory Coherence' (Thagard 1989). It specifies seven basic principles that explanations must adhere to in order to conform to prior beliefs and be accepted by the receiver. Furthermore, Mueller et al. (2019) list eight characteristics of explanatory coherence. However, some features appear to be more important than others. For example, Kulesza et al. (2013) have shown that completeness is more important than soundness and that oversimplification can be problematic.

Explainable AI (social). The socio-technical research of XAI must try to consider psychological and social findings concerning good explainability in addition to the technical realization of new methods. This is due to the need to make AI models explainable and to better grasp what constitutes them in their own context. The term 'explainability' itself is often also a synonym for model interpretability (Wanner et al. 2020c). In XAI research, explainability is defined, e.g., according to Dam et al. (2018) as "[...] the degree to which a human observer can understand the reasons behind a decision (e.g., a prediction) made by the model". For Ribeiro et al. (2016b), a system is interpretable if the input-output relationship can be formally i.e., logically or statistically determined to be optimal or correct. A more user-centered formulation is found in Cui et al. (2019) and Arrieta et al. (2020). For Cui et al. (2019), explainability is the ability of the system to cut down the given information gaps between itself and its intended users. According to Arrieta et al. (2020), explainability refers to the details and reasons a model provides to make its function clear or easy to understand for a given audience.

The need for explainability of (X)AI-based DSSs has several reasons. It is assumed that increased system transparency has a positive influence on the user's trust. In turn, it is only if the user trusts the system that he or she will include the information in the decision-making process, thus rendering the system effective (Dam et al. 2018; Ribeiro et al. 2016b). More specific rationales are provided by Adadi and Berrada (2018). They distinguish four motivations: explain to justify (correct decision-making), explain to control (prevention), explain to improve (models that are interpretable can be improved more easily), and explain to discover (knowledge gain). Challenges related to this include *confidentiality*, *security*, *complexity*, *accountability*, and *unfairness*. *Confidentiality* is about legal or institutional issues that must be addressed. *Security* issues imply a verification capability guarding against internal and external attacks. *Complexity* refers to the algorithm itself, attempting to explain the inner logic in a way that humans can understand. The *accountability* of the results and the check of *unfairness* of moral questions help the user to avoid wrong decisions by providing additional verification information (Arrieta et al. 2020; Felten 2017).

Implications for (X)AI Models. This constitutes several prerequisites for explainable AI models and explanatory techniques. Guidelines are provided by Ribeiro et al. (2016b). According to these, explainers must create explanations that are interpretable and easy for the user to understand. There must be local fidelity, so that explanations actually apply to the predicted instance. Furthermore, explainers are (at best) model-agnostic. Similarly, explainers should provide an appropriate global explanation to build

trust in the model (Ribeiro et al. 2016b). For their part, Arrieta et al. (2020) also lay out four recommendations. According to them, contextual factors must be considered. Examples include the purpose of the AI model and the quality of the existing technology. Extending the explanatory approach must be in line with the context or domain. This includes specific requirements, risks, needs, data resources, and knowledge. Likewise, the style of the explanations chosen should take into consideration the impact on ethics, fairness, and security. Finally, the authors advocate that the chosen explanatory approaches should always be in line with the intended user group. Therefore, the expertise and cognitive abilities of the intended user(s) must be considered (Arrieta et al. 2020).

Explainability of AI models can be manifested on two levels: global explainability and local explainability. Global explainability refers to transparency regarding the internal operations and properties of the AI model. This includes the decision model, individual algorithms, or individual components (Cui et al. 2019; Ras et al. 2018). For example, traceability can be created by an algorithm that is per-se considered explainable, such as that of a decision tree. The same applies to technical realizations such as the disclosure of feature importance by an XAI augmentation framework like SHAP. Nevertheless, these approaches often require specific knowledge concerning the meaning and contexts, so that global explainability primarily aims at explanations among AI experts (Cui et al. 2019). Local explainability or ex-post explainability, on the other hand, refers to transparency regarding the computation of the individual decision (Dam et al. 2018). Taking this further, a distinction is made between model-agnostic and model-specific. In other words, depending on the chosen algorithm specific and/ or generally applicable explanatory approaches can be realized (Arrieta et al. 2020). An overview of available explanatory techniques and approaches is provided, e.g., by Arrieta et al. (2020), Wanner et al. (2020c), Adadi and Berrada (2018), and Guidotti et al. (2018b). Summarizing these, the focus of AI model explainability is on visualizations, textual explanations, and example-based explanations (Lipton 2018).

1.3 Related Work

Several research papers have been written to address the open challenges of criticizing the lack of user orientation in (X)AI research and to provide support for the systematization, perception, and adoption of AI-based DSSs. This has resulted in a large number of contributions related to this work. The following is a brief outline of some of these efforts.

Systematization. The number of publications and the diversity in research in the field of I4.0 is very extensive (Wanner et al. 2021b). Likewise, there are surveys and literature reviews that attempt to reduce the resulting complexity for researchers and practitioners by structuring the I4.0 research field. For example, some authors try to structure application fields of a certain type of technology within I4.0, such as that of ML (e.g., Diez-Olivan et al. 2019; Sharp et al. 2018; Wuest et al. 2016). Others focus on the organization of publications of a specific sub-area such as process monitoring (e.g., Sutharssan et al. 2015; Zhou and Xue 2018) or production planning (e.g., Reis and Gins 2017; Sutharssan et al. 2015). For industrial maintenance in particular, there are a few structuring contributions for modern approaches. Zschech (2018), e.g., provides a taxonomy for maintenance analytics research publications. The author focuses on analysis techniques, data properties, and the objective pursued by a particular maintenance approach. Another example is the publication of Lee et al. (2014b). They develop a

classification framework for algorithms in the field of condition-based maintenance of rotating machinery based on existing literature.

The same problem of a large quantity and diversity of research papers is found in XAI. Few structuring articles exist, despite the high complexity of having a multitude of research areas involved, such as IS and psychology. A survey article that has also sparked a new wave of interpretive AI approaches and related explainable research efforts is that of Gunning and Aha (2019). The author is part of the Defense Advanced Research Projects Agency (DARPA) initiative, which later also did a comprehensive literature review on XAI (Mueller et al. 2019). Another comprehensive literature survey on explainable artificial intelligence was written by Adadi and Berrada (2018). They motivated their work with the changes of the Fourth Industrial Revolution, which will lead to a broad adoption of AI approaches, but might overcome problems related to AI's black-box characteristics (Adadi and Berrada 2018). Likewise, initial structuring of XAI approaches has been found to support certain areas of activity, such as medicine (Tjoa and Guan 2020). A comprehensive review and structuring that provides concepts, taxonomies, opportunities and challenges for XAI has been written by Arrieta et al. (2020).

Perception. In XAI research, the perception of explanations is of great importance. In this context, types of ML algorithms are divided into black, grey, and white boxes (Wanner et al. 2020b). Within related work, white-box models usually refer to decision trees and linear regressions, while black-box models include algorithms from the field of ANNs. Thereby, some theoretical division of common types of ML algorithms exists according to the dilemma between the two dimensions of XAI: model performance and model explainability (e.g., Angelov and Soares 2020; Arrieta et al. 2020; Dam et al. 2018; Duval 2019; Gunning and Aha 2019; James et al. 2013; Luo et al. 2019; Morocho-Cayamcela et al. 2019; Nanayakkara et al. 2018; Salleh et al. 2017; Yang and Bang 2019). In addition, there is research that deals with the changed perception of explainability in the context of different initial situations. Cui et al. (2019), for example, show that explanations are highly dependent on the types of users that the AI-based system is intended to support. A model should therefore always be designed to fit its user(s) (Cui et al. 2019). Furthermore, it is assumed that the implicit criticality of the use case is crucial when determining the need for explainability. Related to this, Rudin (2019) argues against the use of ex-post explained black-box models in use cases with high criticality situations. She justifies this by the fact that the explanatory model neither represents the original model nor provides suitable explanations for the user (Rudin 2019).

Other researchers explore components enabling an effective hybrid intelligence. This has been shown to be the most powerful form of decision-making (Dellermann et al. 2019). However, the user's confidence in the AI-based DSS plays a decisive role in this, as it directly correlates with the effectiveness of such a system (among others, Dam et al. 2018). This, in turn, depends on different criteria related to human decision-making. Here, the related work of Hoffman et al. (2018) can be highlighted in particular, which lists several important XAI metrics. For example, they point to the need for goodness of explanations and user satisfaction with the explanations. They also identify user understanding, perceived trust, and the performance of a human-XAI system as relevant. In their publication, they also offer recommendations for substituting these metrics, e.g., by providing appropriate questioning options (Hoffman et al. 2018). Another key work on this is that of Miller (2019). Here, the author elaborates on existing knowledge about the explanatory process from the perspective of a user, who is subject to

numerous cognitive biases and social expectations. In doing so, he uses prior work from the fields of philosophy, cognitive psychology/science, and social psychology (Miller 2019).

Adoption. The adoption of AI-based DSSs in industrial practice is still being met with some hesitation. Therefore, an attempt has been made to shed light on this problem by identifying adoption barriers. Results from studies indicate that high implementation effort, lack of data, and a lack of necessary knowledge are seen as the most important barriers from a technical and organizational perspective (Chui et al. 2018; Duscheck 2017; Milojevic and Nassah 2018). However, psychological barriers also seem to be of great importance. In particular, the resulting social aspects, such as technology anxiety and alienation from 'known work' due to lack of understanding and trust, are cited as resistance features (Mokyr et al. 2015; Reder et al. 2019). Reder et al. (2019) shows that transparency of the decision-making behind AI-based recommendations is a key factor here. Thus, it is assumed that improved transparency of such systems will increase the likelihood that employees will adopt AI-based decision support tools (e.g., Dam et al. 2018; Reder et al. 2019). However, the studies themselves are often conducted by consulting firms. In contrast, there is a lack of scientific studies that explore the relative importance of individual factors. In IS research, there are extensive empirical methods available (Benbasat and Barki 2007). Most notably, adoption research using the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) seems to be suitable. Here, the contributions of Venkatesh and his co-authors are of central importance (Venkatesh et al. 2003; Venkatesh et al. 2016).

Studies on IT artifact adoption using TAM/ UTAUT exist mainly for e-commerce, social media, and mobile technologies, as shown in a comprehensive review by Rad et al. (2018). Corresponding works investigating users' willingness to adopt new technologies based on AI are less numerous to date (exceptions include e.g., Fan et al. 2018; Hein et al. 2018; Portela et al. 2013). The same is true for the industrial application context. Nevertheless, for example, there are studies on users' adoption readiness in production toward intelligent robots (e.g., Bröhl et al. 2016; Lotz et al. 2019). Bröhl et al. (2016), e.g., examining the extent to which the willingness of users to collaborate with passive robots and active robots differs. For industrial maintenance in particular, Wang et al. (2016c) investigate aviation students' experiences with Augmented Reality (AR)-based training. Similarly, Jetter et al. (2018) assess the adoption readiness toward market-ready AR tools for employee training in automotive maintenance. Related work on adoption research at the intersection of AI and industrial maintenance is rather small. Amadi-Echendu and De Wit (2015) investigated factors that influence the readiness of users of an intelligent maintenance DSS to adopt the system. They found that ex-ante user training had an especially strong positive influence. Kluge and Termer (2017) studied user readiness for a mobile fault-finding application among maintenance employees.

In addition to the 'official adoptions research', there are research efforts to better understand the impact of AI-based DSSs on human decision-making. Here, the two target variables confidence and performance seem particularly important. For example, Zhang et al. (2020) conduct two experiments to investigate the effect of confidence scores and local explanations on user prediction accuracy and confidence. Similar studies can be found in Westbrook et al. (2005), Zhou et al. (2015a), and Heath and Gonzalez (1995). In all cases, additional information seems to improve confidence in the decision, but not performance. However, there are also studies that have demonstrated this improvement in performance in their respective contexts (e.g., Dellermann et al. 2019; Lai and Tan 2019), validating the aim of an effective hybrid intelligence. Additionally, these studies are strongly related to explanatory perception. For ex-

ample, Nourani et al. (2019) show that adequate, human-centered provision of explanations have a positive impact on the user's decision-making ability. However, studies such as Poursabzi-Sangdeh et al. (2018) and Schaffer et al. (2019) suggest that too much information leads to the opposite effect. The user becomes overwhelmed, which reduces the influence of the AI system.

1.4 Methodological Foundation

This chapter serves to provide a better understanding of the methodological context of this thesis and the related research method foundations.

The content is subdivided into *IS Research Foundations* and *Thesis Research Methods*. The former describes the two main fields of IS research as well as their holistic linkage by the IS research framework (cf. Section 1.4.1). The latter is a short summary of the most important research methods applied in this thesis (cf. Section 1.4.2).

1.4.1 IS Research Foundations

The IS research lies at the intersection of economics and computer science, with tools from real, formal, and engineering sciences (Wilde and Hess 2007). Below, the principles of IS research are given first. This is followed by a more specific discussion of the two main types of research and the overarching connection.

IS Research Principles. Fundamentally, the goals of analysis, explanation, prediction, and prescriptiveness are pursued within IS research (Gregor 2006). Thus, the aim is to derive new insights for and from information and communication systems in business, government, and the private sector (WKWI 1994). The research itself is divided into two main scientific paradigms for gaining knowledge (March and Smith 1995): Behavioral Research (BR) and Design Science Research (DSR) (Winter 2008). Both are separate but also connected to one another (Hevner et al. 2004). The BR paradigm relies on truth and its corresponding exploration. In contrast, the DSR paradigm seeks to create artifacts that are effective against a defined problem (Bichler 2006). The close connection of both paradigms results from the lack of separability of the two endeavors: Truth influences design, while utility contributes to the refinement of theory (Hevner et al. 2004).

Behavioral Research. BR originates from natural science research methods (Hevner et al. 2004). It strives to achieve truth or explanatory power. Here, assertions must be consistent with observed facts, and the ability to predict future observations is a sign of explanatory success. Progress is made when new theories provide deeper, more comprehensive, and more accurate explanations (March and Smith 1995). To this end, efforts are made to develop theories – and an understanding thereof – that explain or predict the organizational and human phenomena associated with the analysis, design, implementation, management, and use of information systems (Hevner et al. 2004). Therefore, BR methods analyze information systems with the overarching goal of uncovering cause-effect relationships (Österle et al. 2010). Such theories inform researchers and practitioners about the interactions among people, technology, and organizations that must be managed for an IS to become effective and efficient in an organization. These theories consequently affect and are affected by IS design decisions made with respect to

the system development methodology used and the functional capabilities, information content, and human interfaces implemented in the IS (Hevner et al. 2004).

Design Science Research. DSR has its origin in the engineering sciences and the sciences of the artificial (Simon 1996). It comprises instructions for action regarding the design and operation of information systems as well as research-driven IS innovations (Österle et al. 2010). In this context, the term 'design' describes the deliberate use of organizational resources to achieve goals (Bichler 2006). Hevner et al. (2004) therefore refer to it as a problem-solving paradigm, with the goal of solving problems through artifacts that are created and evaluated for this purpose. Typical examples of such artifacts are constructs, models, methods, and instantiations (March and Smith 1995). The creation of artifacts uses insights from BR and usually builds on its theories, which are applied, tested, modified, and extended through the researcher's experience, creativity, intuition, and problem-solving ability (Markus et al. 2002). However, the design of useful artifacts is complex, requiring creative advances in areas where existing theory is often inadequate. Development progress allows the expansion of human problem-solving and organizational capabilities by providing both intellectual and computational tools (Hevner et al. 2004).

IS Research Framework. The interrelations and differences between the main scientific IS paradigms of BR and DSR are illustrated in Figure 2. This is further divided into three parts: environment (1), IS research (2), and knowledge base (3).

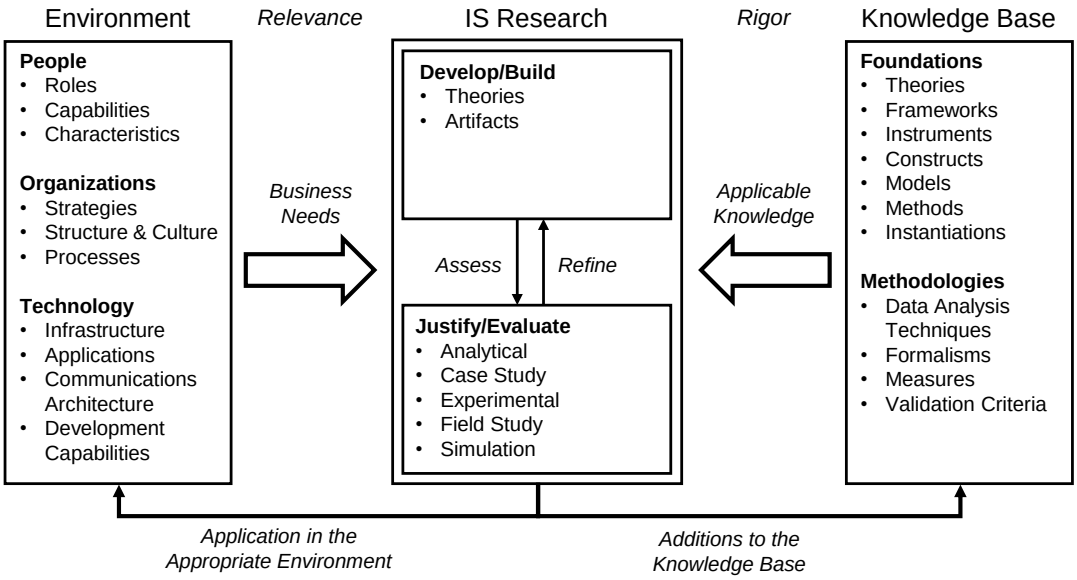


Figure 2: IS Research Framework (Hevner et al. 2004)

The environment (1) is to be understood as a problem space in which the objects of research (people, organizations, and existing/planned technologies) are located and operate (Simon 1996). From this, objectives, tasks, problems, and opportunities are derived, which define perceived, validated, and technologically aligned business requirements (Hevner et al. 2004).

IS research (2) takes these requirements as a starting point to develop a solution in two complementary phases. BR pushes the development and justification of theories that explain or predict the phenomena associated with business requirements. DSR is concerned with designing and evaluating research artifacts that are constructed to address the business requirements (Hevner et al. 2004).

Both scientific approaches are conducted using the existing knowledge base (3). Examples of applicable knowledge include foundations, research methods, and theory. Depending on the maturity of the theory (or theories), their truth can be integrated into the design or must be further researched by following additional cycles to develop/build and justify/evaluate. The results achieved through the research efforts are, in turn, integrated into the existing knowledge base as additions (Hevner et al. 2004).

1.4.2 Thesis Research Methods

To gain new insights, IS research uses different qualitative and quantitative research methods (Becker and Niehaves 2007). Nevertheless, research often uses both approaches in combination. In addition to the basic understanding of the two types, the research methods central to this thesis will also be discussed below. It should be noted that the respective research methods are concretized by specific research techniques, frameworks, and methodologies and thus, often include various design options.

Qualitative vs. Quantitative. Qualitative research methods originate from the natural sciences, while quantitative research methods have their origin in the social sciences (Myers and Avison 2002). The former aims at descriptions, interpretations, and the understanding of cause-effect relationships. In addition, qualitative research methods often serve to establish a classification or a typology. Also, they are a common means to hypothesize. Usually this is achieved with a small sample or individual cases analyzed by ‘experts’ of the relevant domain. The survey itself is typically conducted orally, often with a low degree of standardization of the interview technique (Lamnek and Krell 2010; Winter 2000a). Examples of qualitative IS research methods are the Delphi method, qualitative interviews, or case studies (cf. Patton 2014; Sackman 1974; Yin 2017). In quantitative research methods, the object of investigation is often known, hypotheses are set up and/or evaluation criteria are given. Here, the aims include the objective measurement and quantification of facts, the testing of hypotheses, the verification of statistical correlations, and the achievement of representative results. The survey itself is conducted predominantly in written form, with mostly fully standardized or structured elaboration. The typical scope encompasses large samples and numerical data (Lamnek and Krell 2010; Winter 2000b). Quantitative research methods in IS research include, for example, experiments, questionnaires, and observation (cf. Leung and Shek 2018; Röbken and Wetzel 2020).

Qualitative Methods. The design of qualitative interviews and case studies are relevant qualitative methods for the purpose of this thesis.

A qualitative interview is a method of intentionally interviewing other people in a manner more structured than informal conversations. It is mainly conducted in the form of guided interviews with a predefined questionnaire, a setting in which the interviewer takes on the role of an investigator. The degree of standardization and structuring of the questionnaire depends on the particular form of the interview. In order to deduce certain motives, problems, or opinions of the interviewees concerning the object of investigation, the questions are preferably formulated in an open way (Hug and Poscheschnik 2010; Lamnek and Krell 2010; Mey and Mruck 2011; Röbken and Wetzel 2020).

A case study is a research method used to examine a specific case in its real-world context up close, in depth, and in detail. The main objectives are theory building, derivation of commonalities, state of the art research, or implementation to achieve elementary theories (building blocks). Types of case studies

include illustrative, exploratory, cumulative, or critical single case studies. A case study may include single or multiple cases. It may also incorporate or pave the way for additional quantitative research methods (Stake 1978; Yin 2017; Zainal 2007).

Quantitative Methods. The design of questionnaires and experiments are relevant quantitative methods in the context of this thesis.

A survey or questionnaire uses statistical methods to collect objective (unbiased) quantitative data from a large pool of respondents based on predefined criteria or hypotheses. It can also be used to compare multiple groups based on specific variables. Therefore, standardization is high with many predefined characteristics. In addition, the sample size must be large enough to obtain representative results. The size depends on the size of the reference population and the probability of error. Surveys can be conducted orally in the form of an interview or in writing. Online surveys are also common. Subtypes include cross-sectional surveys (a different variable, same time), longitudinal surveys (same variables, over different durations), or correlational surveys (causal relationship between two or more variables) (Leedy 1989; Leung and Shek 2018; Röbken and Wetzel 2020).

An experimental research design is a collection of techniques in which the researcher specifies various treatments or conditions and studies their effects. The experiment is based on one or more theories that have not been proven in the past and is often used in the natural or social sciences. Necessary conditions for scientifically valid implementation are a randomly selected and assigned sample of participants (experimental group vs. control group), an independent variable (treatment variable), and a dependent variable (criterion variable) that can be measured identically for all groups in the study (Leedy 1989; Leung and Shek 2018; Röbken and Wetzel 2020).

Additional Methods. Some other common scientific IS methods exist in addition to those previously mentioned. For this work, the systematic review is particularly important.

A systematic review is a structured collection of secondary data with the purpose of processing and/or analyzing them. Secondary data are usually existing literature sources that fulfill certain criteria. Overall, many types of systematic review exist (Booth et al. 2016; Grant and Booth 2009). It can be either qualitative or quantitative, or even a mix of several review types (Grant and Booth 2009). Some of them are also frequently used in IS research. For example, literature reviews are found in many IS publications as a means of processing the existing knowledge in one's own research context (Grant and Booth 2009). For this purpose, the two approaches – as set out by Webster and Watson (2002) and vom Brocke et al. (2009) – are particularly widespread. Another popular subtype are conceptual reviews, also called mapping reviews. These try to group the systematically reviewed secondary data appropriately on the basis of similarities (Grant and Booth 2009). Often, further analytical investigations follow. A common practice similar to this in IS research is the taxonomy development procedure as described by Nickerson et al. (2013).

1.5 Research Design

This thesis seeks to further extend the knowledge of related work and to address identified weaknesses. Its primarily goal is to conduct the often-requested social-technical investigation of (X)AI from a user's perspective. The elaboration is subject to a systematic research design (cf. Figure 3).

Research Focus	Research contributions to support the systematization, perception, and adoption of AI-based DSSs in Industry 4.0.	IS Research Methods
Systematization	RO1: Systematization of (X)AI techniques for Industry 4.0 a) Structuring the variety of BA techniques for I4.0 b) Identifying temporal trends of BA techniques in I4.0 c) Elaborating the state of the art of XAI transfer techniques d) Implementing an exemplary XAI transfer in I4.0	**Design Science Research** Systematic Review, Interview, Case Study
Perception	RO2: Perception of (X)AI explanations from a user's perspective a) Endorsing the information perception of users from credibility research b) Positioning of common ML models by performance and explainability c) Assessing common ML models by explainability and comprehensibility	**Behavioral Research** Interview, Experiment, Questionnaire
Adoption	RO3: Adoption factors of (X)AI-based DSS for Industry 4.0 a) Weighting of factors for users' selection of an appropriate DSS tool b) Evaluating the relative importance of adoption factors for users c) Testing the effects of (X)AI augmentations on human decision-making	**Behavioral Research** Interview, Case Study, Questionnaire

Figure 3: Summary of the Research Design

In this thesis, contributions are made to the ultimate research objective (RO) of systematization, perception, and adoption of (X)AI-based DSSs in Industry 4.0. These research objectives are further subdivided into research intentions for each of the three sub-areas mentioned (RO1-RO3). The main intent of each RO, in turn, is to be achieved through various related topics of interest (a-c/d). Finally, additional information on IS research methodologies is provided. The type of IS research is mentioned, along with the research methods used.

RO1: Systematization. The first RO should support researchers and practitioners with a systematization of (X)AI techniques, especially for industrial maintenance. This addresses the multitude and diversity of existing research contributions in the context of Industry 4.0 and explainable AI by structuring the knowledge. This section is located in the IS research course of DSR, trying to solve this business requirement iteratively by structuring and enhancing existing knowledge.

First, an attempt is made to structure the broad research area of I4.0, which is characterized by various BA techniques (1a). Subsequently, a temporal analysis of the research development is undertaken in order to derive trends (1b). Both contributions are employed in the course of a systematic review. On the one hand, a taxonomy development is undertaken. On the other hand, a cluster analysis is applied. As these trends in applied BA methods are evolving toward DL, a review of XAI techniques follows on how these black-box models can be transformed into white-box models (1c). This is processed through a structured literature review. Finally, an exemplary implementation of such an XAI transition is attempted. This represents a case study, using data from a physical factory simulation, in combination with interviews (1d).

RO2: Perception. The second RO intends to provide new insights regarding the user's perception of (X)AI model explanations. This addresses the often-criticized lack of socio-technical investigation within explainable AI research in order to better understand the requirements and design of suitable explanation from a user's perspective of (X)AI-based DSS. This section is located in the IS research course of BR. Its aim is to improve upon the inadequate theories of explanation perception in order to meet (future) business requirements (cf. RO1).

First, existing knowledge from the area of credibility research is reviewed and transferred to the context of (big) data processing (2a). The results are developed through an unstructured literature review and subsequent surveys. The latter comprises a semi-structured expert interview and a quantitative questionnaire. The data analysis is based on a derived structural equation model (SEM). Then, the different ML types are examined with respect to the assumed trade-off between model performance and model explainability (2b). Finally, the extent to which the user's perceived explainability of the model is consistent with comprehensibility is examined (2c). The latter two research discourses mentioned correspond methodologically to a research experiment with combined methods. This includes a technical setup and related measurement. Furthermore, a quantitative survey and the associated data analysis through descriptive and/or inferential statistics are used.

RO3: Adoption. The third RO proposes to shed light on the user's willingness to adopt an (X)AI-based DSS for practical tasks, especially in the context of I4.0. The research contributions aim to form a better understanding of which factors are important and in what relative trade-off. Thus, it is about deriving findings that will contribute to the removal of adoption barriers and the strengthening of positive influences. This section is located in the IS research course of BR. It is intended to further advance the theories of RO2 regarding explanation perception by adding another perspective that is important to meeting (future) business requirements.

First, it is an examination of the importance of potential adoption factors on human adoption propensity (3a). To this end, the relative importance of the sections of effort, performance, and explainability for the system selection decision of an AI-based DSS in the application context of I4.0 is investigated via an Analytical Hierarchical Process (AHP). Likewise, inquiries are made into how and which of these factors influence the intended user's readiness for adoption of such systems (3b). For this purpose, a modified UTAUT model for XAI research is formed first. This is followed by structured expert interviews to effectively measure the constructs derived in the use case of I4.0. The related results are used for further quantitative questionnaires, using an SEM approach with partial least squares (PLS) calculations. Finally, the effects of (X)AI augmentations on human decision-making are tested (3c). An I4.0 case study is used in combination with a quantitative questionnaire and inferential statistics.

1.6 Thesis Structure

The structure of the thesis follows a sequential flow and includes six main chapters (cf. Figure 4). The first main chapter (C1) constitutes the introduction of this research publication. It comprises the motivation for the research (C1.1), followed by the theoretical (C1.2) and methodological foundations (C1.3). Subsequently, an overview of the most important preceding works is provided for the sake of context (C1.4), followed by the research design and related scientific background of the research contributions (C1.5).

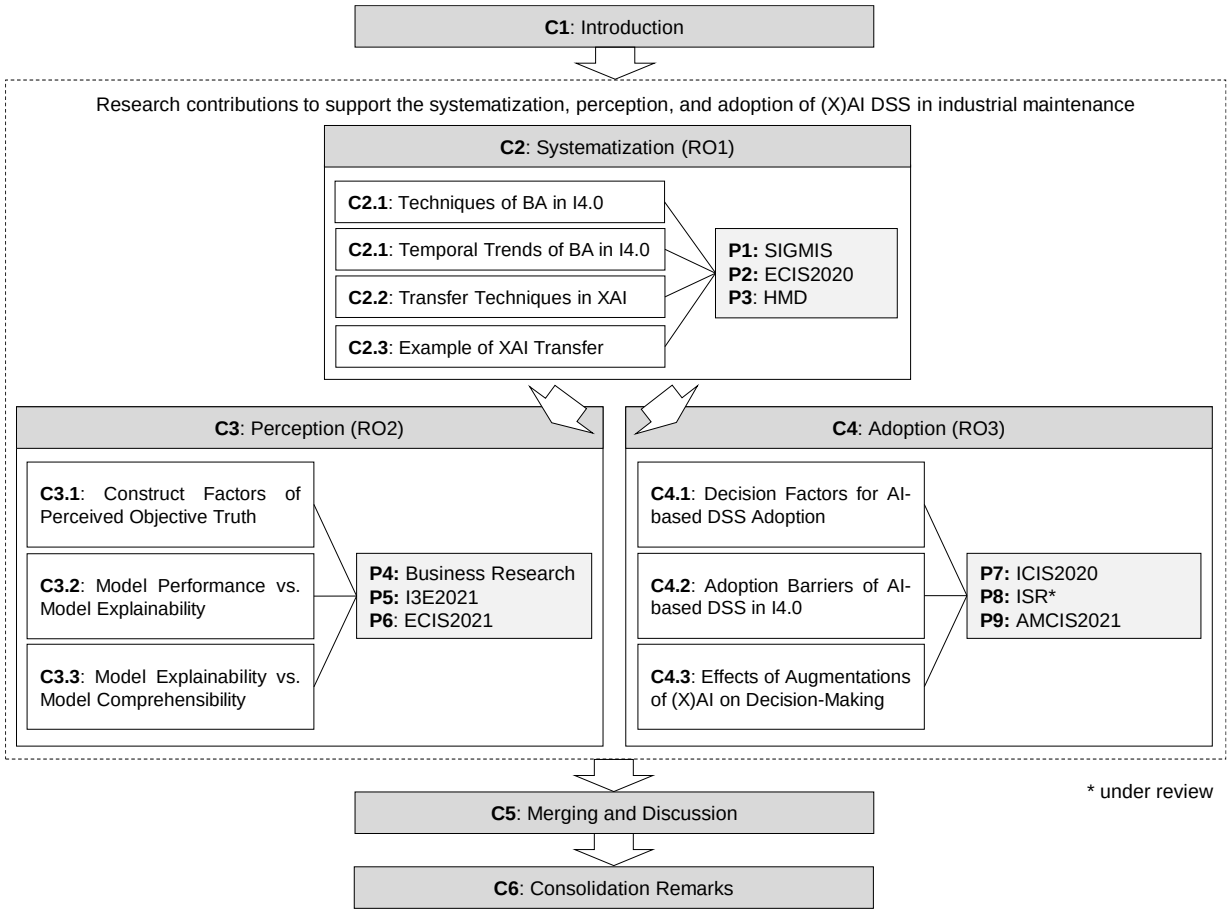


Figure 4: Structure of the Thesis

The scientific work can be found in the following three main chapters, which are structured according to the main topics: systematization (C2), perception (C3), and adoption (C4). Each of these sections contains several scientific publications that constitute the research contributions and are related to one another. These publications were all written between 2018 and 2021 and are part of a cumulative research process. Furthermore, each of these main chapters contains several subsections that represent the sub-questions of interest to the respective RO (cf. Section 1.5). As these are answered by scientific publications, the related scientific medium is listed after the publication identifier (P#: publication media). The papers themselves are either already published or under review (*).

In terms of content, every main chapter starts with a brief outline of the scientific background, related problems and objectives, and its included publications.

Chapter 2 contains research contributions to the systematization of the research context (RO1). This includes the systematization of BA techniques and temporal trends in I4.0 based on the findings of publication P1 (cf. C2.1), the structured review of XAI transfer techniques as a result of publication P2 (cf. C2.2), and a case example of an XAI transfer by the content of publication P3 (cf. C2.3).

Chapter 3 addresses the topic of the limited social-technical (X)AI research by evaluating the perception of (X)AI explanations from a user perspective. This includes the validation of the influence of data quality factors on the perceived objective truth in a modern data context by referring to publication P4 (cf. C3.1), a proof of the theoretically assumed trade-off between model performance and model

explainability with the help of publication P5 (cf. C3.2), and a critical evaluation of the correlation between model explainability and model comprehensibility as a result of publication P6 (cf. C3.3).

Chapter 4 deals with the adoption of such (X)AI-based DSSs in practice. It is the shared intention of both vendors and managers to make progress with respect to digitization. This includes examining the relative importance of decision factors for the selection process of such systems with the help of publication P7 (cf. C4.1), the study of factors influencing employees' readiness to adopt (X)AI-based DSSs through publication P8 (cf. C4.2), and studying the effects of augmentations of (X)AI on human decision-making through publication P9 (cf. C4.3).

Chapter 5 discusses the scientific findings developed. To this end, a link between the publications and results are first provided. Subsequently, the publications' results are put into the context of related work to critically reflect upon the scientific contributions.

In the last section (C6), concluding remarks are given. These comprise a short summary of all publications and their respective limitations. In addition, an outlook on possible future research is offered, which is linked to the developed research contributions.

2 Systematization of the Field

Table 1: Research summary of Chapter 2

Research objectives			
RO1	Systematization of (X)AI techniques for Industry 4.0		
1a	Structuring the variety of BA techniques for I4.0		
1b	Identifying temporal trends of BA techniques in I4.0		
1c	Elaborating the state of the art of XAI transfer techniques		
1d	Implementing an exemplary XAI transfer in I4.0		
Reference to original work			
Wanner, Wissuchek, Welsch, et al. (2021)		Publication P1	Chapter 2.1
Wanner, Herm, Janiesch (2020)		Publication P2	Chapter 2.2
Wanner, Herm, Hartel, et al. (2019)		Publication P3	Chapter 2.3

The Fourth Industrial Revolution is responsible for tremendous changes throughout the entire economic sector. Value networks, business models, and business operations have been affected. In particular, the profitable utilization of the accrued data that can be utilized by smart objects seems to be decisive. Techniques from the field of business analytics promise great added value (Fay and Kazantsev 2018). Nevertheless, it seems that many companies have technical and organizational problems in realizing this change (LaValle et al. 2011; Zhou et al. 2014). In contrast, numerous research contributions can already be found on the topic of making data useful in I4.0 environments through BA techniques (e.g., Arık and Toksarı 2018; Aydın et al. 2015; Aydin and Guldamlasioglu 2017). These have the potential to bring about an improvement in the situation and enable strategic planning. So far, however, there seems to be a lack of structured processing.

In addition to a possible expansion of automation, these smart objects should also interact effectively with humans (Grover 2019; Hermann et al. 2016). This requires that an AI-based system be designed in such a way that the human employee can consider and validate the advice given (Arrieta et al. 2020). Prior research here emphasizes the importance of the explainability of intelligent assistants to enable effective human-machine collaboration (cf. Dellermann et al. 2019). In addition to decision quality, explainability seems equally important from a psychological perspective. A lack of transparency can lead to a lack of trust in system recommendations, which in turn leads to non-consideration by the user (e.g., Dam et al. 2018). Possible transfer techniques for creating such transparency already seem to exist. However, these have not yet been worked up in a structured way.

Continuing the problem of the lack of explainability in the context of I4.0 applications, additional factors seem necessary for the implementation of such application possibilities. Both the technical and the psychological problems must be understood in order to address them effectively. This seems particularly interesting in that until now, for example, industrial maintenance staff have primarily performed their tasks based on experience, and thus, their intuition (Wanner et al. 2019a). On the one hand, a change

from subjectivity to an approach that is as objective as possible (data-based) appears to offer great potential for improvement. On the other hand, routines and knowledge are alienated, which requires strong reasoning and psychological sensitivity (Mokyr et al. 2015). IS research usually tries to investigate such application-oriented research via case studies (among others, Chatzimparmpas et al. 2020; Cheng et al. 2020; Ha et al. 2020).

To this end, there seems to be a particular need for a structured reappraisal of (X)AI techniques for I4.0 (RO1, cf. Table 1). Chapter 2 therefore serves to provide the reader with a structured reappraisal of the diversity of research into BA techniques for I4.0 application areas (1a). Linked to this, respective temporal trends are highlighted to identify disruptive technologies (1b). An important one of these is represented by Deep Learning (DL) techniques, which offer considerable comprehensibility of the computational logic and results for the user. In order to know possibilities for their explanation via XAI transfer techniques, a structured elaboration, which has been missing so far, seems to be worthwhile (1c). An exemplary implementation of such a transfer and the associated problems are demonstrated in an application case (1d).

2.1 Business Analytics in Industry 4.0

Abstract. Fueled by increasing data availability and the rise of technological advances for data processing and communication, business analytics is a key driver for smart manufacturing. However, due to the multitude of different local advances as well as its multidisciplinary complexity, both researchers and practitioners struggle to keep track of the progress and acquire new knowledge within the field, as there is a lack of a holistic conceptualization. To address this issue, we performed an extensive structured literature review, yielding 904 relevant hits, to develop a quadripartite taxonomy as well as to derive archetypes of business analytics in smart manufacturing. The taxonomy comprises the following meta-characteristics: application domain, orientation as the objective of the analysis, data origins, and analysis techniques. Collectively, they comprise eight dimensions with a total of 52 distinct characteristics. Using a cluster analysis, we found six archetypes that represent a synthesis of existing knowledge on planning, maintenance (reactive, offline, and online predictive), monitoring, and quality management. A temporal analysis highlights the push beyond predictive approaches and confirms that deep learning already dominates novel applications. Our results constitute an entry point to the field but can also serve as a reference work and a guide with which to assess the adequacy of one's own instruments.[1]

2.1.1 Introduction

Driven by technological innovations such as cyber-physical systems (CPS) and the (Industrial) Internet of Things (IoT), the age of the fourth industrial revolution is bringing disruptive and radical changes to

[1] This paper will be published at the SIGMIS journal as 'A Taxonomy and Archetypes of Business Analytics in Smart Manufacturing' (Wanner et al. 2021, forthcoming). A preprint is available at https://arxiv.org/abs/2110.06124. The related supplementary material is given in Appendix III.

value networks, business models, and business operations in manufacturing. Thereby, the physical world has become linked to digital entities. Smart objects communicate with each other and humans in real time (Hermann et al. 2016), leaving massive amounts of digital traces, also termed "big data", which are the vehicle for intelligent automation (Grover 2019) and novel business analytics (BA) applications to enable so-called smart manufacturing. The successful application of BA in smart manufacturing can lead to cost advantages, increased customer satisfaction, and improvements in production effectiveness and quality (Fay and Kazantsev 2018).

Studies confirm that a majority of organizations are aware of the importance of BA in smart manufacturing (Haas 2018). However, only a small proportion apply advanced analytics or fully exploit its potential (Derwisch and Iffert 2017; Henke et al. 2016). This can be attributed to high technological and organizational barriers as well as substantial implementation costs (LaValle et al. 2011; Zhou et al. 2014). While there has been a delay in the adoption of advanced analytics in practice, researchers have already embraced applications of BA in smart manufacturing with a variety of different research efforts (e.g., Arık and Toksarı 2018; Aydın et al. 2015; Aydin and Guldamlasioglu 2017) that have not yet been systematized.

With our research, we tackle this issue and identify two underlying problems: i) lack of a holistic conceptualization of the area of research and ii) formidable complexity-related barriers for practitioners.

As a way of structuring areas of interest, taxonomies have been proven useful in both the natural and social sciences. They are increasingly being used in information systems research as they enable the conceptualization and classification of objects (Nickerson et al. 2013) and can serve as theories (Gregor 2006) or for theory building (Bapna et al. 2004; Doty and Glick 1994). Hence, we deem them a suitable artifact for our research objectives. Furthermore, the identification of recurring patterns and the establishment of reusable knowledge can support both researchers and practitioners (Brodsky et al. 2017; Zschech 2018). Recurring patterns represent guidelines or templates and enable the synthesis of existing knowledge in a cumulative form to extract specific archetypes (Russo 2016).

As of today, there is an apparent knowledge gap with respect to common ground for central concepts to integrate perspectives and capabilities, as well as to assess the transformative potential of BA for smart manufacturing. To address this gap, we extend the conceptualization of BA in this context by discerning distinct archetypes of analytics applications based on their common characteristics and exploring their importance for smart manufacturing. Taxonomies are not static and set in stone, but rather evolve over time as a research domain shifts its priorities (Nickerson et al. 2013). How a research domain has changed in the past, how interest has shifted over the years, and the direction of current research trends are not readily apparent from the taxonomy itself. To address this, we perform a temporal analysis to both demonstrate and visualize how the taxonomy's inherent structure and the derived archetypes or recurrent patterns have evolved. While enabling a coherent understanding of the past and current priorities, this also reveals research gaps and possible research trends that may gain traction, empowering both researchers and practitioners to position their work as well as anticipate future considerations.

We summarize these objectives with the following three research questions (RQ):

RQ1: What is a taxonomy that enables to conceptualize and structure the application of business analytics in smart manufacturing?

RQ2: What archetypes of business analytics in smart manufacturing can we derive from the taxonomy and its underlying data?

RQ3: Which temporal variations or trends can be distinguished for business analytics in smart manufacturing?

We analyzed 904 articles on smart manufacturing to build and validate our taxonomy, derive archetypes, and understand temporal variations in research. Through our research, we address two user groups: researchers and practitioners who create and assess BA artifacts and theories. Novices especially can benefit from the comprehensiveness of our survey when first entering the field. By answering our research question, we provide the following concrete contributions to the fields of BA and smart manufacturing.

(1) We create a taxonomy that acts as a theory-building artifact for BA in smart manufacturing research to support structuring the scientific discussion and to enable scientists new to the field to access a comprehensive overview of relevant dimensions and characteristics. For example, these can be used as a codebook for labeling the data and for automated explorative analysis.

(2) We use cluster analysis to derive and analyze archetypes of BA in smart manufacturing present in contemporary research. These help to bring structure to the field and enable us to understand which facets of BA exist in smart manufacturing, how they are composed, and how distinct areas (e.g., production monitoring and security surveillance) may inspire each other through their use of similar techniques such as real-time analysis.

(3) Finally, our survey enables us to see how research has evolved over time and to discover that certain methods, such as deep learning, have experienced an unprecedented uptick of research innovation. Discussion of the results allows for a better understanding of past and current priorities in the field. Likewise, it becomes possible to evaluate research trends, which helps researchers and practitioners alike to classify, structure, and evaluate their work. In addition, our results can serve as a guide for both customers and vendors of BA in smart manufacturing to classify, compare, and evaluate existing applications, as well as design new applications with explicit consideration of relevant features for the intended type of application.

For this purpose, we provide the theoretical background necessary to establish the context of our work in Section 2.1.2. Section 2.1.3 comprises our research methodology. We answer RQ1 in Section 2.1.4 by describing the data collection, building the taxonomy, and introducing the taxonomy artifact. We answer RQ2 in Section 2.1.5 based on a cluster analysis and discussion of the identified archetypes. Subsequently, we answer RQ3 in Section 2.1.6 by using time analysis on both the taxonomies' characteristics and the respective archetypes. In Section 2.1.7, we discuss our contributions before closing with a conclusion and an outlook.

2.1.2 Context and Theoretical Background

While we consider all kinds of BA methods for our study, we only examine those relevant to the context of our research (Johns 2006), that is, smart manufacturing. This contextualization enables us to link our observations to the point of view of smart manufacturing and its related facts (Rousseau and Fried 2001). In order to do so, in the following we highlight those facts that define this field and determine the significance and appearance of BA applications. Context, in this sense, comprises organizational and

technical characteristics such as application areas, data origin and handling, as well as the intentions underlying the use of BA. This context provides the *constant* that surrounds our research (Johns 2006). Consequently, as context we introduce the age of the fourth industrial revolution and the cornerstones of smart manufacturing. Furthermore, we introduce the topic of business analytics and its approaches, as well as an overview of related scientific surveys.

2.1.2.1 Context and Theoretical Background

Technical innovations have continuously advanced industrialization. Figure 5 classifies these advances into four evolutionary steps: i) the introduction of mechanical production facilities using hydro- and steam power at the end of the 18th century, ii) the introduction of the division of labor and mass production using electric energy at the end of the 19th century, and iii) the use of electronics and IT to further automate production in the mid-20th century. Today, the iv) fourth revolutionary industrial change is already in progress and has enabled the ubiquitous connectivity of CPS through the Industrial IoT (Bauer et al. 2014).

CPS link the physical world with the digital world. They comprise objects, devices, robots, buildings, and products, as well as production facilities that feature communication capabilities through system and user interfaces, capture their environment through sensors, process data, and interact with the physical world through actuators (Bauernhansl 2014; Broy 2010). CPS are interconnected, enabling communication and data exchange (Broy 2010; Vaidya et al. 2018) to control and monitor the physical processes (Broy 2010; Lee 2008). The Industrial IoT is the underlying communication and interaction network for physical objects on shop floors (Gubbi et al. 2013).

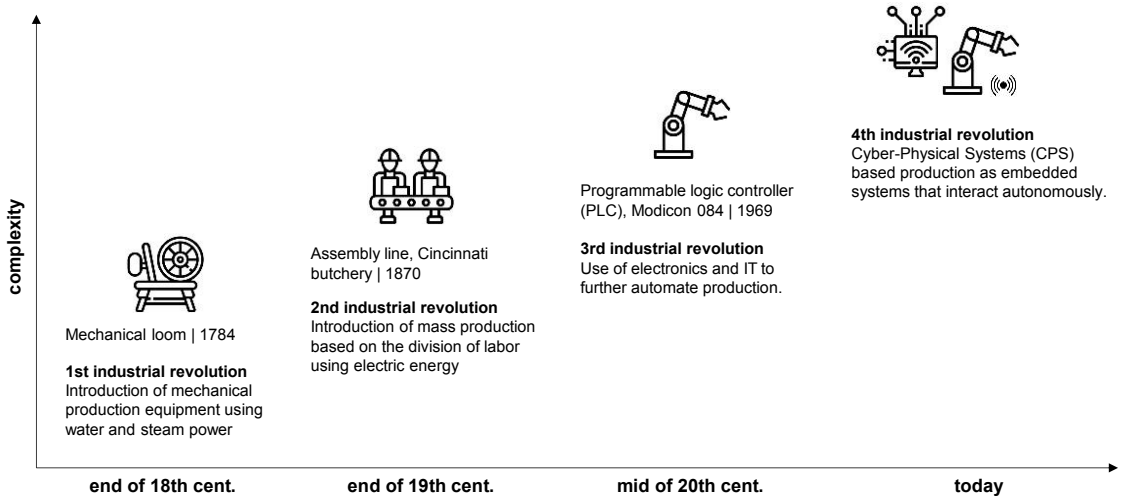


Figure 5: Evolution of Industrial Revolution (cf. Bauer et al. 2014)

Although several definitions for this fourth industrial revolution exist, there is no consensus on its constituent properties (Bauer et al. 2014; Bauernhansl 2016; Hermann et al. 2016). In addition to the German (*Industry 4.0*) and U.S. (*Advanced Manufacturing*) initiatives, comparable efforts to establish high-tech manufacturing are taking place in France (Conseil national de l'industrie 2013), the UK (Foresight 2013), South Korea (Kang et al. 2016), the EU (Europäische Kommission 2016), Singapore (National Research Foundation 2016), and China (Li 2015).

2.1.2.2 Smart Manufacturing

While Industry 4.0 and Advanced Manufacturing designate initiatives undertaken as part of the fourth industrial revolution, the term *smart manufacturing* predominates as a description of production in so-called smart factories (e.g., Chiang et al. 2015; Chien et al. 2014a; Chien et al. 2014b; Chien et al. 2013). Other terms denoting related concepts are the *Industrial Internet* (Evans and Annuziata 2012; Li et al. 2017), *integrated industry* (Bauernhansl 2016), *intelligent manufacturing* (Zhong et al. 2017), *cloud manufacturing* (Liu and Xu 2017), and *smart industry* (Haverkort and Zimmermann 2017; Kaur and Sood 2015). Utilizing Hermann et al.'s quantitative and qualitative literature analysis to structure the field (Hermann et al. 2015; Hermann et al. 2016), we define smart manufacturing as "a collective term for technologies and concepts of value chain organization. Within the modular structured smart factories of Industry 4.0, CPS monitor physical processes, create a virtual copy of the physical world, and make decentralized decisions. Over the IoT, CPS communicate and cooperate with each other and humans in real-time" (Hermann et al. 2015).

Thus, smart manufacturing takes place in an interconnected industrial environment based on CPS and the Industrial IoT. It exhibits several additional characteristics of interest for researchers and practitioners. First and foremost, smart manufacturing takes place in a value network, that is a system of individual value creation processes, which is realized by autonomous, legally independent actors. Its integration provides flexibility, new business opportunities, chances for (partial) automation, as well as intelligence and interchangeability to address greater manufacturing complexity, dynamics-based economics, and radically different performance objectives. Its networked, real-time, information-based setup transforms reactive responses into predictive or even prescriptive approaches, shifts the focus from incident response to prevention, and replaces vertical decision-making with distributed intelligence in order to enable local decision-making with global impact (Davis et al. 2012).

Smart manufacturing relies on several key technologies. Apart from CPS and the IoT, most authors include cloud computing (Mell and Grance 2011) and (big) data analytics (Müller et al. 2016) as central enablers for smart manufacturing. Furthermore, technologies such as cybersecurity (Wells et al. 2014), additive manufacturing (Kang et al. 2016; Thiesse et al. 2015), the Internet of Services (Terzidis et al. 2012), visualization technologies (Paelke 2014; Posada et al. 2015), and simulation (Smith 2003) are crucial, as well.

2.1.2.3 Business Analytics

Analytics is a collection of methods, technologies, and tools for creating knowledge and insight from data to solve complex problems and make better and faster decisions (Delen and Zolbanin 2018). A definition of analytics can be abstracted into three dimensions (Holsapple et al. 2014): i) domain, ii) methods, and iii) orientation. The domain is the field of application – i.e., the context – of analytics: for example the supply chain (Trkman et al. 2010) or manufacturing (Zhong et al. 2017). Methods comprise different techniques for analyzing data. Orientation describes the direction of thinking or the objective of the analysis. It is not idiosyncratic towards a domain and is considered the core perspective of analytics (Delen and Zolbanin 2018; Holsapple et al. 2014).

Prior to the 1970s, domain experts collected and evaluated data using traditional mathematical and statistical methods. These systems were referred to as operations research systems. Due to the spread of integrated enterprise information systems, so-called enterprise resource planning (ERP) systems, analytics has attracted more and more attention and has been consistently further developed (Delen 2014). Later, the ability to derive insights by descriptively analyzing historical data became valuable under the umbrella term of business intelligence.

Today, analytics is a multifaceted and interdisciplinary field of research. Holsapple et al. (2014) generated a taxonomic and definitional framework consisting of six classes to describe the term: i) analytics is a corporate cultural movement in which, among other things, fact-based decisions are made. In addition, ii) analytics includes a collection of technologies and approaches, iii) a transformative process, and iv) an assortment of (organizational) skills as well as v) specific activities, which subsequently lead to vi) optimized decisions and insights. Mortenson et al. (2015) complement these classes' interdisciplinarity with technological approaches rooted in computer science and engineering; quantitative methods from mathematics, statistics, and econometrics; and decision-supporting aspects from psychology and behavioral science. Analytics is further based on the integration of the interdisciplinary research domains of artificial intelligence and machine learning (ML), information systems, and operations research (Delen and Zolbanin 2018; Mortenson et al. 2015).

2.1.2.4 Business Analytics Approaches

Categorization into maturity levels is a widely used classification system to illustrate the orientations and objectives of BA approaches. Their characteristics are related to their increasing complexity and their business potential (see Figure 6). Based on Davenport and Harris (2007) and Lustig et al. (2010), analytics can be categorized into three types: i) descriptive analytics, ii) predictive analytics, and iii) prescriptive analytics. New works extend these categories by iv) diagnostic analytics positioned between descriptive analytics and predictive analytics (Banerjee et al. 2013; Delen and Zolbanin 2018).

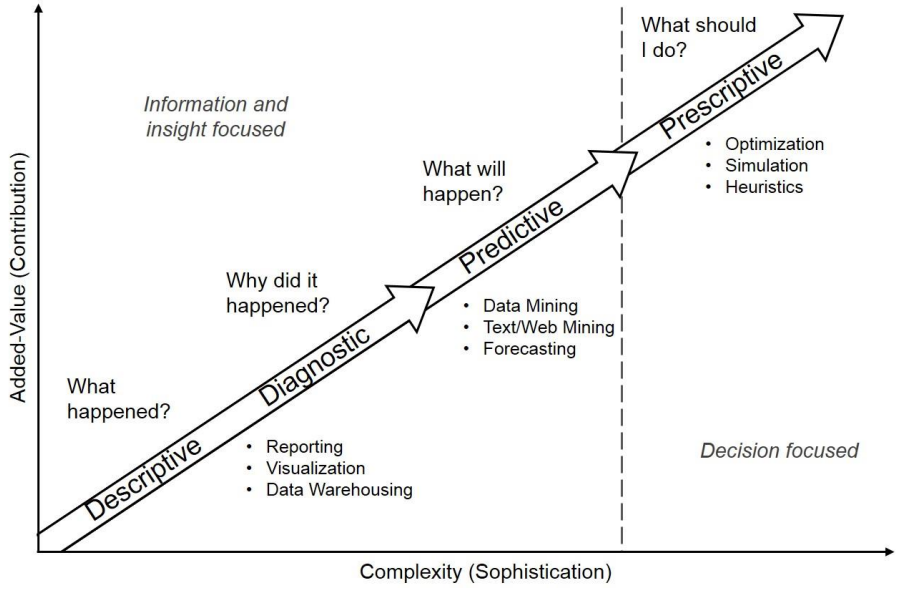


Figure 6: Maturity Levels of Analytics (cf. Delen and Zolbanin 2018)

Descriptive Analytics seeks to create transparency, often through data visualization. It aims at providing answers to the questions "What is happening?" or "What is happening right now?" Tools for analysis include periodic/ad hoc and dynamic/interactive online analytical processing (OLAP) and reporting, as well as exploratory ML algorithms such as clustering. Descriptive analytics typically uses historical data to uncover business potentials and problems that can support decision-making. Business intelligence is frequently used as a synonym for descriptive analytics (Delen and Demirkan 2013; Delen and Zolbanin 2018).

Diagnostic Analytics processes data to answer the question "Why did it happen?" It leverages techniques from descriptive analytics and methods from data discovery and statistics, including explanatory statistical modeling (Shmueli 2010) to determine the cause of problems or incidents (Banerjee et al. 2013; Delen and Zolbanin 2018). Due to its emphasis on the past, insights from diagnostic analytics may not be appropriate for predicting future events (Shmueli 2010).

Predictive Analytics determine phenomena that are likely to happen (e.g., trends and associations). Consequently, it aims at answering the question "What will happen?" To this end, it typically uses methods from ML and forecasting, such as decision trees, random forests, and artificial neural networks (Breiman 2001; Shmueli 2010). In ML, the intention is to find generalizable associations between the predictors (i.e., the independent variables) and the target (i.e., the dependent variable), an approach usually referred to as supervised learning (Fayyad et al. 1996; Marsland 2015).

Prescriptive Analytics processes data to estimate the best possible alternative under certain constraints by using methods of mathematical optimization that calculate the optimal measure or decision. The question to answer is "What must be done?" Prescriptive analytics can help to take advantage of future events or mitigate potential risks by presenting the implications of the various options for action (Delen 2014; Delen and Zolbanin 2018; Lustig et al. 2010). Both predictive analytics and prescriptive analytics are referred to as advanced analytics (Delen 2014).

2.1.2.5 Business Analytics in Smart Manufacturing

Interdisciplinary research on data-driven smart manufacturing has existed for quite some time. However, there is still an inadequate structuring of this knowledge and thus a barrier to implementation in practice. Using a systematic search of survey articles on BA in smart manufacturing as a pre-test (see our search process in Section 4.1), we identified 39 publications that survey BA in smart manufacturing. In these surveys, we identified (1) a lack of a holistic synthesis of the research area and determined that there are (2) complexity-related barriers to the practical application. Table 2 uses Harvey balls to illustrate the degree to which these research gaps have been addressed, differentiating between the categories *fully addressed*, *partially addressed*, and *not addressed*.[2]

[2] In describing the comprehensiveness of each survey, (1) *fully addressed* reflects that the publication takes a broad view on smart manufacturing, *partially addressed* means that it focuses on a specific area or key technology, and *not addressed* suggests that it does not try to synthesize the research area at all. Regarding the reduction of

Table 2: Verification of Problem Relevance and Research Gaps

Research Gap	Bang et al. (2019)	Baum et al. (2018)	Bordeleau et al. (2018)	Bousdekis et al. (2015)	Cadavid et al. (2020)	Çalış and Bulkan (2015)	Cardin et al. (2017)	Cerrada et al. (2018)	Cheng et al. (2018)	Dalzochio et al. (2020)	Diez-Olivan et al. (2019)	Ding et al. (2020)	Dowdeswell et al. (2020)	Fay and Kazantsev (2018)	Gölzer et al. (2015)	Gölzer and Fritzsche (2017)	Khan and Yairi (2018)	Kim et al. (2018)	Kumar (2017)	Kuo and Kusiak (2018)	Lee et al. (2014b)	Lee et al. (2018)	Lei et al. (2018)	Nath et al. (2020)	O'Donovan et al. (2015a)	Precup et al. (2015)	Priore et al. (2014)	Reis and Gins (2017)	Sharp et al. (2018)	Sutharssan et al. (2015)	Wuest et al. (2016)	Xu et al. (2017)	Xu and Hua (2017)	Zarandi et al. (2018)	Zhao et al. (2016)	Zhou and Xue (2018)	Zhang et al. (2019)	Zonta et al. (2020)	Zschech (2018)
1	◐	◐	◐	◐	◐	◐	◐	◐	◐	◐	◐	◐	◐	○	◐	◐	◐	◐	○	○	◐	◐	○	◐	◐	○	◐	◐	◐	○	○	◐	◐	◐	◐	◐	◐	◐
2	○	○	○	○	○	○	○	○	○	●	○	○	○	○	●	●	○	○	○	○	●	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	●

● *Research gap fully addressed* | ◐ *Research gap partially addressed* | ○ *Research gap not addressed*

None of the publications fully addresses the first research gap of a (1) holistic synthesis. Most authors examine only certain topics of BA and position their work in the broader context or sub-areas of smart manufacturing. This means that they focus on specific issues or topics such as the business value of applying BA (Bordeleau et al. 2018; Fay and Kazantsev 2018; Wuest et al. 2016), technological or algorithmic aspects concerning the use of ML (Diez-Olivan et al. 2019; Sharp et al. 2018; Wuest et al. 2016), or selective applications in smart manufacturing (O'Donovan et al. 2015b; Xu and Hua 2017). Some authors review the use of BA in specific domains such as maintenance (Xu and Hua 2017; Zschech 2018), process monitoring (Sutharssan et al. 2015; Zhou and Xue 2018), or production planning (Cadavid et al. 2020; Reis and Gins 2017; Sutharssan et al. 2015). Some offer a categorization schema when doing so.

We identified five surveys that adequately address (2) complexity-based barriers. Zschech (2018) and Dalzochio et al. (2020) each develop a taxonomy for maintenance analytics to provide researchers and practitioners with a reusable knowledge base of analytical techniques, data characteristics, and objectives. Gölzer et al. (2015) and Gölzer and Fritzsche (2017) identify organizational and technical requirements for data and analytical processing to prepare practitioners for smart manufacturing. Lee et al. (2014b) develop a taxonomical framework for selecting optimal algorithms for prognosis and health management of rotary machinery. These contributions reduce complexity for researchers and practitioners. Nevertheless, a comprehensive examination of BA in smart manufacturing – not limited to specific scenarios, domains, or techniques – is still missing.

2.1.3 Methodology

To address both research gaps, we develop a taxonomy as well as archetypes and examine them for temporal variations and trends. To do so, we apply a multi-step approach. Our methodology can be

complexity, (2) we classified each survey as *fully addressed* if the goal is to transfer the synthesized research results to industry and if it is structured accordingly to make these insights applicable in practice (e.g., to present recurring patterns or applications of analytics in industrial practice). *Partially addressed* means results are prepared for practical use, but not in a structured and reusable form. Lastly, *not addressed* suggests that the contribution does not provide for the utilization of analytics in industrial practice.

divided into three main parts: i) taxonomy development, ii) archetypes derivation, and iii) temporal analysis.

Taxonomy Development. First, we carry out the necessary preliminary work to identify suitable foundations for our taxonomy by employing a structured literature search process (Section 2.1.4.1) following the method proposed by vom Brocke et al. (2015). We used these publications as input for taxonomy building (Section 2.1.4.2). Taxonomies are a structured result of classifying things or concepts, including the principles underlying such classification. Nickerson et al. (2013) define a taxonomy T as a set of n dimensions D_i (i=1, …, n), each consisting of k_i ($k_i \geq 2$) mutually exclusive and complete characteristics C_{ij} (j=1, …, k_i), so that each object has only one C_{ij} for each D_i:

$$T = \{D_i, i = 1, \dots n \mid D_i = \{C_{ij}, j = 1, \dots, k_i; k_i \geq 2\}\}$$

Here, 'mutually exclusive' indicates that no object can have two different characteristics in one dimension, while 'complete' states that objects must have at least one characteristic for each dimension. A few authors, who have developed taxonomies according to Nickerson et al. (2013), criticize this restriction because some objects clearly have hierarchical and combinatorial relationships between characteristics. This could lead to confusing taxonomies by introducing additional dimensions or characteristics. Accordingly, these authors recommend performing the taxonomy development without the restriction (e.g., Jöhnk et al. 2017; Püschel et al. 2016; Zschech 2018). We followed the restrictions of Nickerson et al. (2013) in the first iteration, but renounced it in the subsequent iterations (for more details on the taxonomy building process, see Appendix III).

After completing the development of a taxonomy and describing it (Section 2.1.4.3), it is necessary to evaluate its applicability in the domain under consideration (Nickerson et al. 2013). Szopinski et al. (2019) suggest the use of illustrative scenarios as a way of demonstrating the usefulness of a taxonomy (Section 2.1.4.4). We strengthen this by additionally performing a cluster analysis to derive archetypes so that researchers can position their approaches in, or between, research streams – or so that practitioners can select a more specific purpose domain to guide them in real-world implementations initially.

Archetypes Derivation. Cluster analysis is an appropriate means by which to gain understanding from data (Jahirabadkar and Kulkarni 2013). It aims at dividing a dataset into subsets (i.e., clusters), each containing observations that are similar to each other and dissimilar to observations in different clusters (Jahirabadkar and Kulkarni 2013; Kaufman and Rousseeuw 2009). Agglomerative hierarchical clustering is a popular clustering approach that performs a hierarchical separation of observations by their degree of similarity. It is frequently used in information systems research for deriving archetypes from taxonomies and corresponding data (e.g., Oses et al. 2016; Pandiyan et al. 2018; Patel and Choi 2014). As "clustering is a subjective process in nature, which precludes an absolute judgment as to the relative efficacy of all clustering techniques" (Xu and Wunsch 2005), it is necessary to explore the suitability of different clustering algorithms and distance measures.

Therefore, we applied different reasonable combinations of popular agglomerative clustering algorithms (i.e., single linkage, complete linkage, group average linkage, centroid linkage, and Ward's method) (Xu and Wunsch 2005) and distance measures suitable for binary input streams (i.e., Euclidean distance, squared Euclidean distance, Jaccard distance, Hamming distance, Dice distance, and Yule distance) (Choi et al. 2010). Subsequently, we evaluated the different outcomes (i.e., dendrograms and crosstab analyses) by intensively discussing them within a group of four proficient researchers. Ultimately, we

agreed that the combination of Ward's algorithm and the Euclidean distance led to the most reasonable clusters (Section 2.1.5.1). This result is in line with several contributions in the information systems literature that were able to derive meaningful archetypes from taxonomies and corresponding data by applying Ward's algorithm and a Euclidean distance metric (Ragab et al. 2016a; Ragab et al. 2017; Ranjit et al. 2015). Subsequently, we introduce and explore the characteristics of the archetypes (Section 2.1.5.2).

Temporal Analysis. Temporal statistical analysis can be used to examine and model changes in variables of a dataset over a period of time. This allows researchers to draw conclusions about changes of concentrations. In temporal analysis, the behavior of the variable under consideration is modeled as a function of its previous data points in the same series using common tabular representations. A further visualization of this data presents a superficial view of the variety of data by providing quick ways of grasping important areas. As such, it supports trend analysis through the identification of rare anomalies that are increasing in frequency (Vogel 2020).

In our analysis, we take a descriptive analytics approach. We do not include consideration and explanations for influencing factors (Vogel 2020). We use time series plots of the raw data. Here, the time is plotted on the x-axis and the observation(s) of the data series on the y-axis. For our temporal trends of BA applications in smart manufacturing, we employ a two-staged approach. First, we consider changes within the dimensions and characteristics of the created taxonomy. In this way, we derive thematic trends that point towards future developments within the research field. Second, we consider changes within the derived archetypes. In this way, we enable the reader – be it as a researcher or as a practitioner – to develop awareness of future trends in specific coherent clusters of application.

2.1.4 Taxonomy Development

In the course of our taxonomy development, we pass through the following steps: i) data collection; ii) taxonomy building; iii) taxonomy representation; and, finally, iv) showcasing the taxonomy using three illustrative examples.

2.1.4.1 Literature Search Process and Data Collection

Our systematic literature search process follows the methodology recommendations of vom Brocke et al. (2015). Before conducting the search process, we first define the scope of the search and corresponding keywords.

Search Scope. To define and present the scope of our structure literature review, we made use of the taxonomy of Cooper (1988): Our focus is on research and applications. The aim of the research is the integration of the BA research topics in the context smart manufacturing, as well as the exploration of related topics and key technologies. Furthermore, we chose a neutral representation with a representative coverage. The results are to be methodically organized according to Nickerson et al. (2013). We define technology and management-oriented audiences as our target groups.

To conduct the search process, we chose interdisciplinary databases – i.e., IEEE Xplore, AISeL, and ACM Digital Library – to cover IT-related research areas. For business research, we included Business Source Premier (EBSCO). Lastly, we added Web of Science and ScienceDirect.

Table 3: Keywords for Literature Review

Domain	Group	Keywords
Analytics	General	Analytics | Data Science | Business Intelligence | Big Data
	Methods	Data Mining | Machine Learning | Cognitive Computing | Statisti* | Artificial Intelligence
		AND
Smart Manufacturing	General and Related Terms	Industrie 4.0 | Industry 4.0 | Smart Manufacturing | Integrated Industry | Industrial Internet | Smart Industry | Smart Factory | Advanced Manufacturing | Intelligent Manufacturing
	Key Technologies	Industrial Internet of Things | *Cyber-physical Systems

Keywords. To create a comprehensive and uniform search string, we defined the search terms shown in Table 3. This is in line with the explanation of terms and connections given in Section 2.1.2. For our search of surveys (Section 2.1.2.5), we combined the keywords for surveys and reviews with keywords from Table 3.

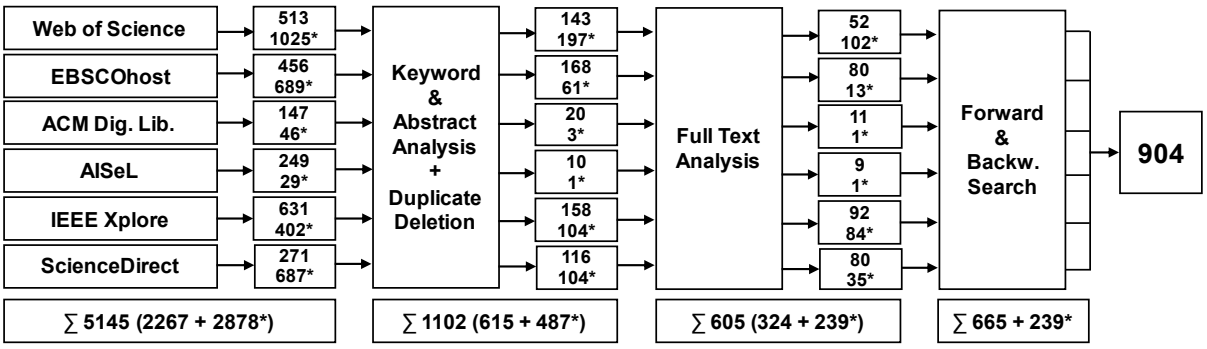


Figure 7: Literature Results Sorted by Database

As Nickerson et al. (2013) conclude, taxonomies are not static but evolve over time as new objects are developed or identified. After an initial search, we revisited the taxonomy at a later point. In total, we screened 5145 publications in two searches and finally considered 904 papers relevant for taxonomy building and evaluation. In the following, we summarize the search processes (see also Figure 7).

Initial search (date: 21 Nov. 2018). To ensure timeliness and relevance, we limited the earliest year of publication to 2013. This is the year in which the article of Kagermann et al. (2013), now regarded as the seminal publication for the development of the research field of smart manufacturing, first appeared. In our initial search process, we identified 2267 results. After keyword and abstract analysis, as well as deleting duplicates, 615 publications remained. Following the full-text screening, we considered 324 publications to be relevant. Finally, we conducted a forward and backward search, which yielded another

341 relevant search results for a total of 665 publications. We performed the forward search by analyzing citation data on Google Scholar. We carried out the backward search manually via the bibliography of the contributions.

Second search (date: 01 Nov. 2020). We used the date of the initial search as a starting point with unaltered keywords, filters, and databases. This resulted in 4179 hits, reflecting the rising amount of research interest in the domain under consideration. Due to the large number of results, we decided to filter the results for the sake of manageability and excluded all publications except peer-reviewed journals, which were represented in 2878 hits. The abstract and keyword analysis resulted 487 relevant articles. For further manageability, we eliminated all articles with a journal impact factor of less than 2.000 (in 2020)[3] and decided to forgo the backward and forward search, since we already carried out a broad coverage of the relevant time frame in the initial search. After a full-text screening, 239 publications remained, resulting in a total of 904 publications. The full bibliography is available in Appendix III.

2.1.4.2 Taxonomy Building

Meta-Characteristics. Meta-characteristics form the basis for the assignment of further characteristics. This prevents naive empiricism in which the researcher assigns a large number of related and unrelated characteristics for the purpose of identifying undiscovered patterns (Nickerson et al. 2013). The objective of our contribution is to structure the research area of BA in smart manufacturing holistically and to reduce complexity barriers for practitioners by creating reusable knowledge. The latter objective is achieved if the taxonomy allows for the derivation of analytics patterns according to Russo (2016). We decided on quadripartite meta-characteristics to classify BA patterns as objects (see Table 4).

Table 4: Meta-characteristics

#	Meta-characteristic	Related Practitioner's Questions of Interest
MC.1	Domain	Which smart manufacturing domains are affected by BA?
MC.2	Orientation	What is the orientation of the use of BA in smart manufacturing?
MC.3	Data	What are the characteristics of the processed data?
MC.4	Technique	Which analytical techniques are used?

Holsapple et al. (2014) define three dimensions of relevance that we use: i) *domain* is the area of application of BA in smart manufacturing (e.g., production or quality control); ii) *orientation* refers to the direction of thought (e.g., predict vs. prescribe) and is concerned with the objective of applying BA (e.g., cost reduction); iv) *technique* describes the way a BA task is performed (e.g., using ML). Furthermore, we added a meta-characteristic based on Tsai et al. (2013): iii) *data* describes the underlying properties of the data available for BA in smart manufacturing.

[3] https://clarivate.com/webofsciencegroup/solutions/journal-citation-reports/

Ending Conditions. Step two of the method of taxonomy development is the determination of the ending conditions (EC). Nickerson et al. (2013) propose both objective and subjective termination conditions, some of which have been adopted and adapted from Sowa and Zachman (1992).

We define the following objective EC: (1.1) all objects or a representative sample of objects have been examined; (1.2) no object was merged with a similar object or split into multiple objects in the last iteration; (1.3) at least one object must have been identified per characteristic and dimension; (1.4) no new dimensions or characteristics were added in the last iteration; (1.5) no dimensions or characteristics were merged or split in the last iteration; (1.6) every dimension is unique and not repeated; and (1.7) every characteristic is unique within its dimension.

Furthermore, we define the following subjective EC: (2.1) concise; (2.2) robust; (2.3) comprehensive; and (2.4) extendible. Nickerson et al. (2013) suggest another restriction that requires characteristics to be mutually exclusive in dimensions. Following other recently developed taxonomies, we include non-exclusive characteristics (Jöhnk et al. 2017; Püschel et al. 2016; Zschech 2018) to avoid a verbose and non-comprehensive taxonomy with a bloated number of combined characteristics.

Dimensions and Characteristics. In the third step, we carried out an iterative selection of the dimensions and the assignment of the characteristics. A taxonomy is never set in stone, as research progresses or new objects are identified or discovered (Nickerson et al. 2013). In line with this notion, we revisited our taxonomy at a later point in time. As summarized in Table 5, we performed four iterations with our initial data set and added two iterations using the text corpus from our second literature search. The details on all iterations can be reviewed in Appendix III.

Table 5: Performed Iterations in Taxonomy Development

It.	Approach	Summary	Quantities	Input
I	Conceptual-to-Empirical	Due to limited availability of real-world data, we analyzed 10 articles that structure a part of the research field and employ categorization schemes to derive an initial set of dimensions and characteristics (cf. Appendix III for details on the selected articles).	D=13; C=53; P=10	Initial Literature Survey
II	Conceptual-to-Empirical	We performed an analysis of related work that synthesizes a specific domain of smart manufacturing (e.g., maintenance), but does not offer a categorization scheme.	D=16; C=69; P=16	
III	Empirical-to-Conceptual	Following the example of Schoormann et al. (2017), we considered a research article as an object. To maintain relevance for our taxonomy's objectives, we only selected contributions that address at least three dimensions of the meta-characteristic. A total of 633 publications met this condition, from which we randomly selected approximately 30%.	D=13; C=53; P=189	
IV	Empirical-to-Conceptual	We selected another random 30%. The fourth iteration enabled us to confirm the third iteration's structure, and we conclusively met the specified ending conditions.	D=13; C=52; P=189	
V	Conceptual-to-Empirical	We repeated the analysis of related work from our second literature survey. We found seven additional papers that synthesize a specific domain of smart manufacturing (cf. again Appendix III).	D=13; C=52; P=7	Second Literature Survey
VI	Empirical-to-Conceptual	Finally, we again followed the example of Schoormann et al. (2017) and considered a research article as an object. We analyzed a total of 232 articles from our second literature survey. This confirmed the structure and characteristics of the taxonomy.	D=13; C=52; P=232	

It.: Iteration | D: (Sub-)Dimensions | C: Characteristics | P: Publications analyzed

2.1.4.3 Final Taxonomy

In the following, we present our final taxonomy on BA in smart manufacturing (see Table 6). The taxonomy is structured based on the quadripartite meta-characteristics of domain, orientation, data, and technique. For conciseness and comprehensiveness, we added auxiliary dimensions to these meta-characteristics (e.g., production or maintenance) that are purely descriptive and do not contradict the definition of the taxonomy (Witte and Zarnekow 2018). They are not considered actual dimensions, but only a means by which to enhance clarity and enable thematic grouping within large dimensions. Table 6 shows the final taxonomy and includes the number of observations of the characteristics.

Table 6: Taxonomy for Business Analytics in Smart Manufacturing

MC	Dimension(s)		Characteristics				EX
Domain	Function	*Product Dev. & Managem.*	Design Analysis 20 | 2.3%		Product Life Cycle Optimization 5 | 0.6%		ME
		Production	Production Planning 80 | 9.2%	Monitoring 118 | 13.6%	Perf. Analysis 21 | 2.4%	Perf. Optimiz. 41 | 4.7%	
		Maintenance	Condition Analysis 215 | 24.9%		Defect Analysis 121 | 14.0%	Maint. Planning 28 | 3.2%	
		Quality Management	Quality Control 115 | 13.3%		Quality Optimization 18 | 2.1%		
		Sustainability/ Security	Energy Consumption Analysis 15 | 1.7%		Energy Con. Optimization 17 | 2.0%	Security/Risk A. 40 | 4.6%	
Orientation	**Maturity**		Descriptive Analytics 227 | 26.2%	Diagnostic Analytics 144 | 16.6%	Predictive Analytics 348 | 40.2%	Prescriptive Analytics 146 | 16.9%	ME
	Objective		Time 687 | 79.4%	Cost 722 | 83.2%	Conformance 170 | 19.7%	Flexibility 60 | 6.9%	NE
			Security 58 | 6.7%		Sustainability 47 | 5.4%	Customer Satisf. 83 | 9.6%	
Data	**Source**		Machine/Tool 547 | 63.2%	Process 253 | 29.2%	Product 129 | 14.9%	Customer 26 | 3.0%	NE
			Reference 48 | 5.5%	ERP 55 | 6.4%	Environment 34 | 3.9%	Human 29 | 3.4%	
	Integration		No Integration 570 | 65.9%	Vertical 186 | 21.5%	Horizontal 107 | 12.4%	End-to-End 35 | 3.9%	NE
	Frequency		Real-time/Stream 342 | 39.5%		Historical/Batch 523 | 60.5%		ME
Technique	Method	*Machine Learning*	Classification 290 | 33.5%	Regression 104 | 12.0%	Probabilistic M. 36 | 4.2%	Clustering 42 | 4.9%	NE
			Dimensionality Reduction 50 | 5.8%		Deep Learning 154 | 17.8%	Reinforcement L. 37 | 4.3%	
		Optimization	Mathematical Optimization 57 | 6.6%		Evolutionary Algorithm 27 | 3.1%	Swarm Intelligence 20 | 2.3%	
		Others	Multi-Agent Systems 13 | 1.5%		Fuzzy Logic 28 | 3.2%	Custom Dev. 222 | 25.7%	

MC: Meta-Characteristic | EX: Exclusivity | ME: Mutually Exclusive | NE: Non-Exclusive

2.1.4.3.1 Meta-Characteristic Domain

The meta-characteristic *domain* refers to the functions to which BA is applied (Holsapple et al. 2014). We identified a variety of functional areas in smart manufacturing. We distinguish a total of 14 mutually exclusive characteristics in one dimension with five auxiliary dimensions.

Product Development & Management. Product development covers all aspects that lead to a marketable product, from product design to preparation for production (Brown and Eisenhardt 1995). Product management deals with subsequent activities along the product life cycle (Murphy and Gorchels 1996). Combined, these represent only 2.9% of applications for BA in smart manufacturing.

Product Development & Management comprises *design analysis* to improve product development based on customer requirements and design data. In contrast, product development is associated with uncertainties since customer preferences regarding product configurations are traditionally non-transparent (Afshari and Peng 2015; Ma et al. 2017). In contrast, *product life cycle optimization* includes further aspects of the product life cycle, going beyond the design phase by using BA, for example, to optimize product repair processes, customer support, remanufacturing, and spare parts management (Cheng et al. 2018; Zhang et al. 2017).

Production. Production comprises all aspects directly related to manufacturing and represents about 29.9 % of all applications. The production cycle starts with planning, covers production and its monitoring, and ends with the finished product (Lee and Rosenblatt 1987).

Production planning covers the efficient allocation of production resources such as machines or personnel. The improvement brought about by BA is not only based on historical data but partly on real-time data, which enables a dynamic adaptation to current circumstances of production (Nouiri et al. 2018; Oses et al. 2016; Shiue et al. 2018; Wang and Liu 2015). BA is also used for *monitoring* of operations. The primary objectives are transparency, fault detection, and the identification of anomalies in processes (Caggiano 2018; He et al. 2013; Kozjek et al. 2017; Peres et al. 2018; Sanchez et al. 2018; Susto et al. 2017). Production planning and monitoring represent the major applications with a share of 9.2% and 13.6%, respectively. In addition to monitoring, *performance analysis* aims to measure production performance (e.g., throughput time) to support decision-making (Kumru and Kumru 2014; Lingitz et al. 2018; Subramaniyan et al. 2016; Wedel et al. 2015). *Performance optimization* utilizes this analysis in order to identify performance weaknesses for subsequent improvement (Chao-Chun et al. 2016; Khakifirooz et al. 2018; Zheng et al. 2014).

Maintenance. Maintenance is about the necessary measures of a unit, as a specific part of a machinery, to keep it in – or restore it to – a state in which it can perform the intended functions (Pawellek 2016). Thus, maintenance addresses all aspects of servicing machines and tools and represents the most significant auxiliary dimension, with roughly 42.1% of applications.

Condition analysis analyzes the condition of machines or tools. It is the most extensive characteristic and comprises a quarter of all applications. The focus of the analysis can be on the overall condition (Villalonga et al. 2018; Yunusa-Kaltungo and Sinha 2017), the condition of specific components (Soualhi et al. 2015), or the degree of wear (Ouyang et al. 2018; Shaban et al. 2017). Condition analysis can lead to the identification of potential machine faults. However, there are objects in which BA is used explicitly for fault analysis. Therefore, these analytics patterns are classified separately under the

function *defect analysis*. The objective is not the monitoring itself, but explicitly identifying faults, anomalies, or defects (Chakravorti et al. 2018; Dou and Zhou 2016; Lu et al. 2017; Wang and Liu 2015; Zhao et al. 2016; Zhu et al. 2018b). In both condition and defect analysis, the ultimate judgment concerning the required maintenance strategy continues to be based on human decision-making (Lee et al. 2014a). *Maintenance planning* aims to enhance this by recommending the optimal maintenance intervals and actions (Luangpaiboon 2015; Mbuli et al. 2017). It is a comparably small function with only 3.2% of all applications.

Quality Management. Manual inspection of product quality is time-consuming, yet even minor irregularities can lead to lower customer satisfaction (Saucedo-Espinosa et al. 2017; Shatnawi and Al-Khassaweneh 2014). It represents 15.4% of applications.

Within this auxiliary dimension, q*uality control* focuses on monitoring quality and identifying defects, typically in finished products or materials. It is the larger area of application with a share of 13.3%. *Quality optimization* goes beyond this and tries to improve the quality proactively (Luangpaiboon 2015).

Sustainability and Security. Sustainability and security summarize BA approaches that focus on the conscious and responsible use of production facilities. It has been a side-topic so far, with a combined share of 8.3% (more than half of which is security/risk analysis).

Energy consumption analysis monitors the energy consumption of industrial systems to create transparency and detect anomalies (Ak and Bhinge 2015; Li et al. 2018a; Oses et al. 2016; Ouyang et al. 2018; Tristo et al. 2015). *Energy consumption optimization* can be used to optimize the energy use to achieve higher energy efficiency (Liang et al. 2018; Shao et al. 2017; Shin et al. 2017). *Security/risk analysis* describes analytic patterns that focus on safety-relevant aspects, risk, and compliance. An example is cybersecurity (Anton et al. 2018; Gawand et al. 2017; Xun et al. 2018; Yang et al. 2018a).

2.1.4.3.2 Meta-Characteristic Orientation

For BA, orientation refers to the direction of thought (Holsapple et al. 2014). We identified two mutually exclusive dimensions with a total of 11 characteristics. While those of maturity are mutually exclusive, as the more mature characteristic subsumes the prior characteristics, the characteristics of objectives are non-exclusive.

Maturity. Maturity describes the complexity and expected business value of BA. It is concerned with what BA offers at different levels of sophistication (see also Figure 6). We identified four characteristics (Baum et al. 2018; Diez-Olivan et al. 2019; O'Donovan et al. 2015b; Zschech 2018). Most applications in the surveyed time frame are predictive (40.2%), followed by descriptive analytics (26.2%), with diagnostic and prescriptive approaches being almost on par for the remainder.

As outlined above, *descriptive analytics* is purely delineative and answers questions through data integration, navigation, and visualization (Delen and Demirkan 2013; Delen and Zolbanin 2018). *Diagnostic analytics* goes beyond the mere creation of transparency and attempts to identify the root cause of incidents (He et al. 2017; Liu and Jin 2013; Tian et al. 2017). While descriptive and diagnostic analytics focus on the past, *predictive analytics* aims to predict future events (Bousdekis et al. 2017; Hsu et al. 2016; Kanawaday and Sane 2017; Wanner et al. 2019b). *Prescriptive analytics* builds on the previous

characteristics to recommend concrete measures or alternative courses of action (Delen and Demirkan 2013; Delen and Zolbanin 2018).

Objective. Objective as the second dimension describes a positive impact, benefit, measure of performance, or value which the use of BA can achieve for businesses. From an economic perspective, there are four areas of performance in manufacturing environments: time, cost, quality (i.e., conformance to specifications), and flexibility (Neely et al. 1995). These can be attributed directly to the application of BA in smart manufacturing (Kagermann et al. 2013) and are confirmed as characteristics in taxonomy development (Bordeleau et al. 2018; Fay and Kazantsev 2018; Wuest et al. 2016). Besides these four fundamental performance measures, we identified the objectives of security, sustainability, and customer satisfaction. All objectives are non-exclusive.

Time is a source of competitive advantage and can be considered a fundamental measure of performance in manufacturing (Neely et al. 1995). It is used in 79.4% of approaches. The objective of *cost* defines the reduction of monetary expenses achieved by using BA. It is the most important objective at 83.2%. Furthermore, it yields the best possible allocation or combination of manufacturing resources. BA in smart manufacturing also addresses the improvement of *conformance* to predefined specifications (Neely et al. 1995), i.e., the quality of operations (19.7%). All other objectives account for less than 10% each. Thereby, *flexibility* describes the ability to adapt efficiently to new circumstances and requirements in daily manufacturing operations (Neely et al. 1995). Work *security* and safety can be an objective at the production site (Domova and Dagnino 2017; Lavrova et al. 2018; Xu et al. 2016). In the age of climate change, the objective of *sustainability* has gained importance and describes the application BA for the purpose of increasing sustainability in manufacturing operations (Dutta et al. 2018; Shin et al. 2017). Finally, the primary goal of *customer satisfaction* is to improve the customer experience (Shatnawi and Al-Khassaweneh 2014; Zhang et al. 2017).

2.1.4.3.3 Meta-Characteristic Data

The meta-characteristic data describes the properties of the processed data and all are non-exclusive without any limitations for object classification. We identified three mutually exclusive dimensions with a total of 12 non-exclusive characteristics and two exclusive characteristics concerning data frequency.

Source. Source describes the origin of data used for analysis (Kwon et al. 2014; Sahay and Ranjan 2008). We distinguished eight prevalent data sources. The most frequently used data source in smart manufacturing is machines/tool with 63.2%. Processes (29.2%) and product (14.9%) represent additional important data sources, with the remainder not exceeding 6.4%

Machine/tool data comprises properties, conditions, parameters, and states. It is collected primarily by CPS-connected sensors (Bousdekis et al. 2015; Bousdekis et al. 2017; Gölzer et al. 2015; Gölzer and Fritzsche 2017; Zschech 2018). *Processes* generate data while connected tasks of production or maintenance are executed (Kim et al. 2018; Reis and Gins 2017). The *product*'s data comprises product specifications and information regarding the usage behavior of customers (Adly et al. 2014; Ding and Jiang 2016). Product data is closely related to *customer* data, such as their requirements or preferences (Lou et al. 2018; Saldivar et al. 2016). *Reference* data, such as test results and specifications, is another data source (Librantz et al. 2017; Ren et al. 2018). In addition to product quality, the data is relevant for

quality control of manufacturing processes (Hu et al. 2016; Zhao et al. 2018). Furthermore, BA uses *ERP* system data for evaluation. Examples are orders and production resources for scheduling and planning (Gölzer and Fritzsche 2017; Zhu et al. 2017). BA in smart manufacturing also takes *human* data (e.g., working hours, health monitoring, activities, and location) into account (Zheng et al. 2018). Finally, *environment* data is collected in the vicinity and does not necessarily have to be related directly to manufacturing operations (Filonenko and Jo 2018; Molka-Danielsen et al. 2018).

Integration. Three forms of integration for BA in smart manufacturing are commonly discussed: vertical, horizontal, and end-to-end integration (Kagermann et al. 2013; Zhou et al. 2016). The integration of IT resources and systems should naturally include the exchange of data, which enables new applications of data analysis.

Vertical integration (21.5%) comprises the integration of data among various hierarchical levels for smart manufacturing, from the actuator and sensor level to the corporate planning level (Gölzer and Fritzsche 2017; Kagermann et al. 2013). *Horizontal* (12.4%) integration encompasses not only the integration of data along the value chain but also across company boundaries (Dou and Zhou 2016; Kagermann et al. 2013). In contrast, *end-to-end* integration describes data integration along the entire product life cycle, from product development to recycling (Dou and Zhou 2016). Applications of this type are comparatively rare, with 3.9%. In addition, we include the characteristic *no integration*, which has been identified as a research gap by Sharp et al. (2018). For instance, in maintenance, most analytics patterns are limited to individual machines, tools, or components. The effects on the overall system, the production process, or other machines are not considered (Shao et al. 2018; Yuwono et al. 2016). It is the de facto situation for most applications, with 65.9%.

Frequency. This dimension comprises the temporal perspective of data availability and collection as well as its subsequent processing (Sahay and Ranjan 2008).

Real-time/stream analytics can be considered a fundamental requirement of smart manufacturing. Saldivar et al. (2016) go as far as to describe the ability to analyze data in real time as the ‘key’ to smart manufacturing. The data is continuously collected and evaluated (Verma et al. 2017). Continuous evaluation of the data enables a dynamic reaction to new requirements and accruing problems, addressing the objectives of time, costs, and flexibility. In contrast, within *historical/batch* analysis, the data is not processed continuously but periodically or irregularly (Carbone et al. 2015). The distribution is roughly 40% to 60%.

2.1.4.3.4 Meta-Characteristic Technique

In this context, the term ‘technique’ refers to the way a BA task is performed (Holsapple et al. 2014). We identified a wide array of techniques applied in smart manufacturing, which are summarized in the single-dimension method with a total of 13 non-exclusive characteristics that can be grouped into the auxiliary dimensions of ML, optimization, and others (with ML being the most significant).

Machine Learning. ML is a paradigm that comprises algorithms, which learn from experience automatically without being explicitly programmed to perform a task such as making decisions or predictions (Marsland 2015; Samuel 1959). It can be divided into three types: supervised learning using labeled

data, unsupervised learning using unlabeled data, and reinforcement learning using reward functions.

Classification is the predominant method in supervised learning and used by roughly a third of all applications. It comprises the assignment of data to predefined classes (He et al. 2013; Ragab et al. 2016b; Ray and Mishra 2016). In *regression* analysis, a function establishes relationships between variables to make predictions (12%). The aim of *clustering* in unsupervised learning is to group similar data in order to recognize undiscovered patterns or correlations. Another unsupervised learning method is *dimensionality reduction*. Its task is to reduce complexity by mapping data from a higher to a lower dimensional level (Marsland 2015). This is also referred to as feature learning or representation learning. Task-specific techniques, such as regression and classification, often require data that is easy to process mathematically (Argyriou et al. 2008). *Probabilistic methods* are applied in supervised and unsupervised approaches in a wide array of applications such as anomaly detection (Park et al. 2017), monitoring (Windmann et al. 2015), and remaining useful lifetime estimation (Zhang et al. 2018b). Lastly, we identified *reinforcement learning* with an explorative character to create new knowledge (Ishii et al. 2002). None of the above goes beyond 5.8% in use. In contrast, *deep learning* is a comprehensive class of ML algorithms that combines feature learning with task-specific approaches (Deng and Yu 2014). In smart manufacturing, deep learning is used when information from the real world (e.g., images, videos, or sensor data) is transferred into the digital world (Sonntag et al. 2017; Srivastava and Salakhutdinov 2014). Its share accounts for 17.8% of applications.

Optimization. Optimization is concerned with the selection of the best element (according to specified criteria) from a set of available options. We identified three common groups of optimization methods in smart manufacturing.

Mathematical optimization, known as nonlinear programming or numerical optimization, can be described as the science of determining the optimal solution to mathematically definable problems. The problems are often models from production and management systems (Shaw et al. 1992). Biologically inspired optimization methods are unique optimization methods inspired by biological processes and phenomena. On the one hand, general *evolutionary algorithms* access collective phenomena such as reproduction, mutation, and selection. On the other hand, there is *swarm intelligence*, based on the collective social behavior of organisms. It entails the implementation of collective intelligence based on many individual agents as inspired by the behavior of insect swarms (Binitha and Sathya 2012).

Others. In addition to optimization and ML methods, other approaches are employed in smart manufacturing which, due to their specificity, cannot be assigned to the other auxiliary dimensions or justify a dimension of their own.

Multi-agent systems (MAS), also known as distributed artificial intelligence, are systems in which several interacting intelligent software agents pursue specific goals or solve collective problems (Ferber and Weiss 1999). MAS can be related to agent-based paradigms such as reinforcement learning or swarm intelligence (Oses et al. 2016; Wang et al. 2016b). The application scenarios of MAS are manifold: agent mining, for example, is an approach in which MAS is used for decision-making problems (Cao et al. 2012). *Fuzzy logic* is a mathematical system to model manifestations of human decision-making (Bothe 1995). Fuzzy logic is a many-valued logic. It can process partial truths, whereby the truth value can lie between entirely true or false. Although fuzzy logic can be deployed with ML or optimization methods (Aydın et al. 2015; Ma et al. 2017), we consider it a separate characteristic (Andonovski

et al. 2018; Arık and Toksarı 2019; Aydın et al. 2015; Baban et al. 2016; Lv and Lin 2017; Niu and Li 2017; Sun et al. 2016; Wu et al. 2018; Zurita et al. 2016). Lastly, the characteristic *custom development* summarizes applications which use an undisclosed or custom-developed method such as, for example, manual data selection, but also expert surveys or architecture concepts (Bekar et al. 2019; Tsai et al. 2014). About a quarter of all applications use custom development, which hints at the diversity and lack of consolidation of the field.

2.1.4.4 Illustrative Application

Nickerson et al. (2013) suggest evaluating a taxonomy's applicability after the development. One option is the illustrative application of the taxonomy on objects (Szopinski et al. 2019). The application of a taxonomy to research real-world objects (in our case articles studying specific approaches to BA in smart manufacturing) enables a reflection on the current state of research on a certain type of object (Khalilijafarabad et al. 2016). Furthermore, it helps to uncover commonalities and discrepancies between studies on this type of object (Szopinski et al. 2019). Hence, the application of our taxonomy enables researchers to position their contribution in a larger context and identify potential research gaps (Hummel et al. 2016).

To illustrate usefulness of our taxonomy, we applied it to three objects, following other taxonomy research in the information systems discipline (e.g., Lis and Otto 2021; Püschel et al. 2020).. To provide and ensure a sufficient level of variance, we randomly chose three applications. We show a classification of the respective examples with the taxonomy in Table 7.

Table 7: Application of Taxonomy, Example I to III

MC	DIMENSIONS	CHARACTERISTICS			
Domain	Function	Design Analysis		Product Life Cycle Optimization	
		Production Planning	Monitoring	Performance Analysis	Performance Optimization
		Condition Analysis	Defect Analysis	Maintenance Planning	
		Quality Control		Quality Optimization	
		Energy Consumption Analysis	Energy Consumption Optimization		Security/Risk Analysis
Orientation	Maturity	Descriptive Analytics	Diagnostic Analytics	Predictive Analytics	Prescriptive Analytics
	Objective	Time	Cost	Conformance	Flexibility
		Security	Sustainability	Customer Satisfaction	
Data	Source	Machine/Tool	Process	Product	Customer
		Reference	ERP	Environment	Human
	Integration	No Integration	Vertical	Horizontal	End-to-End
	Frequency	Real-time/Stream		Historical/Batch	
Technique	Method	Classification	Regression	Probabilistic Method	Clustering
		Dimensionality Reduction	Deep Learning	Reinforcement Learning	
		Mathematical Optimization	Evolutionary Algorithm	Swarm Intelligence	
		Multi-Agent Systems	Fuzzy Logic	Custom Development	
Coloring Scheme		Example I	Example II	Example III	

Example I. Ståhl et al. (2019) employ BA to detect problematic slab shapes in steel rolling. Their application's function is to model the dependencies between the measured product shape and control the product's conformance (*function*). As they predict the ratio of flawed products even before a critical manufacturing operation, their approach is of predictive maturity (*maturity*). The application's goals are to increase customer satisfaction through higher product quality and reduce manufacturing costs (*objective*), as defective products can be detected before further process steps are initialized. There is no data integration, as the approach collects the data at a specific point in the process (*integration*). The data, slab width, and deviation from the targeted position are collected through multiple sensors directly from the product (*data source*). The authors do not employ real-time analytics, but rather use a data set collected before the analysis in their experimental set-up (*frequency*). They apply a classification approach to decide between defective and non-defective steel slabs. Specifically, the application uses recurrent neural networks with long-term memory cells, that is deep learning (*method*).

Example II. Hu et al. (2020) use BA for production planning, specifically the scheduling of automated guided vehicles (AGVs) for material handling (*function*). The goal of their analysis is to find the optimal mixed rule policy to identify the best course of action, which reflects a prescriptive analytics problem (*maturity*). The goal of the analysis is to improve time efficiency, specifically the delay ratio of AGVs, while simultaneously increasing their flexibility by enabling them to participate in various jobs, which also leads to makespan optimization. The data used is multifaceted, including machines (AGVs) and the production process (RFID and Industrial IoT sensors) (*data source*). The data is integrated vertically, as various sources are tapped into and passed on to the analysis (*integration*) continuously in a real-time fashion (*frequency*). Finally, the application employs a deep reinforcement learning-based approach to schedule the AGVs and find the optimal mixed rule policy (*method*).

Example III. In contrast to the other examples, Arpaia et al. (2020) place the factory worker's safety at the center of their application (*function*) by predicting worker stress levels (*maturity*). The proposed solution increases the worker's safety and generally fosters a more secure manufacturing environment. Positive side effects are an increase in product quality (less stress translates to more focused workers) as well as a reduction of the cost of the production process (*objective*). Data is collected through a brain-computer interface, specifically a wearable electroencephalography instrument monitoring the brain-waves of the workers (*data source*). The proposed setup is not integrated (*integration*) and the data is transferred in real time (*frequency*) to the analytical system. Classification algorithms are used to predict the workers' stress level (*method*).

2.1.5 Derivation of Archetypes

In this section, we perform a cluster analysis to derive archetypes for smart manufacturing that comprise similar applications as those illustrated above. After detailing the derivation process, we explore the resulting archetypes' characteristics.

2.1.5.1 Cluster Analysis

To gain more insights into different research streams and archetypes, we performed a cluster analysis. Before applying the clustering algorithm, we transformed the collected literature into binary vector

representations of the individual articles, each consisting of 52 binary values (i.e., the number of characteristics in the taxonomy). In total, we clustered 854 vectors. This excludes all survey papers (*n*=39) and 11 vectors, which we removed as we could not assign characteristics in the dimension function.

We applied different admissible clustering methods and distance measures as outlined above. Figure 8 illustrates the dendrogram of the clustering. For the sake of clarity, the figure only shows the last 75 merged clusters. On the horizontal axis, we illustrate the numbers of elements within the clusters in parentheses. Observing the dendrogram, we uncovered six meaningful clusters, visualized in different colors.

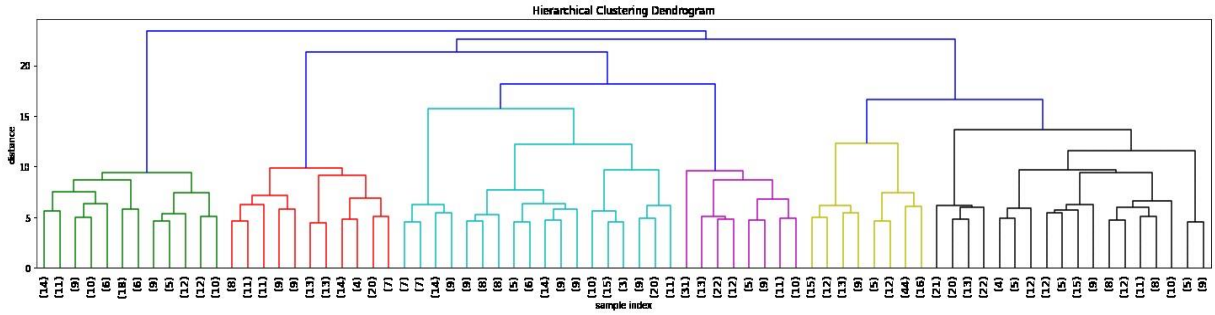


Figure 8: Dendrogram of Clusters

2.1.5.2 Derived Archetypes

The six clusters identified by the clustering represent the major archetypes of BA applications in smart manufacturing. These correspond to six branches of research, which in turn correspond to main intentions for practitioners with similar approaches and/or infrastructural requirements. Due to distinct functional differences, the number of observations contained in each cluster varies.

Clusters C3 and C6 are the largest, with 173 and 201 articles, respectively. Clusters C1, C2, C4, and C5 comprise 122, 119, 113, and 126 articles. Following an iterative exploratory approach, changes to the defined allowed Euclidean distance between related objects, and thus a smaller or larger number of clusters, did not significantly change our results of six major archetypes. They highlighted or masked minor yet distinct characteristics, which we discuss in the respective final clusters.

We summarize these results in Table 8 to provide a multi-perspective analysis of the identified archetypes. We extracted and analyzed the impact of each characteristic to scrutinize the strength and direction of its influence on the clusters. In the following, we elaborate on the archetypes and their contained subthemes.

Table 8: Archetypes of Business Analytics in Smart Manufacturing

			MRO Planning (C2)		Reactive Maintenance (C5)		Offline Predictive Maintenance (C6)		Online Predictive Maintenance (C4)		MRO Monitoring (C3)		Quality Management (C1)	
D	**Characteristics**	***n***	**119**		**126**		**201**		**113**		**173**		**122**	
Function	Design Analysis	*20*	0	0.00	0	0.00	19	0.09	0	0.00	0	0.00	1	0.01
	Product Life Cycle Opt.	*5*	2	0.02	0	0.00	0	0.00	0	0.00	2	0.01	1	0.01
	Production Planning	*80*	66	0.55	0	0.00	10	0.05	0	0.00	4	0.02	0	0.00
	Monitoring	*118*	1	0.01	18	0.14	16	0.08	3	0.03	77	0.45	3	0.02
	Performance Analysis	*21*	0	0.00	1	0.01	10	0.05	0	0.00	10	0.06	0	0.00
	Performance Opt.	*41*	17	0.14	0	0.00	9	0.04	3	0.03	9	0.05	3	0.02
	Condition Analysis	*215*	2	0.02	32	0.25	89	0.44	76	0.67	14	0.08	2	0.02
	Defect Analysis	*121*	1	0.01	74	0.59	21	0.10	20	0.18	5	0.03	0	0.00
	Maintenance Planning	*28*	21	0.18	0	0.00	4	0.02	0	0.00	3	0.02	0	0.00
	Quality Control	*115*	2	0.02	0	0.00	1	0.00	9	0.08	3	0.02	100	0.82
	Quality Opt.	*18*	4	0.03	0	0.00	0	0.00	2	0.02	1	0.01	11	0.09
	Energy Cons. Analysis	*15*	0	0.00	0	0.00	11	0.05	0	0.00	4	0.02	0	0.00
	Energy Cons. Opt.	*17*	3	0.03	1	0.01	11	0.05	0	0.00	1	0.01	1	0.01
	Security/Risk Analysis	*40*	0	0.00	0	0.00	0	0.00	0	0.00	40	0.23	0	0.00
Maturity	Descriptive	*226*	1	0.01	48	0.38	3	0.01	34	0.30	97	0.56	43	0.35
	Diagnostic	*142*	2	0.02	77	0.61	20	0.10	10	0.09	19	0.11	14	0.11
	Predictive	*347*	4	0.03	1	0.01	169	0.84	68	0.60	47	0.27	58	0.48
	Prescriptive	*139*	112	0.94	0	0.00	10	0.05	1	0.01	10	0.06	6	0.05
Objective	Time	*680*	113	0.95	126	1.00	155	0.77	107	0.95	119	0.69	60	0.49
	Cost	*710*	109	0.92	124	0.98	178	0.89	105	0.93	125	0.72	69	0.57
	Conformance	*169*	10	0.08	1	0.01	6	0.03	17	0.15	14	0.08	121	0.99
	Flexibility	*58*	33	0.28	1	0.01	8	0.04	1	0.01	12	0.07	3	0.02
	Security	*57*	1	0.01	3	0.02	5	0.02	8	0.07	40	0.23	0	0.00
	Sustainability	*44*	5	0.04	1	0.01	24	0.12	2	0.02	10	0.06	2	0.02
	Customer Satisfaction	*83*	4	0.03	0	0.00	19	0.09	0	0.00	5	0.03	55	0.45
Data	Machine/Tool	*544*	56	0.47	123	0.98	140	0.70	112	0.99	77	0.45	36	0.30
	Process	*250*	78	0.66	6	0.05	27	0.13	3	0.03	100	0.58	36	0.30
	Product	*129*	19	0.16	2	0.02	29	0.14	2	0.02	9	0.05	68	0.56
	Customer	*25*	4	0.03	0	0.00	14	0.07	0	0.00	4	0.02	3	0.02
	Reference	*46*	5	0.04	3	0.02	6	0.03	4	0.04	4	0.02	24	0.20
	ERP	*50*	33	0.28	0	0.00	5	0.02	1	0.01	11	0.06	0	0.00
	Environment	*34*	4	0.03	0	0.00	13	0.06	7	0.06	9	0.05	1	0.01
	Human	*29*	6	0.05	0	0.00	4	0.02	2	0.02	13	0.08	4	0.03
Integration	No Integration	*566*	50	0.42	110	0.87	137	0.68	109	0.96	65	0.38	95	0.78
	Vertical	*183*	47	0.39	11	0.09	35	0.17	2	0.02	74	0.43	14	0.11
	Horizontal	*101*	28	0.24	10	0.08	11	0.05	0	0.00	40	0.23	12	0.10
	End-to-End	*35*	3	0.03	0	0.00	21	0.10	1	0.01	7	0.04	3	0.02
Freq.	Real-time/Stream	*339*	44	0.37	9	0.07	18	0.09	113	1.00	122	0.71	33	0.27
	Historical/Batch	*515*	75	0.63	117	0.93	183	0.91	0	0.00	51	0.29	89	0.73
Method	Classification	*289*	16	0.13	66	0.52	45	0.22	55	0.49	51	0.29	56	0.46
	Regression	*102*	6	0.05	4	0.03	50	0.25	16	0.14	9	0.05	17	0.14
	Probabilistic Methods	*35*	6	0.05	3	0.02	8	0.04	6	0.05	8	0.05	4	0.03
	Clustering	*41*	1	0.01	6	0.05	12	0.06	8	0.07	7	0.04	7	0.06
	Dim. Reduction	*49*	3	0.03	8	0.06	9	0.04	13	0.12	9	0.05	7	0.06
	Deep Learning	*154*	12	0.10	28	0.22	53	0.26	22	0.19	18	0.10	21	0.17
	Reinforcement Learning	*37*	30	0.25	0	0.00	3	0.01	2	0.02	2	0.01	0	0.00
	Mathematical Opt.	*57*	37	0.31	1	0.01	8	0.04	5	0.04	2	0.01	4	0.03
	Evolutional Algorithm	*27*	9	0.08	1	0.01	5	0.02	2	0.02	2	0.01	8	0.07
	Swarm Intelligence	*18*	10	0.08	0	0.00	2	0.01	2	0.02	3	0.02	1	0.01
	Multi-Agent Systems	*12*	5	0.04	1	0.01	0	0.00	2	0.02	2	0.01	2	0.02
	Fuzzy Logic	*26*	6	0.05	6	0.05	5	0.02	4	0.04	3	0.02	2	0.02
	Custom Development	*220*	25	0.21	19	0.15	41	0.20	26	0.23	86	0.50	23	0.19

total count | relative count of objects in the respective cluster

MRO Planning (C2). This cluster, with 13.9% (*n*=119) of all research, focuses on Maintenance, Repair and Operations (MRO) planning activities. MRO planning ensures overall manufacturing effectiveness, including addressing scheduling problems for production or maintenance as well manufacturing performance optimization. Most applications are prescriptive, as the tasks require various optimization techniques to find optimal policies. As with the maintenance-based archetypes, time and cost dominate the objectives. The archetype has a noticeable share of the flexibility objective. Here, optimized planning seems to lead to a more flexible production environment. Production planning and maintenance planning are the main consumers for ERP data. Furthermore, applications use machine and process data. All frequencies are present, but historical analyses outweigh real-time applications. Methods focus on typical prescriptive techniques like mathematical optimization but also include reinforcement learning, swarm intelligence, and multi-agent systems.

Reactive Maintenance (C5). This cluster is also medium-sized, with 14.8% (*n*=126) of all research. It includes reactive maintenance approaches of the functions condition analysis and defect analysis, with the latter dominating this archetype. It constitutes a counterpart to both predictive maintenance archetypes (C4, C6). Here, the focus is not on proactive but reactive industrial maintenance measures (Pawellek 2016). The distribution of characteristics is mostly comparable with the other two archetypes. Two distinct exceptions exist: First, the analytical maturity is only diagnostic. That is, future behavior is not considered, and the applications are rather reactive in their detection of existing defects or conditions in machine operations. Second, analysis is performed mainly on historical data. That is, the maintenance task takes place after a malfunction has occurred. This is in contrast to the processing of real-time data streams and predictive measures to avoid such malfunctions proactively (Pawellek 2016).

Offline Predictive Maintenance (C6). This is the largest cluster, with 23.5% (n=*201*), and it reflects maintenance-based approaches that are of a proactive nature. This archetype exhibits great similarities to C4. The distribution of the characteristics is close to identical. That is, analytics is primarily of predictive maturity in combination with functional applications of condition analysis followed by defect analysis, both of which are typical maintenance operations. The main objectives are related to cost and time. The machine is the central data source in this archetype, and the data is mostly not integrated, which suggests that the overall production system is not considered. However, this archetype relies on historical data collected up to a certain point in time. That is, in contrast to C4, approaches in this category generally do not employ real-time analytics, but rather fall back on historical or batch-based data frequencies. Furthermore, we see regression analysis as the primary method. From a functional perspective, energy consumption analysis, energy consumption optimization, and design analysis can be distinguished as distinct domains. In line with this, the sustainability objective is of a higher frequency. Consequently, we see similarities between both use cases. Energy-related applications also predominantly utilize predictive analytics, tap into the machine directly as a data source, and feature no integration, indicating a possible novel research stream or gap in smart manufacturing. Finally, the objective of customer satisfaction, aligned with the function design analysis, is present and refers to another (smaller) comparable research stream.

Online Predictive Maintenance (C4). The fourth archetype represents the smallest cluster with 13.2% (*n*=113) of all research and is the online rather than offline sibling of C6. In contrast to C6, all approaches employ BA techniques in real-time, and thus online, having an intact and operational connection to (smart) manufacturing objects. We mostly see the application of classification and deep learning

methods, two characteristics that are closely related, followed by regression analysis. In summary, this archetype has a clear focus on the machines and equipment by predicting machine conditions and defects in an online fashion.

MRO Monitoring (C3). This is the second largest cluster, with 20.3 % (*n*=173), and focuses mainly on the functions of monitoring and security/risk analysis, followed by a small number of performance-related functions and condition analysis. The maturity of the approaches is mostly descriptive, followed by predictive, with some diagnostic objects. The frequency exhibits a distinct trend towards real-time analysis, as a defining trait of monitoring applications. Compared to other archetypes, the process is a dominant data source. In addition, the forms of data integration are much more diverse, that is, it has vertically integrated solutions, includes data from various machines or steps in a production process, and monitors manufacturing operations more holistically. From a methodological perspective, we see many custom-developed solutions as well as classifications to discern between normal and anomalous states in manufacturing. Lastly, we observe a connection between more generic monitoring operations (e.g., process monitoring) and the more specific security/risk analysis (which, e.g., includes applications such IoT network security monitoring). Both show a similar distribution of characteristics (except the security objective).

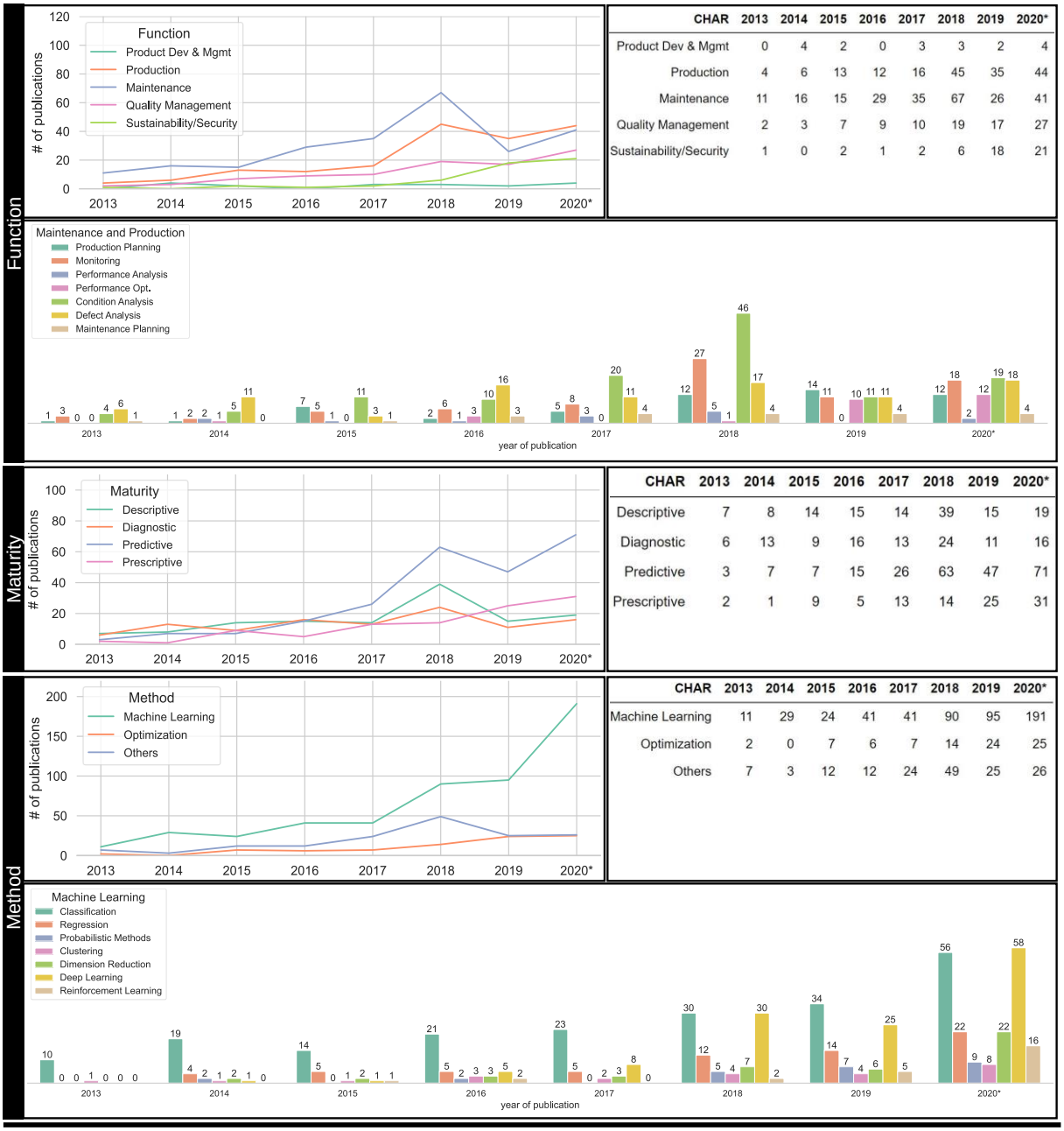
Quality Management (C1). The final archetype represents one of the medium-sized clusters with 14.3% (*n*=122) of all research. It covers typical quality management tasks such as checking whether the products and processes conform to specification, which is decidedly different from planning, MRO, and monitoring. Analyses are mostly descriptive or predictive with the objective of improving conformance (quality) as well as time, cost, and customer satisfaction (albeit to a lesser degree in the latter case). Much of the data is product and reference data with the obvious reliance on machine and process data. Most applications are not integrated, although vertical and horizontal integration does sometimes occur. Quality management methods use more historical than real-time data. Furthermore, methods center on classification – especially image recognition – with some applications of regression and deep learning in addition to custom development.

2.1.6 Analysis of Temporal Variations and Trends

In this section, we examine trends and highlight temporal variations in our data. First, we apply a temporal trend analysis to the taxonomy's dimensions and characteristics. Second, we apply this analysis to the derived archetypes. In order to create a consistent data set for the temporal analysis that does not complicates the interpretation, we have only included those research articles from the first iteration that match the filters we used for the second iteration from 2019 onwards (i.e. journal articles; Impact Factor >= 2.000).

2.1.6.1 Variation and Trends by Dimension and Characteristics

In the following, we present temporal trends and variations for the three dimensions of function, maturity, and method. These dimensions contained the most interesting findings. A more detailed visualization of all characteristics can be found in Appendix III.



CHAR	2013	2014	2015	2016	2017	2018	2019	2020*
Product Dev & Mgmt	0	4	2	0	3	3	2	4
Production	4	6	13	12	16	45	35	44
Maintenance	11	16	15	29	35	67	26	41
Quality Management	2	3	7	9	10	19	17	27
Sustainability/Security	1	0	2	1	2	6	18	21

CHAR	2013	2014	2015	2016	2017	2018	2019	2020*
Descriptive	7	8	14	15	14	39	15	19
Diagnostic	6	13	9	16	13	24	11	16
Predictive	3	7	7	15	26	63	47	71
Prescriptive	2	1	9	5	13	14	25	31

CHAR	2013	2014	2015	2016	2017	2018	2019	2020*
Machine Learning	11	29	24	41	41	90	95	191
Optimization	2	0	7	6	7	14	24	25
Others	7	3	12	12	24	49	25	26

only journal articles with Impact Factor 2.000 (2020) or higher || 2020 not fully covered.

Figure 9: Temporal Development of BA in Smart Manufacturing

Function. The upper part of the section *Function* of Figure 9 illustrates the publications related to this particular dimension and its five auxiliary dimensions. Here, data shows that *maintenance* and *production* are being most actively researched. While the number of publications in both areas were similar up to and including 2015, the research focus seems to have shifted to *maintenance* thereafter, which dominated until 2018. Subsequently, in 2019, production took over and continues to lead as the most researched function in smart manufacturing. It is also noticeable that in contrast to all other functions, *sustainability/security* has been increasing steadily since 2017. The area of *product development and management* seems to be a marginal topic.

Maintenance and Production. A more detailed analysis of *production* and *maintenance* as the two key auxiliary dimensions reveals that research has focused predominantly on *condition analysis* and *defect analysis* (cf. the lower part of the section *Function* of Figure 9). From 2017 on, a propensity towards *condition analysis* has emerged. The two topics of *performance optimization* and *monitoring* show a strong trend of growing interest. While both have been researched most heavily from 2015 onwards, an increasing tendency towards research into optimization is evident. In contrast, *maintenance planning* and *production planning* seem to be specialized and relatively stable topics after 2015. From 2018 onwards we also observe a more diversified research interest as compared to the years before, when *maintenance* dominated.

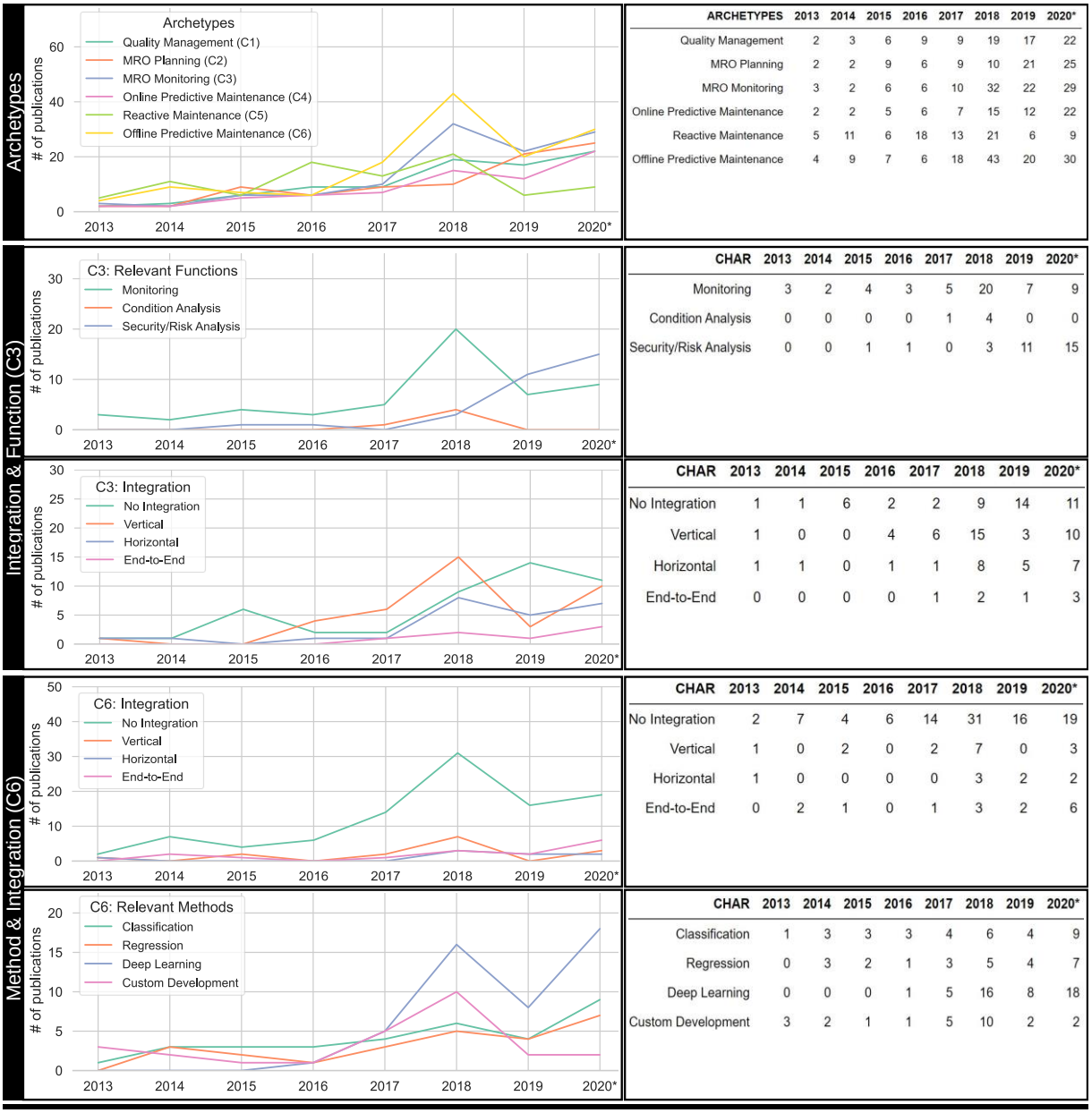
Maturity. The middle part of Figure 9, *Maturity*, demonstrates the temporal development of the respective dimension of the taxonomy. *Descriptive analytics* approaches were especially popular at the beginning of Industry 4.0 initiatives. Despite reaching a new high in 2018, the number has decreased significantly in the last two years. *Diagnostic analytics* approaches, on the other hand, have grown slightly over time, but without reaching a comparable number of publications. *Predictive analytics* approaches were already showing strong growth in the early years and, as of 2017, were the dominant BA approach in smart manufacturing. *Prescriptive analytics* research was less pronounced, but it grew steadily to become the second most applied approach. This suggests that as BA in smart manufacturing research matures, we may see it moving from predominately predictive to prescriptive approaches in the next couple of years.

Method. The upper part of the section *Method* of Figure 9 illustrates the publications related to this dimension. We have subdivided it into the three auxiliary dimensions of *machine learning*, *optimization*, and *others*. From 2013, it shows that there has been a strong trend towards the application of *ML*, peaking and dominating in 2020. We recorded a smaller number of publications for the auxiliary dimension *others*, but we see a small drop in interest after 2018, possibly pointing towards a standardization of the ML methods being used. *Optimization* shows a lower uptick, which points to the fact that the rise of performance optimization is fueled by methods from ML.

Machine Learning. The focus in the auxiliary dimension is on supervised ML techniques (cf. lower part of the section *Method* of Figure 9). Here, the use of *classification* techniques dominates in all years. Several waves are discernible, with the first from 2013 to 2014, the second from 2015 to 2017, and the third from 2018 onwards. *Regression* has not experienced a comparable uptick. In contrast, *deep learning* has rapidly gained in popularity since 2017 and now represents the most popular method This trend seems likely to continue. In addition, *reinforcement learning* has been more widely explored in the last two years, which has a rather prescriptive BA maturity. This observation is in line with the trends identified in the section *Maturity*.

2.1.6.2 Variations and Trends by Archetypes

In the following, we present variations and trends on archetype level. Additionally, we further examine two archetypes – namely *MRO Monitoring* (C3) and *Offline Predictive Maintenance* (C6) – due to their diversity in certain dimensions (see Table 8). Figure 10 provides a visualization for the discussion. The visualizations of all characteristics for each archetype can be found in Appendix III.



ARCHETYPES	2013	2014	2015	2016	2017	2018	2019	2020*
Quality Management	2	3	6	9	9	19	17	22
MRO Planning	2	2	9	6	9	10	21	25
MRO Monitoring	3	2	6	6	10	32	22	29
Online Predictive Maintenance	2	2	5	6	7	15	12	22
Reactive Maintenance	5	11	6	18	13	21	6	9
Offline Predictive Maintenance	4	9	7	6	18	43	20	30

CHAR	2013	2014	2015	2016	2017	2018	2019	2020*
Monitoring	3	2	4	3	5	20	7	9
Condition Analysis	0	0	0	0	1	4	0	0
Security/Risk Analysis	0	0	1	1	0	3	11	15

CHAR	2013	2014	2015	2016	2017	2018	2019	2020*
No Integration	1	1	6	2	2	9	14	11
Vertical	1	0	0	4	6	15	3	10
Horizontal	1	1	0	1	1	8	5	7
End-to-End	0	0	0	0	1	2	1	3

CHAR	2013	2014	2015	2016	2017	2018	2019	2020*
No Integration	2	7	4	6	14	31	16	19
Vertical	1	0	2	0	2	7	0	3
Horizontal	1	0	0	0	0	3	2	2
End-to-End	0	2	1	0	1	3	2	6

CHAR	2013	2014	2015	2016	2017	2018	2019	2020*
Classification	1	3	3	3	4	6	4	9
Regression	0	3	2	1	3	5	4	7
Deep Learning	0	0	0	1	5	16	8	18
Custom Development	3	2	1	1	5	10	2	2

only journal articles with Impact Factor 2.000 (2020) or higher || 2020 not fully covered.

Figure 10: Temporal Development of BA Archetypes in Smart Manufacturing

Archetypes. The top section of Figure 10 illustrates the temporal development of the six archetypes. Throughout the years, we see a steady increase for all archetypes, while both *reactive maintenance* and *offline predictive maintenance* dominate 2013 and 2014. From 2014 to 2017, it is noticeable that *reactive maintenance* and *online predictive maintenance* gain traction. After 2017, *MRO monitoring* and *offline predictive maintenance* grow particularly rapidly. In contrast, the interest in *reactive maintenance* significantly decreases after 2017. *MRO planning*, *quality management*, and *online predictive maintenance* are rather steady in their growth. In 2019 we can observe a drop of research interest in *MRO monitoring* and *offline predictive maintenance*. After 2019 we see continuous growth over nearly all archetypes, with *online predictive maintenance* growing most rapidly. Again, both *MRO monitoring* and *offline predictive maintenance* outperform the other clusters, but their growth rate has dropped considerably. *Reactive maintenance* is the least considered in research.

MRO Monitoring. This archetype is relatively diverse regarding the *function* dimension. Our temporal analysis confirms the novel research stream or gap in *security/risk analysis*. The characteristic *monitoring* is dominant in our first search iteration with data until 2018. *Security/risk analysis*, on the other hand, exhibits rapid growth through 2020. Thus, s*ecurity/risk analysis* constitutes a novel research trend in smart manufacturing and may even constitute a distinct archetype in the future. Regarding integration, this archetype shows a significant percentage of vertical integration, pointing to multi-level monitoring. In general, this archetype implemented more integration than others did.

Offline Predictive Maintenance. As the name suggests, this archetype relies not on *integration*, but rather data that is copied for offline analysis. While we observe a slow increase in integration options, it does not seem relevant for implementation in the near future. Furthermore, the archetype displays dissimilar characteristics in the dimension *method*. The distribution and growth of *classification, regression*, and *custom development* are steady with no clear frontrunner until 2017, when a new contender appears. *Deep learning* exhibits rapid growth and surpasses all other methods by 2018. It is by far the most popular method today.

2.1.7 Discussion and Conclusion

Our study contributes to the descriptive knowledge of BA in smart manufacturing, as it explores a diverse, evolving, and not-yet-well-conceptualized domain. We conceptualized a taxonomy and derived archetypes for BA in smart manufacturing and discussed their appearance as well as temporal trends in this field. Our taxonomy, which comprises 52 characteristics, is based on the four meta-characteristics of domain, orientation, data, and technique. Our archetypes summarize the field's foci as MRO planning, maintenance (reactive, offline predictive, online predictive), MRO monitoring, and quality management. Our results reduce complexity for scientists and practitioners, in particular for those who are new to the field, by organizing research into archetypes, which can serve as orientation and context for new artifacts. Our work has revealed several theoretical and practical implications.

Our main contributions are a theoretically well-founded and empirically validated multi-dimensional taxonomy, which focuses on the functional and non-functional characteristics of BA applications in smart manufacturing, and archetypes of applications, derived exploratorily through cluster analysis of our comprehensive, coded bibliography.

As a first theoretical contribution, our taxonomy can be used to systematize BA in smart manufacturing for later analysis and provides a new level of understanding of the novel innovations and technologies within this emerging field. Scientists can use the taxonomy to study and hypothesize about relationships among techniques and applications as well as their characteristics. Our taxonomy not only supports the discussion about the area of research, but also provides a more profound knowledge of the emerging patterns of BA in smart manufacturing by providing a scheme to classify BA applications into archetypes.

While we said that Industry 4.0 and smart manufacturing represent the context as a constant for our research, our results enable us to turn the tables. Our taxonomy is a concise conceptual representation of the rich body of knowledge of BA in smart manufacturing literature. As Gregor (2006) points out, taxonomies can serve as a theoretical basis for analysis beyond their descriptive and classificational

purpose. In their most basic form, they serve as taxonomic theory (Nickerson et al. 2017), which can be the basis for more advanced theories that aim to explain and predict. Thus, our taxonomy can itself be used as context for further investigations as it enables one to understand the domain and to describe elements that take part in the phenomena of examination. Summarizing, Bapna et al. (2004) assert that "a robust taxonomy can then be used to perform ex post theory building". Given the comprehensiveness of our data collection and analysis, we consider our taxonomy robust enough to serve such purposes.

Second, our cluster analysis revealed six archetypes, which explain different foci and applications of BA, as well as their respective roles in smart manufacturing. This distinction can be used to differentiate among the scientific results of BA and their uses. It supports clarifying terminology and thus can make the academic discourse more concise. Furthermore, it helps to better interpret findings by being able to judge them in the context of comparable applications. In sum, the taxonomical systematization of BA and the uncovering of archetypes in smart manufacturing provide new tools for the scientific community to understand better application opportunities. For example, it can help to uncover applications within archetypes that exhibit comparable infrastructure and skill requirements despite being functionally distinct at first glance.

Moreover, our archetypes enable a more detailed analysis of the temporal variations of trends in research topics of BA for smart manufacturing. Beyond the general observation of the importance of offline maintenance and monitoring topics, as well as the demise of reactive maintenance research, we found a generally stable relationship between the BA domains. Our archetype analysis further revealed that security topics have gained more traction in recent years. In addition, the maturity of BA research has moved from descriptive to predictive approaches and may eventually transition to a predominant focus on prescriptive approaches. While the data dimension did not reveal insights per se, a look at the archetypes revealed that the distribution of characteristics is rather specific to them. Lastly, machine learning, and in particular deep learning, has come to dominate contemporary method use in recent years. From a scientific – but even more from a practical – point of view, this enables people to question and adjust their priorities to address contemporary challenges with their research or in their work environment.

From a practical perspective, our taxonomy provides dimensions and characteristics that can serve as a blueprint for BA selection and application in concrete real-world scenarios. Our taxonomy provides measures to evaluate the different options for BA, to address a specific problem, area, or requirement. We provide a distinction among archetypes that enables practitioners to find or review suitable configurations of BA to address their requirements. Assuming that research is several years ahead of productive practical applications, identifying these trends can create the awareness necessary to shape organizational and technical developments towards these future opportunities, for example by acquiring the requisite workforce skills.

As with any research, our study is not without its limitations. Taxonomies are never complete and should be considered as a starting point for further contextualization. Ours is the result of a design search process, which we have further documented in the appendices. While our data collection was rigorous, there may be further relevant applications of BA in smart manufacturing that have appeared in other domains of research and which we did not uncover in our data collection. The interpretation of data was not without issues, either. Clustering algorithms and segmentation metrics rarely point to the consistent segmentation of binary data. We consistently scrutinized our results qualitatively to ensure coherence and applicability.

In conclusion, in moving to establish smart manufacturing, businesses must adapt to disruptive and radical changes in value networks, business models, and operations due to the ever-emerging technological manufacturing innovations of the fourth industrial revolution. A massive increase in data, computing power, and connectivity is fueling novel applications of BA that can lead to cost advantages, increased customer satisfaction, and improvements in production effectiveness and quality.

Future research could examine the archetypes in more detail and, for example, focus on security/risk analysis, both energy consumption characteristics, and design analysis, as they represent relatively uniform subclusters that we have not yet explored in greater depth. In addition, research should revisit trending areas and, for example, explore the use of machine learning in smart manufacturing in more detail as this will shed light on important future topics such as transfer learning and explainable artificial intelligence.

2.2 Transfer Techniques in Explainable AI

Abstract. Machine learning enables computers to learn from data and fuels artificial intelligence systems with capabilities to make even super-human decisions. Yet, despite already outperforming preexisting methods and even humans for specific tasks in gaming or healthcare, machine learning faces several challenges related to the uncertainty of the analysis result's trustworthiness beyond training and validation data. This is because many well-performing algorithms are black boxes to the user who – consequently – cannot trace and understand the reasoning behind a model's prediction when taking or executing a decision. In response, explainable AI has emerged as a field of study to glass box the former black box models. However, current explainable AI research often neglects the human factor. Against this backdrop, we study from a user perspective the trade-off between completeness, as the accuracy of a model's prediction, and interpretability, as the way of model prediction understanding. In particular, we evaluate how existing explainable AI model transfers can be used with a focus on the human recipient and derive recommendations for improvements. As a first step, we have identified eleven types of glass box models and defined the fundamentals of a well-founded survey design to understand better the factors that support interpretability and weighing them against improved yet black-boxed completeness.[4]

2.2.1 Introduction

Today's society and economy have firmly settled into the digital age. Data is generated everywhere and offers a multitude of valuable possibilities (Guidotti et al. 2018b), such as for example the right time to maintain an industrial machinery (Civerchia et al. 2017). A mature and common technique to uncover information in data analytically is to apply statistical methods such as regression analysis. Artificial intelligence (AI) systems promise to improve this process. By AI, we refer to the concept of machine

[4] This paper is published within the 28th European Conference on Information Systems as 'HOW MUCH IS THE BLACK BOX? THE VALUE OF EXPLAINABILITY IN MACHINE LEARNING MODELS (Wanner et al. 2020). The related supplementary material is given in Appendix III.

learning (ML), the science of mathematical models and algorithms that machines employ to solve tasks without being explicitly programmed to do so (Bishop 2006). These ML systems tend to outperform existing analytical methods or even humans for specific tasks, e.g., in medicine or gaming (e.g., Akay 2009; Kourou et al. 2015; Silver et al. 2016).

Despite its analytical benefits, ML faces several challenges. In particular, the remaining uncertainty and its dependence on data quality are problematic (Patel et al. 2008; Quionero-Candela et al. 2009). Researchers have addressed this issue by developing more robust and accurate model algorithms. While reducing the bias problem, often the results simultaneously reduces traceability (Dam et al. 2018). These algorithms are *black box* models whose internals are either unknown to the observer or they are known but essentially uninterpretable by humans (Guidotti et al. 2018b). This results in a lack of trust (Dam et al. 2018). Trust in our context refers to the confidence in an AI-based recommendation to act based on it. Studies have shown that this is influenced by how much a person understands the behavior of a model, rather than considering it a black box (Ribeiro et al. 2016b). Thus, an appropriate way of model explanation will improve the user's trust of model predictions and vice versa its acceptance (Dam et al. 2018; Gilpin et al. 2018). We define explanation as the ability to fill the information gap between the AI system and its user in an understandable way (Cui et al. 2019).

This is the objective of explainable AI (XAI). It aims to produce more explainable models, while maintaining a high level of learning performance (Gunning and Aha 2019). The technical feasibility of explaining black box models is already advanced, but there is a lack of knowledge about the evaluation of these models by humans (Miller 2019). Therefore, Cui et al. (2019) distinguish two types: functional and social explanation. The former is about the explanation between AI experts, such as AI engineers and AI developers (Ras et al. 2018). The latter is about the explanation between AI experts and intended users, with the aim to strengthen trust and use by an appropriate type of presentation (Miller 2019). Miller (2019) argues that AI researchers today are building explanatory agents for themselves, rather than for the intended users. Various researchers in the XAI community are therefore calling vehemently for further research on the social evaluation of AI (e.g., Miller 2019; Ribeiro et al. 2016b).

Especially in the last couple of years, XAI transfer techniques have been developed to convert black box models into *glass box* models. A wide variety of initial and final models has been proposed. However, it remains questionable whether the research is also in line with the expectations of the intended users. For this purpose, it must be understood, which model presentation is suitable, and which is not. Further, the challenge behind the XAI transfer techniques remains to create explanations that are both, complete and interpretable. This faces the trade-off that most accurate explanations are not easy for humans to interpret and, inversely, most understandable explanations often lack predictive power (Doran et al. 2017; Gilpin et al. 2018; Guidotti et al. 2018b). Against this background, we intent to reveal the willingness of users to dispense accuracy of model prediction in favor of better explanations. Our intention can be summarized with a research question, which partly also goes beyond the scope of this paper:

"Which of the existing XAI transfer techniques from academics promise the best approach for the trade-off between model accuracy and model explainability from an intended user perspective?"

The result allows us to guide future research in two ways: (i) to understand the explanatory goodness of different ML model presentations and (ii) to understand the importance of the model's degree of accuracy against its degree of explanation. This can be an important enabler for targeted optimizations.

Correspondingly, our paper is structured as follows: In Section 2.2.2, we describe the theoretical background and related work. Section 2.2.3 covers the status quo of XAI model transfer implementations. We present our planned study design in Section 2.2.4. Finally, we conclude the paper and provide an outlook for the upcoming research steps in Section 2.2.5.

2.2.2 Theoretical Background and Related Work

2.2.2.1 Machine Learning and Explainable Artificial Intelligence

Machine Learning. ML is the science of mathematical models and algorithms that machines employ to solve tasks without being explicitly programmed (Bishop 2006). The internal computation often remains incomprehensible due to its complexity. Thus, how and why of a result remain problematic (Holzinger et al. 2017). This intensifies regarding several problems. Practitioners often overestimate the accuracy of their models (Patel et al. 2008) as known test data might differ from the unknown 'real world' data (Quionero-Candela et al. 2009). It is also possible that there is an unintentional leakage of data distorting the overall accuracy (Kaufman et al. 2012). Furthermore, adversarial attacks, as a conscious manipulation of data to trick the ML system, are potential threats (Barreno et al. 2010). In consequence, ML predictions cannot be acted upon in blind trust (Guidotti et al. 2018b; Ribeiro et al. 2016b).

Explainable AI. XAI is a research area, trying to address these problems. The main objective called out is to produce more explanatory models whereas retaining a high learning performance (Gunning and Aha 2019). Thus, it is foremost about dissolving the model's black box problem. For this purpose, the internal processes of the models are made explainable by algorithms and mathematical methods (Abdul et al. 2018). So, today's XAI research focuses on a transfer of *black box* models into so-called *glass box* models (Holzinger et al. 2017). A glass box model is transparent. This makes the internal model's reasoning comprehensible, so that it creates trust and increases its acceptance. This may be necessary in companies for example due to legal liabilities (Dam et al. 2018; Gilpin et al. 2018). Nevertheless, XAI aims at the multifaceted term of explanation. It is therefore important to understand what constitutes an explanation (Miller 2019; Miller et al. 2017).

2.2.2.2 Artificial Intelligence Model's Explanation Dilemma

Model Explanation. Research in various disciplines including philosophy, social science, psychology, and computer science has pursued the question of what constitutes explainability and further how explanations should be expressed to be readily grasped and valued by humans (Miller et al. 2017). We adopt the definition of Dam et al. (2018) who state that "*explainability or interpretability of a model measures the degree to which a human observer can understand the reasons behind a decision (e.g. a prediction) made by the model.*" Understandable reasoning can be presented either by making the process of decision making transparent (named as global explainability) or by providing explicit rationale

for the decision (named as local explainability) (Dam et al. 2018). A global explainability provides transparency into the decision model (simulatability), components such as parameters (decomposability), or algorithms (algorithmic transparency). This is typically addressed by a functional focus of XAI, ensuring an appropriate explanation between AI experts (Ras et al. 2018). Local explainability enables post-hoc interpretability of the concrete results through textual explanations (in natural language), visualizations, or examples (Lipton 2018). This is typically addressed by a social focus of XAI, aiming to strengthen trust and use by an appropriate type of explanation presentation for intended users (Miller 2019).

Trade-off Dilemma. To provide the required explanation, explainers must address two constraints in parallel: interpretability and completeness (Gilpin et al. 2018). In research, interpretability is often also termed as explainability, comprehensibility, and transparency while completeness is used synonymous to accuracy (Dam et al. 2018; Guidotti et al. 2018b). Interpretability on the one hand is defined as the ability to explain or to present reasoning of the model's prediction in understandable terms to a human (Doshi-Velez and Kim 2017). The degree of interpretability is strongly depending on the individual's cognition, knowledge, and prejudices (Gilpin et al. 2018). Completeness on the other hand is defined as the accuracy of the system operation description (Gilpin et al. 2018). A description, which is not complete, has some kind of unquantified bias (Doshi-Velez and Kim 2017).

Highly accurate explanations, such as a pure mathematical expression of the model's reasoning, are not easy for humans to interpret. Therefore, attempts like Ribeiro et al. (2016b) focus on finding an explanation that abstracts from 'real world' complexity towards fast perception. Inversely, if an explanation is more abstract, and thus, better understandable it often lacks predictive power (Gilpin et al. 2018; Guidotti et al. 2018a). However, it is not always necessary to provide a ML model with an explanation of reasoning that is perfectly complete (Doran et al. 2017). It is rather depending on the expectation of the individual, that, thus, must be understand first before optimizing the given trade-off.

2.2.3 Related Work and Research Gap

The idea of making models explainable is not new. It exists since the advent of first expert systems in the 1970's (Swartout 1983). These decision support systems (DSS) are defined as generation one, evolving to today's DSS of generation three (Mueller et al. 2019). Apart from the technical progress of new models, which tends to improve the accuracy at the expense of increased model complexity, the problem remains the same: How to explain the model-based decision reasoning in an understandable manner, without losing completeness? Primary within the last two years, several XAI transfer techniques have been developed to convert black box models into glass box models. A wide variety of initial and final models has been proposed but without a critical acknowledgement whether the research is also in line with the expectations of the intended users. Thus, there seems to be a lack of user-based research to understand the given trade-off (Sheh and Monteath 2018).

Classification and review. According to Lipton (2018), a classification will be a helping hand to address this by identifying transparent or interpretable ML algorithms. This requires an comparison evaluating the different ML algorithms. Dam et al. (2018) classify explainability as a three-part component consisting of the transparency of the model, the individual components as well as the ML algorithm itself. The division into different levels of explanation was carried out by the authors themselves without

giving further evidence. Gunning and Aha (2019) and Duval (2019) follow a similar procedure. García et al. (2009) try to make a simplified measurable calculation for this trade-off feasible. Further, Kotsiantis et al. (2007) try to classify different ML algorithms by different criteria such as accuracy or transparency. Adadi and Berrada (2018) and Mohseni et al. (2018) provide a review of existing XAI model transfer approaches, but without differentiating between multiple ML algorithms.

User survey. Further, there are contributions concentrating on questioning the user perspective. However, these contributions primarily focus on proving the importance of such an approach, rather than seeking to optimize the trade-off. Exceptions are the publications by Cui et al. (2019) and Hoffman et al. (2018). Cui et al. (2019) study the trade-off from a functional explanation perspective. By applying their developed framework they found out that a rule extraction method is the most advanced and promising method among current XAI transfer techniques. Hoffman et al. (2018) have designed metrics for dimensioning the XAI model through literature and own psychometric evaluations. They present a research design concept and corresponding survey possibilities as well as recommendations. They considering trust and the reliance of the trade-off between interpretability and completeness.

In summary, the evaluation and consideration of various XAI approaches from a user perspective is rarely found in related work. This applies in particular to the comparison of different XAI approaches for certain ML algorithms against the trade-off between interpretability and completeness. Further, we could not find any contribution conducting a qualitative study that critically analyzes different, existing XAI approaches and ML algorithms against the trade-off from a social user perspective.

2.2.4 Status Quo of XAI Model Transfers

We conducted a structured literature review based on the recommendations of Webster and Watson (2002). Our aim was to identify research papers, which developed an XAI method including a practical implementation. Therefore, we have focused on the Computer Science databases of IEEE Xplore and ACM Digital Library. Further, we queried Information Systems related databases AIS eLibrary, Science Direct, and Web of Science. Through Scopus, we addressed the topic's interdisciplinary. Our search term conforms to the following pseudocode: *"((Interpretability | Explainability | Transparency | Comprehensibility | Understandability | Explanatory | Black box | Blackbox) AND (Machine Learning | Artificial Intelligence | AI | Deep Learning | Neural Net*))"*. Through the extension of a forward and backward search, we have identified 13.201 contributions. After screening title, keywords, abstract, and a full-text analysis, a total of 74 contributions has been considered as relevant, excluding preprints (cf. Table 41 in the Appendix III).

Figure 11 provides an overview of the distribution of the applied XAI methods. The left part sorts the publication by date and by the applied black box ML model. The result underlines that only a few procedures for transferring black box models into glass box models existed before 2016 (n=13). Subsequently, the past couple of years show an exponential growth on new XAI model transfer techniques (n=75). Approaches based on neutral nets dominate: Convolutional Neutral Networks (CNN) foremost since 2018 (n=7) and Artificial Neural Networks (ANN) intensifying since 2019 (n=11). Also, there is an increasing attempt to explain clustering algorithms (n=6). The data for 2020 only covers the first quarter and does not allow for any quantitative assessments.

The right part of Figure 11 highlights the amount of XAI model transfer techniques of black box ML model types into glass box models such as for example *linear regression*. It is noticeable that in particular deep learning algorithms (*n*=65) are being translated. These are transferred foremost into Visualization (*n*=26) and "*if-then*" rulesets (*n*=11). Due to the underlying complexity of the algorithmic prediction process, the representation can become highly detailed and thus opaque (Liu et al. 2018a; Vásquez-Morales et al. 2019). While these techniques enable a high degree of completeness, the interpretability often lacks, even after model transfer. Also, the completeness suffers from the XAI transformation into more explainable approaches (e.g., Alzantot et al. 2019). There are also techniques for 'less complex' ML algorithms such as support-vector machines (SVM) (*n*=16) or various types of clustering algorithms (*n*=5). These are foremost transferred into rulesets, decision trees, or multiple visualizations. Also, the transfer decreases the degree of completeness of the prediction in favor of an increasing interpretability (e.g., Karevan et al. 2015).

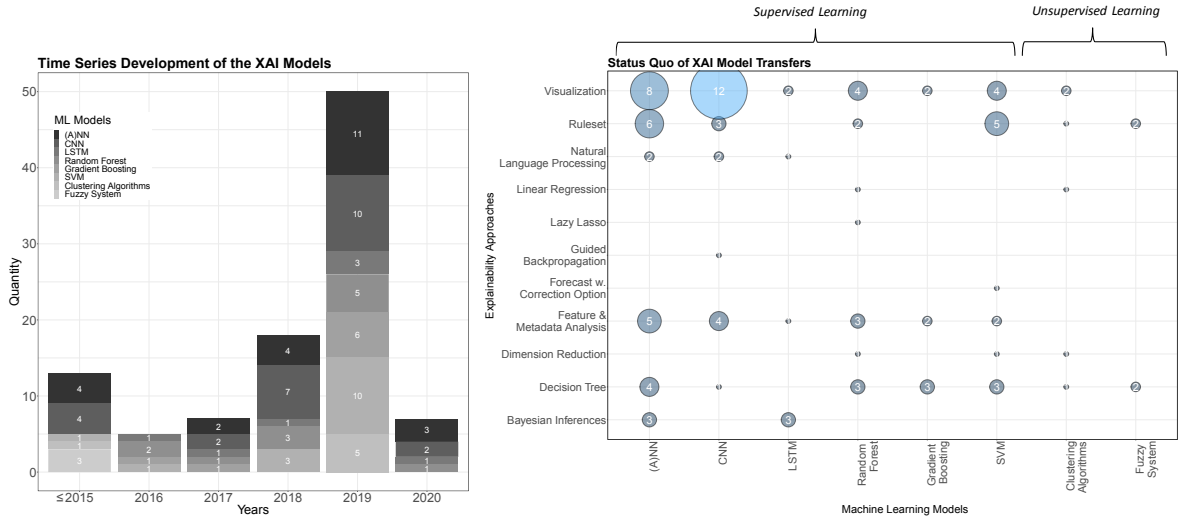


Figure 11: Analysis of the Structured Literature Review

2.2.5 Planned Research Design

2.2.5.1 Evaluation Approaches in XAI

There are three different approaches for the evaluation of XAI methods: application-grounded, human-grounded, and functionally-grounded (Doshi-Velez and Kim 2017).

In the *application-grounded evaluation*, real application scenarios are proposed to participants. The aim is on the evaluation of the method's quality, identifying new errors or correlations within models. By integrating domain expert knowledge, additional subject-specific problems can be revealed (Antunes et al. 2012). The *human-grounded evaluation* can be conducted with several approaches. Most commonly the model's prediction is based on the input; by participants; or by manual calculation of the difference between the input vs. the output. Further, it is possible to conduct a pairwise comparison of explanations for a model. The quality of the explanation, for example can serve as an evaluation factor (Lakkaraju et al. 2016). The third method, the *functionally-grounded evaluation*, does not involve interaction with participants. Here, it is necessary to derive a formal definition of explainability to enable a quantitative

evaluation. It is recommended when an evaluation cannot be carried out practically (Freitas 2014). However, a human-based pre-evaluation must be applied first.

A functionally-grounded evaluation is not applicable, as we aim at a social explanation evaluation by the intended users. The application-grounded evaluation was excluded as well as its focus is more on a functional explanation evaluation to improve model prediction. Conversely, the human-grounded evaluation seems most promising for a XAI methods and trade-off assessment, using a pairwise comparison of explanations for XAI models (Narayanan et al. 2018).

2.2.5.2 Metrics for a Human-centered XAI Study

Adopting the social user perspective, we try to understand why explanatory model representations are better or worse suited for the intended user. There are numerous studies and measures in the field of information quality research (e.g., McKinney et al. 2002). Preliminary work has already been done to develop and adapt these metrics for the XAI research area. Our selection represents an intersection of these preliminaries (Gregor and Benbasat 1999; Hoffman et al. 2018; Mueller et al. 2019).

We have chosen the metrics of: i) trustworthiness; ii) satisfaction; iii) understandability; iv) usefulness; v) sufficiency of detail; and vi) overall acceptance. i) Trustworthiness is the generalized expectancy of the user that the AI recommendation is reliable (Rotter 1980). ii) Satisfaction is "*the degree to which users feel that they understand the AI system or process*" (Hoffman et al. 2018). iii) Understandability measures the traceability of the recommendation given, so that a user is able to comprehend what happened (Hoffman et al. 2018; Mueller et al. 2019). iv) Usefulness is about the degree a user believes that the system would advance his or her performance (Davis 1989). It is seen as a fundamental determinant of user acceptance of a system (Mueller et al. 2019). v) Sufficiency of detail "*entails a concept of Minimum Necessary Information*", assessing whether enough information is given (Mueller et al. 2019). In contrast, vi) overall acceptance entails the degree of explanation goodness in total to be able to act based on the given information (Hoffman et al. 2018; Mueller et al. 2019). This will especially address the trade-off of between interpretability and completeness.

2.2.6 XAI Study Design

The respective targets of the XAI transfer techniques we identified are assumed to be glass box models, promising an explanatory result presentation. We could identify a total of eleven types of glass box models: decision trees, ruleset, natural language processing (NLP), visualization, Bayesian inference; linear regression, feature and metadata analysis, guided backpropagation, forecast with correction option, lazy lasso, and dimension reduction (cf. Section 2.2.3). Further, we know that a transfer is associated with a loss in accuracy. For example, by using Bayesian interference to interpret the result of a long short-term memory (LSTM) the authors lose over 13 % (Kraus and Feuerriegel 2019). A rule-based translation of an ANNs showed a loss of 6 % (Vásquez-Morales et al. 2019).

Proposed Research Procedure. We plan a Web-based survey to answer our research question (cf. Section 2.2.1). Due to the possible bias of the participants (Gilpin et al. 2018), we decided to develop a scenario that is comprehensible for a broad audience and to exclude those biases through a large-scale survey (of n>200). We suggest a three-staged procedure: i) initial questionnaire, ii) pretest, and iii) user

study. In the i) initial questionnaire, we define all relevant units that need to be retrieved from the respondents, for example demographic information (e.g., gender and age) or the measurement items to assess the interrelations between completeness and interpretability. Further, we will conduct a ii) pretest to ensure that the measures of the questionnaire are applicable in our context. We plan to have several individuals, split up into two groups (Brown et al. 2010). This allows us to understand problems of time, language, and content. In addition, we will get an understanding of the usefulness of the results' measures. Subsequently, we modify the survey and we plan to validate it equivalently with the second group. Finally, we carry out the iii) user study in a two-staged process as described in the following.

User Study. First, we will introduce an overview to all XAI glass box models included in the survey. Then, we begin our survey by presenting different scenarios to the participants (cf. Figure 12 left). Each of which includes the presentation of a different glass box model result. The participants have to rate on a 5-point Likert-scale how good they think the model explanation is (Adams et al. 2003). Afterwards, there will be questions on the measures as described in Section 2.2.5.2. In this stage, participants are not given any information about the accuracy of the model deliberately, so, that they assume them to be equal first and will not take them into consideration in their choice making procedure. This allows us to identify the best glass box model presentation independent of the trade-off with accuracy as the 'ideal' to strive for. By using the associated measurement criteria, we get a better understanding of the reasons.

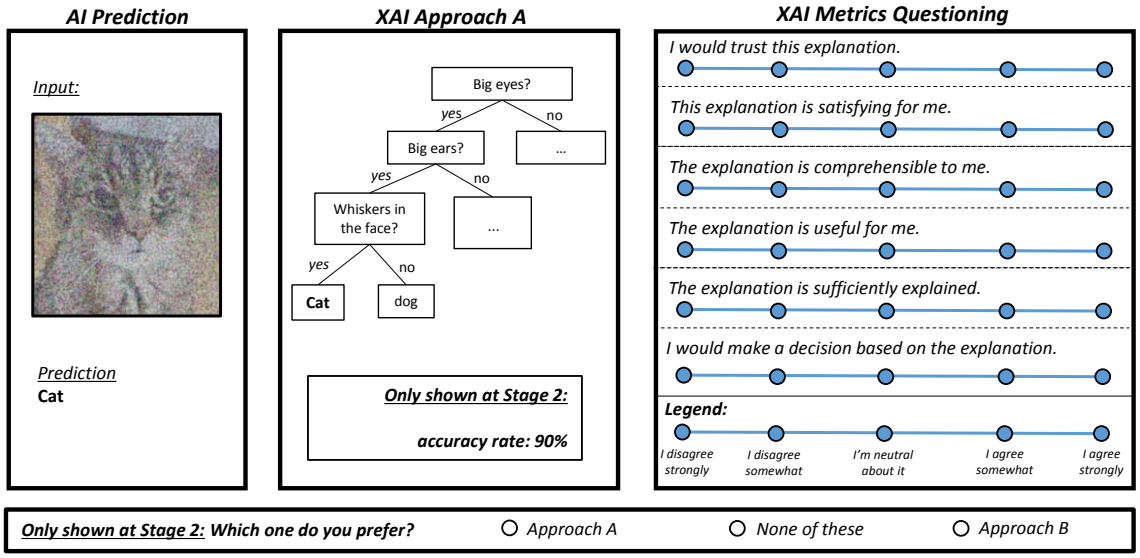


Figure 12: Scenario of Human-centered Pairwise XAI Model Transfer Comparison

In stage two, we will have a pairwise comparison of the same glass box model explanations with the same measures presented in stage one (cf. Figure 12). This time we reveal the information about the accuracy of each model. Thus, we vary the accuracy independently of realistic values to find out the pure trade-off between interpretability and accuracy. We further ask the participants on their model preferences as this might differ due to the accuracy against their previous decision made.

2.2.7 Conclusion and Outlook

Besides the already proven advantages of modern AI algorithms based on ML, the development of robust and precise ML algorithms also results in a decrease of traceability of the results among

practitioners (Guidotti et al. 2018b). This lack of traceability is accompanied by a lack of trust in ML algorithms (Dam et al. 2018). To address the general objective of more explainable models while maintaining a high level of learning performance (Gunning and Aha 2019), XAI researchers build a variety of model transfers to make AI models explainable. Thus, better performing but opaque AI models (black box models) are transformed into less accurate, explainable AI models (white box models).

However, these approaches have not been verified from a user's perspective yet. Consequently, the procedure for verifying these approaches constitutes a research gap, which we addressed with our research-in-progress report. We have systematized the field of XAI research through a structured literature review. Further, we have proposed a comprehensive user study on the effects of XAI model transfers on the explainability of AI decisions and their perception by human users.

On the one hand, the results of our planned study will provide an understanding of the explainability of the result presentation of the assumed glass box models. On the other hand, we will contribute to the optimization of the trade-off between interpretability and completeness. This allows future research in the field of XAI to concentrate on promising model transfer approaches and to optimize these towards the expectations of intended user. Only with the trusting and understanding user in the loop, AI technology can become a successful part in industrial and home applications of our digital age.

2.3 Example of Explainable AI Transfer

Abstract. The fourth industrial revolution is quickening the digital transformation of shop floors, enabling immense potential for optimization. Maintenance is an important area that can profit decisively from making digital information serviceable. It serves to guarantee a smooth production process. Currently, unexpected problems still lead to high opportunity costs. Effectively addressing them is hampered by a lack of transparency, which makes it difficult for service staff to detect, localize, and identify faults. Innovative data analysis methods, which allow to intelligently evaluate and use machine condition data, promise a remedy. In the future, these will support maintenance issues and optimize the overall process. However, the condition of current shop floors in German medium-sized manufacturing companies appears inadequate. As a survey conducted by us revealed, machinery data still comes mainly from light sensors, motor voltages, and positioning scanners. Such binary data values complicate data analysis of modern evaluation methods. The paper at hand addresses this problem without a need for shop floor extensions. Together with partners from industry, a step-by-step development approach was developed to show how comprehensive maintenance support is possible despite restrictions on binary data values. The implementation is based on techniques from the areas of process mining and machine learning. A demonstrator evaluates the practical suitability.[5]

[5] This paper is published at the HMD journal as 'Verwendung binärer Datenwerte für eine KI-gestützte Instandhaltung 4.0' (Wanner et al. 2019). The DOI is: https://doi.org/10.1365/s40702-019-00560-3.

2.3.1 Nutzenmachung von Daten für intelligente Wartungsansätze als Wettbewerbsfaktor in der Fertigung

Die vierte industrielle Revolution fordert Unternehmen zum Umdenken. Durch eine umfassende Vernetzung von Einzelkomponenten (bspw. Sensoren, Auswertungseinheiten und Maschinenbauteile) gelangt ein Produktionsfaktor immer mehr in den Fokus: Information. Diesen gilt es wettbewerbsgerecht zu nutzen, was eine zielorientierte Ausrichtung der Kommunikation und Reaktion der Einzelkomponenten sowohl untereinander als auch mit dem Menschen bedingt (Hermann et al. 2016). Auch für die in der Fertigung wichtige Aufgabe der Instandhaltung bestehen Bestrebungen einer intelligenten Nutzenmachung von Daten. Unter der Instandhaltung wird hier die Wahrung bzw. Wiederherstellung der Betriebsbereitschaft eines Fertigungsablaufs verstanden, mit dem Ziel die Opportunitätskosten minimal zu halten. Damit verbundene Tätigkeiten können reaktiv, nach Auftreten eines Fehlers, oder proaktiv, hinsichtlich einzuleitender Gegenmaßnahmen, sein (Delen 2014). Im Allgemeinen gilt jedoch auch hier die Beachtung des Pareto-Prinzips. Eine kostenintensive Erweiterung der Fertigungsanlage um neue Sensorik kann u. U. zu einem negativen Gesamtergebnis aus erhöhten Instandhaltungskosten gegenüber den gewonnenen Einsparungen führen, und ist daher kritisch abzuwägen.

Eine effiziente Adressierung von Instandhaltungsfragen bedarf demnach einem umfangreichen Verständnis und der effektiven Handhabung komplexer Abläufe. Wie eigene Interviews (siehe unten) gezeigt haben inspizieren, reparieren, und bessern Servicekräfte Fertigungsanlagen überwiegend auf Basis von Erfahrungswerten, und damit ihrer Intuition, aus obwohl oft eine umfangreiche Dokumentation der Hersteller vorliegt.

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Eine effektive Nutzenmachung von Maschinenzustandsdaten bedingt das Verständnis über die Gegebenheiten der abgreifbaren Daten. Um dies zu erlangen wurden mit Fokussierung auf den deutschen, produzierenden Mittelstand qualitative Interviews mit Maschinenherstellern und Serviceprovidern (n = 6) sowie eine quantitative Erhebung auf der *Hannover Messe 2019* (n = 32) zum Thema Industrie 4.0 durchgeführt. Das Ergebnis bestätigt ein großes Interesse an automatisierten, informationsbasierten Auswertungsmöglichkeiten für Instandhaltungsfragen (86,8 %). Aktuelle Fertigungsanlagen verfügen (hierfür) aus Datensicht überwiegend über Lichtschranken, Motorenspannungen und Positionierungstaster (76,3 %). Eine moderne Lösung für die Verbesserung der Instandhaltung muss demnach mittels binärer Datenwerte realisierbar sein. Bisher besteht hierzu keine Lösung (siehe Kapitel 2.3.3).

Unter Nutzung moderner Datenanalyseverfahren nimmt sich dieser Beitrag der Problemstellung an und präsentiert einen schrittweisen Entwicklungsansatz. Dabei wird sowohl auf Nachrüstungen externer Informationsquellen (z. B. Sensorik), als auch auf Veränderungen gegenüber dem aktuellen Produktionsablauf verzichtet, um entstehende Mehraufwände für die Instandhaltung minimal zu halten. Die Absicht des Beitrags lässt sich durch die nachfolgende Forschungsfrage zusammenfassen:

Wie können Fertigungsproduzenten die Möglichkeiten binärer Datenwerte für eine Optimierung ihrer Maschineninstandhaltung auf Basis moderner Datenanalyseverfahren nutzen?

Im Nachfolgenden wird die Erarbeitung des schrittweisen Entwicklungsansatzes für eine moderne Instandhaltung auf Basis binärer Datenwerte vorgestellt. Zunächst werden die notwendigen theoretischen Grundlagen vermittelt (Kapitel 2.3.2). Diesen folgt mit Kapitel 2.3.3 die sukzessive Vorstellung der Entwicklung, unterteilt in die gewählte Methodik, den deskriptiven Ansatz als grundlegende Überwachungsinstanz und dem prädiktiven Ansatz als erweiterte Überwachungsinstanz. Kapitel 2.3.4 veranschaulicht die prototypische Ausgestaltung anhand eines Industrie 4.0 Demonstrators. In Kapitel 2.3.5 finden sich eine abschließende Einordnung und Wertung des Beitrags mit Hinblick auf Forschung und Praxis.

2.3.2 Theoretische Grundlagen der Datenanalyse

2.3.2.1 Datenanalyse in der Instandhaltung

Mit dem übergeordneten Ziel die Opportunitätskosten zu minimieren definieren Fertigungsunternehmen eine individuelle Instandhaltungsrichtlinie. Unabhängig der unterschiedlichen Methoden, wie dem korrektiven Wartungsansatz, basieren moderne Optimierungen auf der Nutzung von Daten. Die akademische Literatur teilt die Instandhaltungstypen daher in drei Arten ein: deskriptive, prädiktive und präskriptive Datenanalyse (Delen and Demirkan 2013).

Die deskriptive Datenanalyse unterstützt bei der Erkenntnisgewinnung über auftretende Probleme und Chancen der Instandhaltung auf Basis der Auswertung historischer Daten (Wang et al. 2016a). In der prädiktiven Datenanalyse werden mathematische Methoden angewendet, um erklärende und prädikative Muster für die Darstellung von inhärenten Beziehungen zwischen Datenein- und -ausgängen zu finden (Delen and Demirkan 2013). Dies erlaubt eine vorausschauende Instandhaltung. Die präskriptive Datenanalyse erweitert dies durch eine multikriterielle Entscheidungsfindung mittels Optimierungsmethoden (Wang et al. 2016a). Das Ergebnis ist entweder die beste Vorgehensweise zum jeweiligen Zeitpunkt oder ein unterstützender Ratschlag an den Entscheidungsträger der Instandhaltung (Delen and Demirkan 2013).

2.3.2.2 Process Mining

Process Mining erlaubt eine deskriptive Untersuchung von Prozessdaten, um Sequenzen und Problembereiche zu identifizieren. Ausgangsbasis stellen Eventlogs dar, eine Sammlung von Prozessdaten mit vordefinierter Struktur. Als Voraussetzung für deren Nutzbarkeit müssen die darin aufgezeichneten Daten einerseits einer Abfolge-basierten Speicherung (Zeitstempel) unterliegen, und andererseits einzelne Prozessschritte (Events/ Aktivitäten) den zugehörigen Prozessinstanzen (CaseID) eindeutig zuordenbar sein. Zusätzlich werden für Analysezwecke oft weitere Merkmale gespeichert (van der Aalst et al. 2011), wie der Aktivitätslebenszyklus. Dieser beschreibt den Zustand, in welchem sich die Aktivität zum jeweiligen Zeitpunkt befindet und wird mindestens in die Zustände *Start*, *in Bearbeitung* und *Ende* unterteilt. Dies erlaubt eine intuitive Nachvollziehbarkeit bei entsprechenden Auswertungen der Prozessdaten.

Innerhalb der Technik selbst werden drei Aufgabenbereiche voneinander unterschieden: Process Discovery, Conformance Checking und Process Enhancement. Process Discovery erlaubt die

Transparenzschaffung von Ablaufprozessen aus den aufgezeichneten Datenlogs. Conformance Checking dient der Überprüfung auf Prozessabweichungen vom identifizierten Standardprozess, als meist frequentierter Prozessablauf. Process Enhancement erweitert die gewonnenen Prozesserkenntnisse, z. B. durch Nutzung von Kennzahlen, um die Einhaltung von Service Levels zu prüfen oder kritische Engpässe zu identifizieren (van der Aalst et al. 2011).

2.3.2.3 Machine Learning

Machine Learning (ML) ist ein Teilgebiet der künstlichen Intelligenz und unterstützt bei der manuellen Datenanalyse. Ansätze aus dem ML zielen auf eine automatisierte Aufdeckung von Mustern und Abhängigkeiten auf Grundlage vorhandener Daten und Algorithmen ab. Oftmals werden mathematische Modelle verwendet, um den Algorithmus so zu trainieren, so dass er ein hinreichend valides, künstliches Wissen generiert, welches vom Menschen nur unter großen Mühen erreichbar wäre (Marsland 2015).

Im ML werden drei grundlegende Lernansätze für die Schulung des Algorithmus differenziert: überwachtes Lernen (engl. *supervised ML*), unüberwachtes Lernen (engl. *unsupervised ML*) und verstärktes Lernen (engl. *reinforcement learning*). Beim überwachten Lernen werden vordefinierte Input-Output-Paare verwendet, um künftige Zuordnungen (bspw. durch Klassifizierung) automatisiert durchzuführen (Marsland 2015). Das unüberwachte Lernen beschränkt sich auf Inputs. Durch Vergleich sollen nutzbare Muster (bspw. durch Clustering) erkannt werden (Wang et al. 2012). Verstärktes Lernen hingegen schult einen Lernagenten, der durch Versuch und Irrtum in Kombination mit Belohnungen versucht seine angenommenen Zustände und Aktionen auf die Maximierung der Belohnungen auszurichten (Kober et al. 2013).

2.3.3 Schrittweiser Entwicklungsansatz für die Nutzung binärer Datenwerte hinsichtlich moderner Instandhaltungsansätze

2.3.3.1 Methodische Stringenz der Erarbeitung

Für die Erarbeitung des schrittweisen Entwicklungsansatzes wurde das Vorgehen der Aktionsforschung aus dem Bereich der Wirtschaftsinformatik adaptiert. Deren Fokus liegt auf dem Aufgreifen praxisorientierter Probleme, welche durch engen Austausch zwischen Beteiligten aus Forschung und Praxis gelöst werden. Über mehrere Iterationsschritte werden ein wissenschaftliches Verständnis über den designtechnischen Aufbau und ein praxisinspiriertes Artefakt geschaffen (Peffers et al. 2018). Das Vorgehen selbst unterteilt sich in vier Abschnitte: Zunächst ist das (1) Problem auf Basis von existierendem Wissen auszuformulieren. Dies stellt oft eine Instanz einer Klasse von Problemen dar, die schrittweise gelöst wird. Anschließend (2) beginnt die Umsetzung mit einer begleitenden Evaluierung. Wichtig dabei ist, dass parallel (3) kontinuierlich reflektiert wird und ein fortdauerndes Lernen erfolgt. Das (4) finale Artefakt muss letztlich eine generalisierbare Problemlösung sein (Peffers et al. 2018).

Als Problem wurde das Fehlen einer datenbasierten Instandhaltungsunterstützung auf Basis binärer Datenwerte definiert, welche durch Praxisbefragungen als relevant identifiziert und durch Literaturrecherche als bisher nicht adressiert erkannt wurde. Das Problem unterteilt sich in die Bereiche der deskriptiven und prädikativen Datennutzung, die jeweils eigene Teilprobleme beinhalten (siehe Kapitel 2.3.3.2

und 2.3.3.3). Die schrittweise Erarbeitung eines praxisorientierten Artefakts wurde im engen Austausch mit zwei Unternehmen realisiert, einem mittelständischen Serviceanbieter für Automatisierungstechnik und einem mittelständischen Maschinenbauer für Sägewerkanlagen. Durch ständige Evaluierung und Anpassung auf Basis gewonnener Erkenntnisse ließen sich die Anforderungen der Aktionsforschung sichern. Alle Ergebnisse wurden entsprechend generalisiert und aufbereitet.

Die verbundene Literaturanalyse basiert auf den Empfehlungen nach (Webster and Watson 2002). Um der Interdisziplinarität der Thematik gerecht zu werden, wurden sechs Datenbanken ausgewählt: *IEEE Xplore*, *AISeL* und *ACM Digital Library* um informatiknahe Forschungsgebiete und jene der Ingenieurswissenschaften abzudecken, *Business Source Premier (EBSCO)* für wirtschaftswissenschaftliche und wirtschaftsnahe Inhalte sowie *Web of Science* und *ScienceDirect* für eine umfassende Auswahl übergreifender Publikationen. Hinsichtlich der Qualität wurde sich zunächst auf Journal-Beiträge mit einem Mindestrating von B nach *VHB-Jourqual 3* konzentriert. Mittels einer Rückwärtssuche konnten weitere, relevante Beiträge identifiziert werden. Ebenso wurde, mit Hilfe des hierfür empfohlenen *Web of Science* (Webster and Watson 2002), eine Vorwärtssuche durchgeführt. Als verwendeter Suchterminus für die jeweiligen Problemabschnitte (siehe Kapitel 2.3.3.2 und 2.3.3.3) dienten die nachfolgenden Pseudocodes:

(1) (*process mining | descriptive analytics | maintenance) & (binary (sensor* | value* | feature* | input* | file* | data | attribute* | descriptor*))*

(2) *(((supervised | machine) learning) | ((diagnostic | predictive) analytics)) & (binary (sensor* | value* | feature* | input* | file* | data | attribute* | descriptor*))*

Insgesamt konnten die Resultate auf 38 relevante Publikationen eingegrenzt werden. Nach einer durchgeführten Volltextanalyse verblieben 12 Beiträge für den (1) deskriptiven und 8 für den (2) prädiktiven Bereich.

2.3.3.2 Deskriptive Datennutzung als grundlegende Überwachungsinstanz

Die Initialisierung einer grundlegenden Überwachungsinstanz wird durch Transparenzschaffung im Fertigungsprozess mit Hilfe von Process Mining möglich. Process Mining erlaubt die Visualisierung und Nachvollziehbarkeit der gesamten Ablaufqualität und das Erkennen von Problemabschnitten. Im Kontext von Fertigungsprozessen finden sich bereits Anwendungen. Er et al. (2018) setzen Process Miningein, um den Produktionsplanungsprozess eines großen Fertigungsbetriebs auf Basis seiner ERP-Daten zu untersuchen. Halaška and Šperka (2018) erläutern mehrere Process-Mining-Anwendungsfälle und deren Potenziale im Kontext der Industrie 4.0. In Yang et al. (2014) wird Process Mining verwendet, um nach standardisierten Vorverarbeitungsschritten aus strukturierten und unstrukturierten Daten analysierbare Eventlogs zu generieren, die anschließend ausgewertet werden. Eine instandhaltungsbezogene Nutzenmachung via Process Mining besteht bisher hingegen nicht.

Die Idee der Nutzenmachung besteht darin, aus den binären Datenwerte durch Process Mining (siehe Kapitel 2.3.2.2) einen Referenzwert zu ermitteln, welcher künftig auf Abweichungen geprüft werden kann. Dazu wird der damit identifizierbare Standardprozess als SOLL-Prozess definiert und zur Laufzeit der Fertigung mit dem jeweiligen IST-Prozess (Echtzeitdaten) verglichen. Weicht der IST-Prozess vom

SOLL-Prozess über eine definierte Standardabweichung hinweg ab, gilt das Verhalten als Anomalie und wird gemeldet. Neben einer schnelleren Reaktionszeit können so im Bedarfsfall die zum Eintritt der Anomalie aufgezeichneten Messwerte (van der Aalst et al. 2011) als Unterstützung für die Servicekraft wiedergegeben werden, um die Problemlokalisierung und -lösung zu beschleunigen. Es empfiehlt sich daher unbedingt eine parallele Datenspeicherung aller binärer Datenwerte. Ebenso sollten die erkannten Anomalien als weiteres Attribut in die Datensammlung mit aufgenommen werden (Zeitstempel, Lokalisierung, Fehlerbezeichnung). Über den Zeitverlauf entwickelt sich daraus die Grundlage für die Entwicklung einer fortschreitenden Überwachungsinstanz auf binären Datenwerten (siehe Kapitel 2.3.3.3).

Für die technische Realisierbarkeit der grundlegenden Überwachungsinstanz und des weiteren Vorgehens besteht die Notwendigkeit die Mindestvorgaben eines auswertbaren Eventlogs sicherzustellen (siehe Kap. 2.3.2.2). Während moderne IT-Systeme diese Voraussetzungen i. d. R. erfüllen, ist es für objektorientierte Systeme, wie bei Fertigungsabläufen, schwieriger passende Eventlogs zu erzeugen (Ferreira and Gillblad 2009; Redding et al. 2008). Die Attribute Zeitstempel und Events/ Aktivitäten sind trivial erreichbar. Schlägt ein Sensor aus, gilt dies als Event und der Zeitpunkt des Ausschlags als Zeitstempel. Für die Zuordnung eines Events zur Prozessinstanz (CaseID) bedarf es jedoch einer komplexeren Vorverarbeitung, sollte nicht bereits RFID-Technologie eingesetzt werden die einen Werkstücke digital verfolgen lässt. In der Wissenschaft wird dieses Thema bisher nur wenig diskutiert und unter dem Fachbegriff „unlabeled event logs“ untersucht (Bose et al. 2013; Suriadi et al. 2017). Die wenigen existierenden Verfahren (Andaloussi et al. 2018; Bayomie et al. 2016; Ferreira et al. 2007; Ferreira and Gillblad 2009; Walicki and Ferreira 2011) wurden nachfolgend aufbereitet und geclustert. Das im Anwendungsfall geeignetste Verfahren ist abhängig vom eigenen Prozessvorwissen und der Ablaufkomplexität des Fertigungsvorgangs.

In Figure 13 finden sich fiktive Fertigungsabläufe, wobei jeder Buchstabe eine(n) Messpunkt/ Aktivität darstellt. Der Entscheidungsbaum im rechten Bildrand komprimiert die nachfolgenden Informationen und unterstützt bei einer schnellen Entscheidungsfindung zum geeigneten Verfahren.

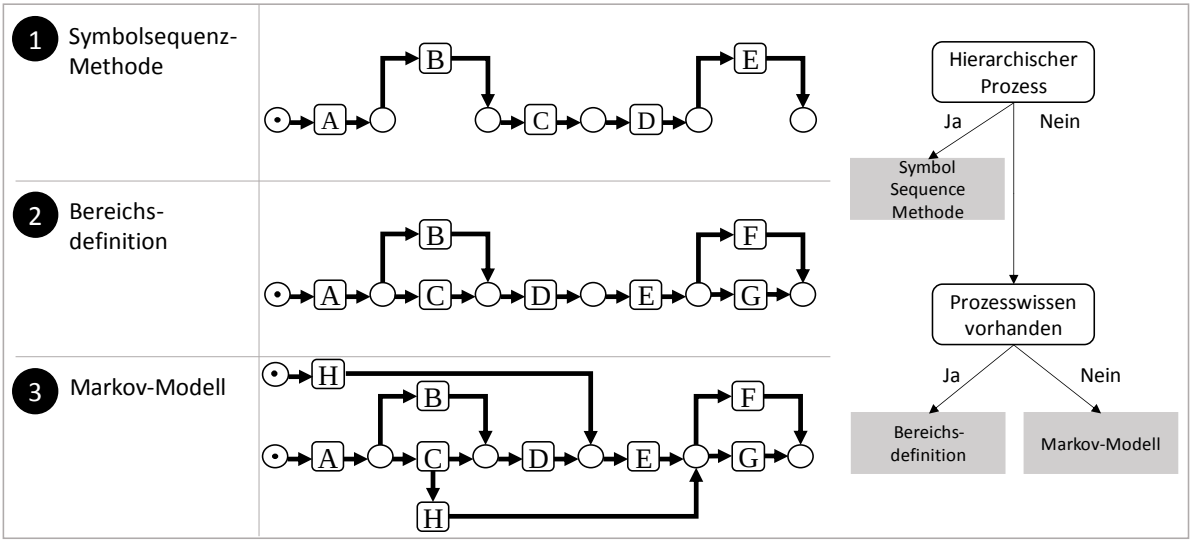


Figure 13: Verfahren für die Erzeugung künstlicher CaseIDs

Fall 1 zeigt einen hierarchischen Prozess, ohne Fertigungsschleifen. Hier eignet sich die Methode der *Symbolsequenz* nach Ferreira and Gillblad (2009). In jeder Startaktivität wird eine neue CaseID initialisiert und schrittweise in sequenzieller Abfolge mit Aktivitätswerten bis zur letzten Messinstanz befüllt.

Bei einem nicht hierarchischen Prozess sollte zwingend eine andere Vorgehensweise verwendet werden, z. B. ein Markov-Modell wie in Fall 3. Besteht Wissen über den Fertigungsablauf ist die Umsetzung nach der *Bereichsdefinition* wie in Fall 2 geeignet. Die Vorgehensweise wurde von uns entwickelt und platziert sich zwischen den beiden anderen. Sie ist genauer als jene in Fall 3, und ermöglicht eine Berechnung trotz Fertigungsschleifen gegenüber jener in Fall 1. Eine algorithmische Definition findet sich in dem nachfolgenden Pseudocode:

Eingabe: iterators *caseID*, Sensordaten *data*, Sensor *n*, Event *e*, Eventlog *L*
Ausgabe: Eventlog *L*

```
1:  caseID = 0
2:  zeitstempel, lifecycle, L, e = null
3:  d ∈ data
4:  n ∈ d
5:  # Ablauf für alle Datensätze
6:  for d ∈ data do
7:      # Ablauf für jeden Sensor im Datensatz
8:      for n ∈ d do
9:          # Festlegung des Attributs Lebenszyklus mit "Prozessstart"
10:         if n(d) := 1 ∧ n(d-1) := 0 then
11:             lifecycle(d,n) := "Prozessbeginn"
12:             caseID(d) := caseID +1
13:             zeitstempel(n) := zeitstempel(d)
14:         end if
15:          # Festlegung des Attributes Lebenszyklus mit "Prozesssende"
16:         else if n(d) := 1 ∧ n(d+1) := 0 then
17:             lifecycle(d,n) := "Prozessende"
18:             caseID(d) := caseID +1
19:             zeitstempel(n) := zeitstempel(d)
20:         end if
21:          # Festlegung des Attributes Lebenszyklus mit "aktiv"
22:         else if n(d) := 1 then
23:             lifecycle(d,n) := "aktiv"
24:             caseID(d) := caseID +1
25:             zeitstempel(n) := zeitstempel(d)
26:         end if
27:     end for
28:     # Zusammenführung der einzelnen Datensätze anhand caseID
29:     e(d) := caseID(d)
30:     for n ∈ d do
31:         e(d) := e(d) + lifecycle(d,n)
32:         e(d) := e(d) + zeitstempel(n)
33:     end for
34: end for
35: # Sortierung des Eventlogs sowie Rückgabe
36: return L := sort(e(d ∈ data))
```

Coding 1: Bereichsdefinition in Anlehnung an Kap. 2.3.2.2

Das Prozesswissen wird anhand historischer Daten entwickelt, wobei die Zeitstempel iterativ analysiert werden (Z:6-27). Pro Durchlauf (je Zeitstempel) werden alle Sensoren und Abschnitte ausgewertet (Z:7-27) und anhand der Merkmalsausprägungen im Vergleich zu weiteren Zeitstempeln überprüft. Wechselt ein Abschnitt von inaktiv zu aktiv (Z:9-14), werden eine neue CaseID, ein Zeitstempel sowie der Lebenszyklus als „Start" festgesetzt. Im umgekehrten Fall werden für die CaseID nur ein neuer Zeitstempel

und der Lebenszyklus als „Ende“ festgesetzt (Z:15-20). Trifft keine der beiden Bedingungen zu, ist der Abschnitt weiterhin aktiv (Z:22-26). Abschließend findet eine Sortierung der erzeugten Daten statt, welche als Eventlogs zurückgegeben werden (Z:29-36).

Sind weder die Voraussetzungen des hierarchischen Prozesses noch Prozessvorwissen vorhanden, ist Vorgehensweise 3 zu wählen. Sie wird typischerweise für komplexe Fertigungsprozesse eingesetzt und basiert auf Wahrscheinlichkeiten, was einen Unsicherheitsfaktor impliziert. Dabei wird die Methode der Erwartungsmaximierung angewendet, um CaseIDs zuzuordnen. Basierend auf einem Markov-Modell sind nach der Methode von Ferreira et al. (2007) Wahrscheinlichkeiten einer Vorgänger-Nachgänger-Beziehung der Aktivitäten zu berechnen.

2.3.3.3 Erweiterte Datennutzung als fortschreitende Überwachungsinstanz

Die Initialisierung einer fortgeschrittenen Überwachungsinstanz für Instandhaltungsfragen wird durch maschinellen Lernverfahren möglich. Gegenüber der grundlegenden Überwachungsinstanz, mit einer Benachrichtigung über anormales Verhalten und einer Ausgabe verbundener Messwerte, erfolgt erweiternd eine explizite Benennung des Problems anhand maschinell erlernter Interpretationsregeln. Diese werden mit festen FehlerIDs versehen und damit programmiertechnisch ansprechbar, z. B. in Verbindung mit hinterlegtem Wissen in einer Wissensdatenbank. Ebendies erfolgt für proaktive Benachrichtigungen i. S. v. expliziten Warnungen, welche durch maschinelle Lernverfahren auf Basis von Assoziationsregeln erlernbar sind.

Die technische Realisierung basiert auf dem im Zeitverlauf aufgebauten Datensatz (siehe Kapitel 2.3.3.2). Damit werden Techniken aus dem Bereich des überwachten Lernens anwendbar. Der große Vorteil besteht in der konfigurationsarmen Entwicklung der Modelle gegenüber unüberwachten und agentenbasierten Lernansätzen (Kotsiantis et al. 2007). Ebenso besteht eine höhere Nachvollziehbarkeit, aufgrund der gegebenen Vorklassifizierung. Auch große, innovative Unternehmen wie Amazon haben das Potenzial erkannt und betreiben Plattformen wie *Amazon Mechanical Turk*, um als Intermediär nicht-klassifizierte Datensätze gegen Entgelt durch Anwender klassifizieren zu lassen. Eine generalisierbare automatische und unmittelbare Klassifikation, z. B. durch Algorithmen aus dem Bereich des unüberwachten maschinellen Lernens, ist nicht garantiert (Saul and Roweis 2003).

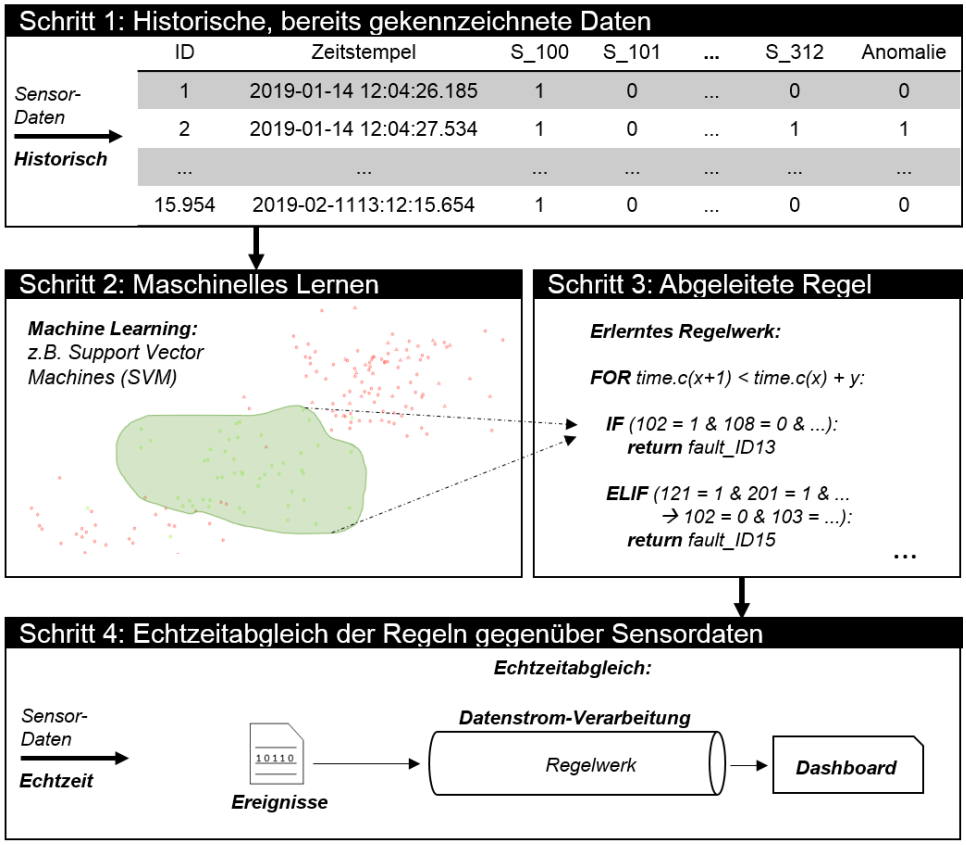


Figure 14: Aufbau der fortschreitenden Überwachungsinstanz

Das aus der Literatur und den durchgeführten Befragungen abgeleitete und erarbeitet Vorgehen wird in Figure 14 dargestellt. Ausgangsbasis für das Vorgehen sind die *Schritt 1: Historische, bereits gekennzeichnete Daten*, aus der grundlegenden Überwachungsinstanz (siehe Kapitel 2.3.3.2). Sie dienen als Input für das überwachte, maschinelle Lernen in Schritt 2: Maschinelles Lernen. Im illustrierten Beispiel wurde ein Algorithmus aus dem Bereich der Support Vector Machines (SVM) gewählt und visualisiert. Das Ergebnis ermöglicht eine tiefere Analyse und exaktere Klassifizierung des Datensatzes hinsichtlich spezifischer Fehlerklassen. Das Trainieren der SVM erfolgt anhand bereits klassifizierter Sensordaten, welche produktionsrelevante Anomalien enthalten. Die SVM wird somit auf diese Anomalien sensibilisiert. Anhand der Schwellenwerte werden anschließend über *Schritt 3: Abgeleitete Regeln*, welche den Fehler künftig erkennen und benennen lassen. Durch die hohe Nachvollziehbarkeit mittels Visualisierung und expliziter Regeldefinition sowie einer manuellen Prüfmöglichkeit wird die Hemmschwelle bei der Benutzung maschineller Lernverfahren für Instandhaltungsfragen abgebaut. Diese galt in den durchgeführten Befragungen als größtes Hindernis für den aktiven Einsatz maschineller Lernverfahren im Fertigungsumfeld und wurde dementsprechend adressiert. Die Regeln selbst werden einer Echtzeitverarbeitungseinheit übergeben, welche mit den binären Datenquellen verbunden ist und generierte Events dauerhaft empfängt, sodass ein *Schritt 4: Echtzeitabgleich der Regeln gegenüber Sensordaten* erfolgt. Dabei werden die eintreffenden Events mit dem hinterlegten Regelwerk abgeglichen und bei Bedarf aussagekräftige Rückmeldungen gegeben.

2.3.4 Evaluation des schrittweisen Entwicklungsgangs anhand eines Demonstrators

Das erarbeitete Entwicklungskonzept (Kapitel 2.3.3) wird anhand eines Demonstrators verdeutlicht. Hierfür dient die *Fabrik-Simulation 24V* der Firma Fischertechnik, mit einer verbundenen Siemens *SITOP PSU8200* Steuerungsinstanz und SPS-programmierten *SIMATIC ET 200SP* Modulen. Die Fabrik imitiert eine moderne Fertigungsanlage und erlaubt die parallele Bearbeitung mehrerer Werkstücke. Als Messinstrumente dienen Lichtschranken, Motorspannungen und Positionierungstaster.

Parallel zum Fertigungsbetrieb wurde durch Abgriff und Speicherung der binären Datenwerte in *Schritt 1: Erfassung und Transformation von Sensordaten in Sensorlogs* eine Ausgangsdatenbasis geschaffen. Je Event (= Messwert) bestand eine ID, ein Zeitstempel und ein zugehöriger Messwert. Jeder gespeicherte Eintrag (= Zeile) stellt wiederum die Aggregation mehrerer Events mit selbem Zeitstempel dar. Aufgrund des Fehlens einer Trackingmöglichkeit einzelner Werkstücke (bspw. via RFID-Tags), und damit einer fehlenden Prozessinstanz (CaseID), musste diese im Nachgang künstlich erzeugt werden, um entsprechende Auswertungen mit Techniken aus dem Process Mining zu ermöglichen. Aufgrund von Prozessvorwissen und Fertigungsschleifen wurde die Methode der Bereichsdefinition (siehe Kapitel 2.3.3.2) gewählt.

Anschließend konnte durch *Schritt 2: Definition des Referenzprozesses anhand von Process Mining* der Standardprozess mit festgelegter (zeitlicher) Standardabweichung als Referenzpunkt gegenüber des IST-Ablaufs definiert werden. Die Benachrichtigung über auftretende Anomalien erfolgte über ein simples Dashboard, mit Ampelsystem und der Ausgabe der letzten Messeinträgen. Ebenso wurde die Datenbasis um das „Anomalie-Attribut“ klassifizierend fortgeschrieben.

Nach gewisser Zeit erlaubte diese Klassifizierung des Datensatzes eine fortschreitende Überwachungsinstanz, in *Schritt 3: Spezifische Benachrichtigung und Benennung durch maschinell erlernte Regeln*. Hierfür wurden nach Beispiel von Wang et al. (2018b) verschiedene Verfahren aus den ML-Bereichen der Entscheidungsbäume und der probabilistischen Klassifikatoren angewendet. Im aufgezeigten Beispiel in Figure 15 wurde ein Support Vector Machine (SVM) Algorithmus verwendet, um zu erkennen, wann und welche Probleme bei der Weitergabe eines Bauteils vom Fertigungsprozess des Brennofens zu jenem der Säge auftreten sowie ob sich dies bereits proaktiv über bestimmte Sensorkombinationswerte und Zeitabstände erkennen lässt. Durch eine visuelle Aufbereitung der Ergebnisse und eine Überführung der Erkenntnisse in geeignete Assoziationsregeln konnte ein umfassendes reaktives wie proaktive Regelwerk erstellt werden. Dieses dient fortan als Vergleichsbasis der Echtzeitverarbeitungseinheit. Dementsprechend auftretende Anomalien sind durch die hinterlegten Fehlercodes benennbar, was eine effektive Adressierung erlaubt. Da jedoch auch neue Fehlertypen oder Veränderungen an der Produktionsanlage auftreten können sollte die erweiterte Überwachungsinstanz nach Schritt 3 nicht als final abgeschlossen angesehen werden. Vielmehr stellt das schrittweise Vorgehen einen iterativen Ansatz dar, um die datenbasierte Überwachungsinstanz schrittweise zu verbessern und oder zu erweitern.

Die Umsetzung wurde in Figure 15 visuell dargestellt und anhand der erarbeiteten Methodik konzipiert und realisiert:

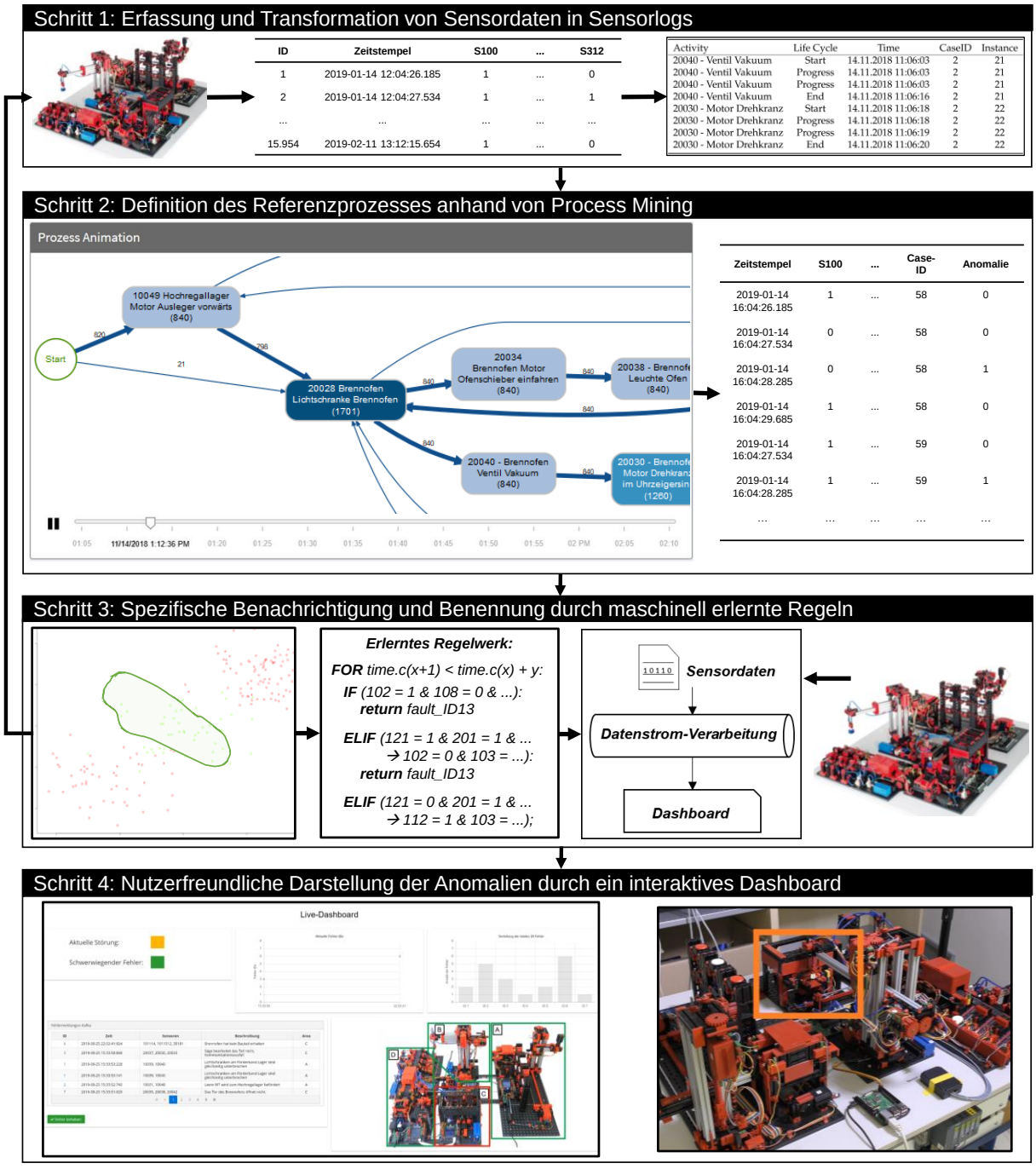


Figure 15: Aufbau des Demonstrators für die entwickelte Instandhaltungsüberwachung

2.3.5 Zusammenfassende Betrachtung für Praxis und Forschung

Der vorliegende Beitrag zeigt einen schrittweisen und iterativen Entwicklungsansatz für eine datenbasierte Instandhaltungsunterstützung im industriellen Fertigungsablauf trotz Beschränkung auf binäre Datenwerte. Das Resultat des geschaffenen Artefakts erlaubt eine deutlich verbesserte Reaktionsgeschwindigkeit und Problemadressierung für auftretende Anomalien. Durch ständige Evaluierung der Ergebnisse mit Praxispartnern sowie einer vorausgegangenen Anforderungserhebung wurden die Generalisierbarkeit und Einsatzmöglichkeit sichergestellt. Die Methodik ist unabhängig des Fertigungs-

prozesses i. S. v. notwendigen Nachrüstungen oder Veränderungen – ausgehenden aktuell gängiger infrastruktureller Gegebenheiten im deutschen, produzierenden Mittelstand – realisierbar und kann damit von nahezu jedem Fertigungsbetrieb angewendet werden. Ebenso wurde die Intransparenz maschineller Lernverfahren als Einsatzhemmnis durch nachvollziehbare Assoziationsregeln adressiert.

Der schrittweise Entwicklungsansatz unterteilt sich in zwei Teilbereiche: eine grundlegende und eine fortschreitende Überwachungsinstanz. Erstere erlaubt bereits nach kurzer Zeit eine komplexarme Überwachung, indem Abweichungen gegenüber des SOLL-Prozessablaufs erkannt und gemeldet werden. Diese eignet sich damit auch für weniger informationsaffine Fertigungsunternehmen. Für die Forschung stellen hierbei die Eigenentwicklung eines neuen Ansatzes für die Erzeugung einer künstlichen CaseID (siehe Kapitel 2.3.3.2) und die durch das Vorgehen erschaffene Klassifizierung von Datenpunkten einen Ausgangspunkt für weitere Bemühungen dar. Die fortschreitende Überwachungsinstanz wird hingegen erst im Zeitverlauf umsetzbar und bietet insbesondere Unternehmen mit stärkeren informationstechnischen Ambitionen ein methodisches Vorgehen. Für die Forschung bietet hierbei wiederum die Reduzierung der Blackbox-Thematik maschineller Lernverfahren einen weiteren Ausgangspunkt.

3 (X)AI DSS User Perception

Table 9: Research summary of Chapter 3

Research objectives			
RO2	Perception of (X)AI explanations from a user perspective		
2a	Endorsing the information perception of users from credibility research		
2b	Positioning of common ML models by performance and explainability		
2c	Assessment of common ML models by explainability and comprehensibility		
Reference to original work			
Wanner, Janiesch (2019)		Publication P4	Chapter 3.1
Wanner, Herm, Heinrich, et al. (2021)		Publication P5	Chapter 3.2
Herm, Wanner, Seubert, et al. (2021)		Publication P6	Chapter 3.3

Current research on machine learning is dominated by a focus on the improvement of algorithmic performance (La Cava et al. 2021). This is also reflected by today's data challenges, since more complex algorithms, especially from the field of DL, outperform classic ML algorithms for most tasks (e.g., Hyndman 2020). While the development shows success in improving performance, the user of the (X)AI DSS seems to be of secondary importance. That is, complex models often lack explanatory power due to their opaque inherent logic, rendering it impossible for human users to review their decision-making process or interpret the results. Nevertheless, an (X)AI DSS in use is often reliant on the user's action – and thus the user's perception – to be effective (Ribeiro et al. 2016b).

Today it is assumed that, in addition to model performance, the explainability as perceived by the user plays a major role in his decision for or against a system's recommendation (e.g., Dam et al. 2018; Ribeiro et al. 2016b). As a trade-off between performance and explainability is assumed, it is difficult to find a suitable solution for an ML model to convince a user to accept the artificial advice. In other words, models with higher performance are often complex and thus lack explainability (and vice versa). The research area of XAI tries to better understand this supposed trade-off, developing techniques that maintain high model performance while also providing good model explainability (Gunning and Aha 2019).

Progress is being made mainly with regard to the technical side of XAI. Several XAI transfer techniques (cf. Wanner et al. 2020c) and XAI augmentation frameworks (e.g., Lundberg and Lee 2017; Ribeiro et al. 2016b) have been developed over the last couple of years. But there is still a tremendous call for more behavioral (X)AI user studies to understand the perception of the systems' recommendations and related explanations from a user perspective (among others, Lu et al. 2020; Saha et al. 2019; Springer and Whittaker 2019). These socio-technical insights are important to better understand the users' needs. Efforts in this area can drive technical XAI developments in the right direction and must therefore be addressed.

To this end, it seems that there is a special need for behavioral evaluation of the users' perception of (X)AI DSS recommendations (RO2, cf. Table 9). Chapter 3 serves to form a better understanding of both the expectations of data-centered information and its related credibility (2a). Likewise, in order to differentiate between black-box and white-box models, it seems important to understand how good current ML model types already solve the supposed trade-off (2b). This corresponds to a critical validation of Rudin's call to avoid conversions of black-box models into white-box models and instead use interpretable models from the beginning (Rudin 2019). Beyond these concerns, the ultimate goal to achieve the best possible decision quality is seen in a hybrid intelligence of man and machine (Dellermann et al. 2019). This implies the need for an understanding of the extent to which the perceived explainability corresponds to the human capacity for comprehension (2c).

3.1 Big Data Analytics and Perceived Credibility of Information

Abstract. The credibility of sustainability reports has been the subject of scientific research for several years. The problem is often referred to as the so-called credibility gap, which is based on information asymmetries. The situation is further complicated by the limited rationality of human action as improvements to reports do not necessarily translate into credibility gains. Research has proposed and extracted several methods to overcome the issue. Hitherto, most approaches to solve the problem focused on marketing-oriented approaches. This work takes a new approach and explores the extent to which information technology can increase credibility using the potential of big data analytics. We base our research on the relationship of the quality of information and on the perception of objective truth as postulated in the Habermas Theory of Communicative Action. We use the forecast oriented Partial Least Squares Methodology for the review of hypotheses extracted from literature and expert surveys. The result confirms potential of the criteria of volume and veracity while velocity and variety do not yield comparable potential concerning sustainability reporting. Big data analytics in sustainability reports: an analysis based on the perceived credibility of corporate published information.[6]

3.1.1 Introduction

In recent years, more and more companies and organizations have been trying to make their activities more sustainable. To manage and measure own goals, performance, and operational changes, sustainability reports have become a very popular means (GRI 2016, p. 3). Sustainable actions and their transparency through reporting activities lead to several advantages perceived by external groups of interest such as an improved reputation (Weber 2014, p. 13f).

Despite the EU directive 2014/95/EU, the scope of this kind of reporting leaves companies with a lot of room to maneuver (Nachhaltigkeitskodex 2016). For example, criticism is directed at the traceability of

[6] This paper is published at the Journal *Business Research* as 'Big data analytics in sustainability reports: an analysis based on the perceived credibility of corporate published information' (Wanner and Janiesch, 2019). The DOI is: https://doi.org/10.1007/s40685-019-0088-4. The related supplementary material is given in Appendix III.

the sources and the methods of data collection. The same applies to the completeness of measures and their information value (Knebel and Seele 2015, p. 198ff). This raises the question of the perceived credibility of published data and facts. The situation is regarded as precarious (Lock and Seele 2016, p. 186f; Nawratil 2006, p. 200ff) and is unfavorable for both sides – company and report recipient (Weber 2014, p. 97f). In science, the problem is referred to as the *credibility gap*, which is based on information asymmetries as a state of insecurity due to differing efforts and levels of information.

Regardless of initial successes, this gap has not been closed yet (Knebel and Seele 2015, p. 196; Lock and Seele 2016, p. 192). Previous approaches have in common that they only considered a situation where the discovery of information and the processing has already been completed. Until now, the focus has been chiefly on marketing-oriented approaches. We aim for a novel, alternative solution and investigate whether improvements to the credibility gap are possible before or during information retrieval and processing. Our approach considers big data analytics as the key factor for information generation.

The assumption of the potential improvement is based on the recognition that the perceived credibility correlates with the information quality of the report, which in turn depends on the quality of the data. This indication is supported by psychological credibility research. We examine whether an approach using innovative information processing capabilities, viz. big data analytics, can have a positive impact on data quality in sustainability reports. That is in particular: Does the perceived credibility of sustainability reports improve?

Summarizing, the starting point of our own investigation is the overlap between the properties of credible communication with those of information quality and its improvement by big data analytics. This leads to the following research questions:

RQ1: How can we conceptualize the credibility gap in sustainability reporting and operationalize information quality criteria to assess their impact on the perceived credibility of sustainability reports?

RQ2: Which criteria of information quality and which characteristics of big data have an influence on the credibility of sustainability reports and how can this finding be used to improve sustainability reporting?

In doing so, we aim to contribute to research on the (ir)rationality of decisions in business research and practice. We conceptualize criteria, which can guide complex management decisions regarding sustainability reports by examining the limited rationality of human action when consuming and perceiving reports, to derive practical recommendations on the effectiveness of big data analytics through its characteristics.

The paper is organized as follows: We begin with the foundations of sustainability reporting, perceived credibility, and the credibility of communication. The following section comprises the state-of-the-art of scientific research on the credibility gap, which we use to identify the research gap. Section 3.1.4 links this gap to information quality and the potentials of big data analytics. Subsequently, we detail our research methodology. In our main contribution, we establish hypotheses, perform operationalization as

well as construct a structural equation model, and present the results of a survey. Finally, we analyze the findings and discuss them in light of related work.

3.1.2 Sustainability Reporting and its Credibility Problem

3.1.2.1 Sustainability Reporting

Sustainability. Sustainability is defined as "development that meets the needs of the present without compromising the ability of future generations to meet their own needs" (Development 1987, p. 41). Sustainable development therefore implies balancing three dimensions: economic, ecologic, and social (Zimmermann 2016, p. 5). The objective of the economic dimension is to ensure long-term returns. To achieve this, the use of resources is necessary. Sustainable management constrains this use through the other two dimensions and, thus, provides a responsible scope for action. The ecological dimension emphasizes the elusive value of nature and the finiteness of nature's resources. Its focus is on the protection of the ecosystem as the basis of human existence. The social dimension focuses on distributive justice. It is about equal opportunities and access to resources for countries, societies, and generations (Bansal 2005, p. 198f).

Concept of Corporate Social Responsibility. The concept of Corporate Social Responsibility (CSR) is the entrepreneurial answer to integrate the idea of sustainability into economic action (Zimmermann 2016, p. 17). It refers to a broad spectrum of activities with which companies assimilate social and sustainability interests into their business activities, mostly on a voluntary basis (Standardization 2010, p. 3; Zimmermann 2016, p. 11). In doing so, any enterprise must take into account the expectations of stakeholders, that is any group or individual who is affected by the achievement of corporate objectives (BAMS 2011, p. 12; Freeman 2010, p. 46f). *Stakeholder contribution to business activities is therefore essential. Business must engage with those directly and indirectly involved* (BAMS 2011, p. 26f).

Sustainability report. According to the Global Reporting Initiative (GRI) (de Boer et al. 2013, p. 12), a sustainability report is the key platform for communicating qualitative and quantitative corporate sustainability performance and impact in all three aforementioned dimensions – positive as well as negative (GRI 2016, p. 3 and 13). According to Fifka (2014), p. 4) the information contained in the reports serves internally for more sustainable control and the optimization of processes. Externally, it supports the communication with stakeholders. A sustainability report can be part of a larger integrated report also containing financial performance indicators.

In the following, we focus on sustainability reports of non-financial segments in all three dimensions. Exemplary content are explanations or key figures of identified future trends, strategic orientations and intentions, statements on corporate research and development, corporate energy consumption, occupational accidents, or social projects supported.

Credibility doubts. Frameworks for reporting such as the GRI, which have been largely compliant with the EU directive 2014/95/EU before it became mandatory legislation, are widely used. Yet, at times there are doubts as to whether the published information of the reports is true to the word (Fifka 2014, p. 5; Weber 2014, p. 97). On the communicator side, there is temptation to achieve advantages from positively communicated sustainability activities without carrying out the necessary efforts

(Zimmermann 2016, p. 10 & 17). This deception is called *greenwashing*. By deliberately exaggerating or misreporting, companies try to be perceived in a more environmentally friendly and responsible manner (Weber 2014, p. 104). The intent is to gain advantages such as improved reputation, an improved awareness of the customer to purchase, or an improved motivation and recruiting of employees (Fifka 2014, p. 12; Weber 2014, p. 103). On the other hand, the credibility is at risk due to (unintentional) deception if information is left out. A recipient of information itself does not distinguish between these possibilities in his or her perception of truth (Köhnken 1990, p. 4).

3.1.2.2 Perceived Credibility

Credibility. In scientific literature, one can find two views on credibility. According to the *communicator-centered view*, a message is credible if a communicator passes on information that he believes to be accurate. Thus, the communicator does not have any intention to mislead the recipient (Köhnken 1990, p. 4). Conversely in the *recipient-centered view*, a message is not considered credible based on the sender's intention. It defines credibility as result of a subconscious appraisal process by the recipient as an individual. This is applicable to persons or institutions, to spoken words, to texts, or even to visualizations (Nawratil 1999, p. 15).

Perception of truth. Accordingly, the perception of truth is not directly related to the truth value of a message. It is about the subjective belief that the message is true (Spelthahn et al. 2009, p. 62). Nevertheless, both views have in common that the perception of truth can be explained as one's (i.e., the communicator's or recipient's) subconscious comparison between the reality as an intended ideal of truth and the given set of information. Reality itself can be understood as an objective external world, which enables a subjective interpretation with a structured and systematic character by means of certain characteristics or stimuli (Früh 1994, p. 22ff & 54). Hence, a credible message is subconsciously always associated with a perceived truth value, which assumes a precise representation of the assumed real-world (model).

Information asymmetries. The question of credibility itself arises when information becomes relevant for decisions or actions but is not known yet from personal knowledge or experience (Köhnken 1990, p. 1). In this sense, a sustainability report represents the starting point of an information asymmetry between the sender and the recipient on whether or not the report contains the (full) truth. This represents a state of uncertainty. At the same time a company aims to present information credibly as the recipient will consider it in his decision-making if he perceives it as credible (Bentele 1988, p. 407). Conversely, the potential benefits of a sustainability report are linked to a credible perception of its content, otherwise its creation was for nothing or may even be harmful.

Agency dilemma. Agency theory is referred to as the scientific explanation for the state of insecurity due to information asymmetries with two parties of different intents. One party (principal) is dependent on the actions of another party (agent) (Pratt and Zeckhauser 1985, p. 2). Due to an information disadvantage, the principal cannot effectively control the agent and does not have direct control over him. The agent will often deviate from the principal's expectations in favor of his own interests. The greater the asymmetry, the more difficult it is to counteract the principal. Aim of the theory is an incentive-compatible remuneration system, which motivates the agent to make a decision in the sense of the principal, so that direct control is not necessary (Kleine 1995, p. 1f & 29ff).

In the context of this paper, the publishing company is the principal, the respective recipient is the agent. An agent will initially be critical of the published content, in this case a sustainability report (Fifka 2014, p. 5; Weber 2014, p. 97). This raises the question of credibility. The problem has consequences for both parties. It begins with an untruthful perception of the information in a sustainability report. The recipient will not take the new knowledge into (future) decision-making process(es) (Bentele 1988, p. 407). Thereby, the recipient's lack of information on certain issues reduces the quality of his decision-making with respect to the company. On the company side, the sustainability report becomes worthless or even has a detrimental effect (Weber 2014, p. 97) towards its relation to the agent. To counteract these problems, a company publishing sustainability reports must focus on credible communication of content. The aim must therefore be, to close the confidence gap, also known as the credibility gap, which is derived from the information asymmetries of the agency dilemma and is closely linked to credible communication.

3.1.2.3 Credibility of Communication

Communication. Communication and sustainability reporting are directly linked to each other (Lock 2016, p. 425). To overcome the credibility gap, one needs to gain an explicit understanding of the key points responsible for the perception of a recipient on corporate communication. On the one side, the communication act itself always consists of three entities: sender (communicator), message, and recipient. On the other side, (moral) legitimacy is the central problem of corporate communication and can be traced back to the above-mentioned information asymmetries (Bentele and Seidenglanz 2015, p. 411f). Legitimacy itself is defined as the perception, whether the company is in line with some socially constructed system of norms, values, beliefs, and definitions (Suchman 1995, p. 574).

Credibility. The *Habermas Theory of Communicative Action* discusses the sender, the recipient, the message, and the legitimacy of the company (Habermas et al. 1984). The theory takes the practical and theoretical meaning of communicative action of the modern society into account and tries to (theoretically) solve the questions of truth, truthfulness, and normative justice by examining different meanings of rationality (Habermas et al. 1984). For a discourse leading to a credible interpretation, the theory postulates that all participants have to communicate intelligibly, honestly, truthfully, and normatively correct to reach mutual understanding and agreement among all participants (Lock 2016, p. 422f). While credibility describes the believability of a source or message, rationality characterizes those who are agreeable to reason. In deliberative discourse, the best argument wins and prevails as a consensus (Habermas et al. 1984, p. 96). Despite its original context of speech situations, the theory is applicable to (written) communication on sustainability issues as it has a political-normative character (Lock 2016, p. 423ff). Hence, the theory can be regarded as an ideal to strive for in the context of sustainability reporting (Lock 2016, p. 415).

Properties of credible communication. In his theory, Habermas prescribes the four properties, which must be satisfied to perceive an interpretation of a message as credible (Habermas et al. 1984, p. 329):

1. *Sincerity*: Statements are reproduced honestly.
2. *Truth*: Statements are in line with objective truth.
3. *Normative rightness*: Statements are morally appropriate to society's requirements.
4. *Intelligibility*: Statements are formulated intelligibly.

We regard *intelligibility* of the formulated statements as a foundational prerequisite. It is the only way, language itself can be used as a medium to allow a rational assessment of honesty, truth, and moral appropriateness. This counteracts possible misunderstandings and perceived falsifications (Habermas et al. 1984, p. 88). Since any corporation seeks its published information to be perceived as credible, we assume this dimension always to be met. Using the three further dimensions, we examine and structure knowledge about the credibility gap to extract possible starting points.

3.1.3 State-of-the-Art of Research on the Credibility Gap

3.1.3.1 Currents State of Research

The *credibility gap* describes a lack of confidence in the abilities and intentions of the publishing company from the viewpoint of stakeholders (Dando and Swift 2003, p. 196ff). It has not yet been closed (Knebel and Seele 2015, p. 196; Lock and Seele 2016, p. 192). Hence, a general statement about credibility in sustainability reports cannot be made. However, in principle it is undisputed that it poses a problem (Knebel and Seele 2015, p. 197; Milne and Gray 2013, p. 21; Sethi et al. 2015, p. 61). So far, the focus of research has been largely on studying the dissemination of sustainability reports, the characteristics of the publishing companies (such as size, country, industry), and the impact on financial indicators. The empirical findings of Lock and Seele (2016) indicate that sustainability reports tend to become more credible in recent years. Findings on perceived credibility from the recipient's point of view are rather rare (Lock and Seele 2016, p. 186).

Following Liljenström and Svedin (2005), we have categorized topics on countering the credibility gap in sustainability reporting in three core levels of a corporate environment: micro, meso, and macro. Macro or 'macroscopic' describes the entire ecological system. Meso or 'mesoscopic' describes a group or population within the macro system. Finally, micro or 'microscopic' describes the individual. Due to the importance of reporting standards and the undergoing changes of legal requirements for sustainability reports, we distinguish *external influencing factors* and *standards and legal requirements* on the macro level. On the meso level, we have subsumed all actions and decisions of corporate external services as *external audits*. On the micro level, we summarize corporate *internal potentials*, which infer the possibility of a closer cooperation or access to information for involved parties. An overview of the mentioned topics and their activities is given in Table 10. The table also includes references for proven and refuted impacts of the subtopics.

Table 10: Categorization and summary of current findings to counter the credibility gap

Topic	Subtopic	Impact	References
External influencing factors (macro)	Culture	+	Adnan et al. (2009); Fifka (2013); Freundlieb et al. (2014)
	Industry differences	0	Fifka and Drabbler (2012); Lock and Seele (2016)
	Size	(+)	Fifka (2013); Lock and Seele (2016)
	Reporting experience	(+)	Albertini (2014)
Standards and legal requirements (macro)	Legal requirements	+	Schaltegger (1997); Vormedal and Ruud (2009); Ioannou and Serafeim (2014); Habek and Wolniak (2016); Lock and Seele (2016)
	Reporting standards	+	Marhardt et al. (2002); Adams and Evans (2004); Knebel and Seele (2015); Lock and Seele (2016)
External audits (meso)	Reasons external review	+	Blackwell et al. (1998); Carey et al. (2000); Dando and Swift (2003); Hodge et al. (2009)
	Review standard	+	Manetti and Becatti (2009); Hodge et al. (2009); Frost and Martinov-Bennie (2010); Knebel and Seele (2015)
	Extent of the review	(+)	Manetti and Becatti (2009); Hodge et al. (2009); Frost and Martinov-Bennie (2010); Knebel and Seele (2015); Hsueh (2016)
	Selection of auditor	+	Wallage (2000); Ball et al. (2000); Dixon et al. (2004); Hodge et al. (2009); Simnett et al. (2009); O'Dwyer et al. (2011); Perego and Kolk (2012); Ackers and Eccles (2015); Gürtürk and Hahn (2016)
	Independence of auditor	(+)	Ball et al. (2000); Hodge et al. (2009); Simnett et al. (2009); O'Dwyer et al. (2011); Gürtürk and Hahn (2016)
	Stakeholder involvement	+	Thomson and Bebbington (2005); Perrini (2006); Manetti and Becatti (2009); Manetti (2011); O'Dwyer et al. (2011); Manetti and Toccafondi (2012)
	External rating	(+)	Chatterji and Levine (2006); Robinson et al. (2011); Windolph (2011)
Internal potentials (micro)	Sustainability committee	+	Adnan et al. (2009); Amran et al. (2014)
	NGO cooperation	+	Amran et al. (2014)
	Internal audits	+	Trotman and Trotman (2015); Gürtürk and Hahn (2016)
	Integrated report	0	Adnan et al. (2009); Lock and Seele (2016)
	Length of report	0	Fifka and Drabble (2012); Lock and Seele (2016)
	Balance of information	+	Guthrie and Farnetti (2008); Milne and Gray (2013): Mishra and Modi (2013); Lock and Seele (2016)

Impact: '+' = positive given impact proven; '(+)' = positive impact under discussion; '0' = no positive impact proven

External influencing factors. As *external influences* on the perception of credibility, *culture* (Fifka 2013, p. 24f), *industry differences* (Fifka and Drabble 2012, pp. 461 & 464-468), *size* (Lock and Seele 2016, p. 188), and *reporting experience* (Albertini 2014, pp. 237-252) have been investigated. The studies only confirm an influence of *culture* (Fifka 2013, p. 24f; Freundlieb et al. 2014, pp. 32-41).

Depending on their own cultural background, recipients expect the publication of certain sustainable activities (Adnan 2009, p. 9 & 14ff; Fifka 2013, p. 24f). Differences between sectors are also suspected. However, it was not possible to establish a link between the increased credibility of reports from environment-related areas and reports from other industries (Fifka and Drabble 2012, p. 466ff; Lock and Seele 2016, p. 189 & 192f). In contrast, the size of a company has a positive influence on reporting (Fifka 2013, p. 24ff). Even so, according to Lock and Seele (2016), p. 188), this does not lead to

increased credibility. Reporters, however, go through a learning curve that can have a positive effect on the relevance of the published information and its credibility in general (Albertini 2014, pp. 237-252).

Standards and legal requirements. Studies on the impact of (national) *legal requirements* (Habek and Wolniak 2016, p. 412ff; Lock and Seele 2016, p. 189 & 193) and the use of (common) *reporting standards* (Knebel and Seele 2015, p. 199f & 204f; Lock and Seele 2016, p. 188 & 193) reveal that both contribute to an increased credibility. The extent of this depends on the associated review methods of a company.

Ioannou and Serafeim (2017) show that there is general improvement due to legal requirements. According to Schaltegger (1997), government regulations do not necessarily lead to an increase in quality. Vormedal and Ruud (2009) attribute this to limited political and social options to influence. Legal requirements only contribute to increased quality and credibility if the conditions and governmental controls are appropriate (Habek and Wolniak 2016, p. 414).

A major problem of non-financial reporting is its incompleteness (Adams and Evans 2004, p. 104f). Morhardt et al. (2002) indicate that the guidelines of the GRI lead to expanded reporting requirements and improved completeness. Lock and Seele (2016) verify that the use of standardized GRI guidelines leads to more credible reports than non-standardized reports. On the other hand, they refuted the assumption that a stricter compliance with the guidelines leads to reports that are more credible.

External audits. An *external audit* is positively correlated with the perceived credibility of the respective recipients for several reasons (Hodge et al. 2009, p. 179ff). In addition, a *review standard* increases the trustworthiness of the review process itself, whereas there is no general consensus on the *extent of the review* (Hsueh 2018, p. 10ff; Knebel and Seele 2015, p. 201f & 206f). The *selection* and *independence of the auditor* is also important (Hodge et al. 2009, pp. 181-190). *Stakeholder involvement* in the review process seems to have a positive impact as well (Manetti and Becatti 2009, pp. 292-295). Considering *external ratings* opinions differ (Chatterji and Levine 2006, p. 31ff; Robinson et al. 2011, pp. 498-503).

Blackwell et al. (1998) identified the reduction of information asymmetries to lenders as the main *reason* for an external audit. Carey et al. (2000) confirm that external audits lead to better conditions and lower monitoring efforts by financial institutions. Ball et al. (2000) found that no investigated report was verified independently in its entirety. The problem is payment of the reviewer by the communicator (principal) rather than by the recipient (agent). Dando and Swift (2003) also confirm that a certified report is no guarantee for credible perception.

Review standards counteract heterogeneity and arbitrariness of the auditing process. Hodge et al. (2009) argue that the declaration of the audit statement does not lead to a more credible perception. For Frost and Martinov-Bennie (2010), this is due to a considerable lack of understanding among the recipients of the report. Related to this, the *extent of the review* seems to be related to legislation. However, the selection and calculation of many indicators in a sustainability report vary, which makes them difficult to assess (Knebel and Seele 2015, p. 198ff).

The *selection* and *independence of the auditor* has a direct effect on the quality of the reports (Perego and Kolk 2012, pp. 176-186). According to Wallage (2000), professional auditors lead to higher quality reports and better credibility. Ball et al. (2000) also share the same view. Perego and Kolk (2012) as

well as Ackers and Eccles (2015) confirm this finding. However, it is contradicted by the view of Dixon et al. (2004) and Hodge et al. (2009). For them, specialized consultants have a higher level of competence and provide a more balanced audit explanation. Simnett et al. (2009) and O'Dwyer et al. (2011) confirm this view.

For Manetti and Becatti (2009) further problems lie in the insufficient *stakeholder involvement*. Thomson and Bebbington (2005) demonstrate a link between reporting quality and stakeholder engagement. Nonetheless Perrini (2006) and Manetti (2011) prove that companies have so far been reluctant to involve stakeholders in the decision-making process on the content of sustainability reports. This can have advantages as shown by O'Dwyer et al. (2011) as well as Manetti and Toccafondi (2012).

The improvement through *external ratings* such as ranking lists, awards, and sustainability indices is under discussion. They should serve as a neutral instance with own evaluation systems and criteria (Chatterji and Levine 2006, p. 31f) to be an intermediary between corporations and their stakeholders (Robinson et al. 2011, p. 495). Despite good intentions, there is criticism since they are depending on the disclosure of quality information by the companies themselves as the issuing bodies do not make their own measurements (Chatterji and Levine 2006, p. 32f). This has a weakening effect on their positive impact on credibility (Windolph 2011, p. 47f).

Internal potentials. Further research has been carried out on the impact of *internal potentials* of organizations. Here, positive effects of an own *sustainability committee* (Adnan 2009, p. 10 & 13ff; Amran et al. 2014, pp. 222f & 226-230), a *non-governmental organization (NGO) cooperation* (Amran et al. 2014, pp. 223 & 226-230), and *internal audits* (Gürtürk and Hahn 2016; Trotman and Trotman 2015) of non-financial key figures could be demonstrated. This also applies to the *balance* of published positive and negative information (Guthrie and Farneti 2008, p. 363ff; Mishra and Modi 2013, pp. 434 & 441-446). Despite that, *report length* (Fifka and Drabble 2012, p. 461 & 465; Lock and Seele 2016, p. 187f & 191ff) and the type of *integrated report* (i.e. regular annual report with sustainability report) (Lock and Seele 2016, p. 188f) does not improve the perceived credibility. In the case of the latter, the credibility of the report even worsens (Adnan 2009, p. 7 & 13ff; Lock and Seele 2016, p. 192f).

3.1.3.2 Identified Research Gaps

When analyzing the current state of the art using the remaining three properties of credible communication, we found that both, the dimensions of *sincerity* and *normative rightness*, have been well covered in attempts to improve perceived credibility and to close the credibility gap. The dimension of *truth* seems to drag behind.

Sincerity. The initiation of *sustainability committees* as well as the *balance* of the content have a positive effect on sincerity. Sustainability committees ensue intensified efforts of employees involved in sustainability; balance is explained through a more honest representation of information. *External audit standards* and the *involvement of stakeholders* seem to have positive effects as well. External audits limit the scope of action of the publishing company. The involvement of stakeholders leads to an accelerated need for explanations for the intended dissemination of information.

Normative rightness. *Reporting standards*, *external audits*, and the build-up of *internal knowledge* have a positive impact on normative rightness. This can be attributed to the improved competence for

the implementation of an appropriate sustainability report. In combination with the influences of *legal requirements* and the *involvement of stakeholders* into the creation and review process, the dimension seems to be well covered.

Truth. We observe a research gap in methods to improve the objective truth as well as the perception of truth as we only found few attempts dealing with this topic. Therefore, in the following we use it as the focus for our own research. As a first step, we need to examine the relationship between the perception of the objective truth by the recipient and information quality as the key factor for representing and improving objective truth as the actual state of reality in sustainability reports.

3.1.4 Bridging the Credibility Gap through Information Quality

3.1.4.1 Link between Truth and Information Quality

A comparison between the psychological construct of credibility and that of information quality shows that it is difficult to make a clear cut. Recipients do not distinguish between credibility and quality of given information (Wirth 1999, p. 57f). Both constructs are multidimensional (Bentele 1988, p. 421) with similar to congruent criteria for their operationalization. This also applies to their evaluation: the better an individual quality assessment for presented information is, the more likely it is that the content will be used (Früh 1994, p. 22ff & 54f; Wolling 2004, p. 174).

Information quality. The quality of information is essential for the realistic and error-free reproduction of information. *Quality* is defined as an individual rating criterion in the context of quality management and assurance. The measurement is based on the ability of a product to satisfy declared or implied needs, based on its totality of characteristics (Standardization 2000). *Information* is a multi-dimensional construct that can be described by means of layers. On four hierarchy levels, characters with syntax form data, data embedded in a context becomes information, and networked information come to be knowledge (Krcmar 2015, p. 11f). Deduced from this, high decision quality is always based on a high quality of information, which is based on high quality data. In line with this insight, we speak of 'fitness for use', the suitability of information to the respective application context (Wang and Strong 1996, p. 6).

Information quality framework. In the following, we use the framework of Wang and Strong (1996). They have defined a set of dimensions for information quality with criteria to measure. A critical review of the framework has been mandated by the German Government and conducted by the *Deutschen Gesellschaft für Informations- und Datenqualität (DGIQ)* (Rohweder et al. 2015). Their result can be found in Table 11, an asterisk marks interpretational deviation from the original of Wang and Strong.

Table 11: Criteria for the quality of information (Rohweder et al. 2015; Wang and Strong 1996)

Dimension	Criteria	Explanation
Intrinsic	*Information must have a high data value itself.*	
	Reputation	Reputation of a high level of trustworthiness and competence of the source, the transport medium, and the processing system through repeated positive experiences with similar information
	Accuracy*	Consistent with the real world in terms of accurate, correct, reliable, and certified error-free data
	Objectivity	Strictly factual and impartial
	(Data-)Believability	Certification shows high quality standard of information processing or high effort for information acquisition and dissemination
Contextual	*Information must be of high quality in its context.*	
	Timeliness	Contemporary mapping of the properties of the object
	Completeness*	Required information scope and detail from data basis possible
	Appropriate amount of data	Available amount of information meets the requirements
	Value-added	Economically profitable for decision making
	Relevancy	Providing necessary and useful information for users
Representational	*Information must be easily and comprehensibly cognitively understandable.*	
	Interpretability	Evident and purposeful for the user
	Ease of understanding	Required information presented concisely and comprehensibly
	Representational consistency	Represented continuous homogeneously
	Concise representation	Unmistakable for different users
Accessibility	*Information must be easily retrievable and editable with the company's information systems.*	
	Accessibility	Retrievable by simple procedures and directly
	Access security	Easy to change and multilateral usable

As introduced above, we focus our research on the truth dimension. Hence, we deem two dimensions of information quality to be of particular importance: the *intrinsic dimension* and the *contextual dimension* (Bentele and Seidenglanz 2015, p. 421). The dimensions of *representational* and *accessibility* are associated with the other dimensions of Habermas' theory (in particular intelligibility). Hence, we made the conscious decision to not consider them for the remainder of our research.

Intrinsic information quality. *Sustainability committees*, *NGO cooperation*, and *internal audits* have a positive impact on intrinsic information quality. As a consequence of the resulting increase in know-how in terms of competence and trustworthiness, the criterion of reputation seems to be satisfied. This also applies to the criterion of objectivity due to the *involvement of stakeholders* with major interests of sustainability. (Data-) Believability, in the sense of a high expenditure for data acquisition and processing as well as a certification, can also be confirmed. This is based on a combination of the measures outlined above with the further, limited actions of an external audit by a *high-quality auditor* and the *involvement of stakeholders*. On the other hand, the criterion of accuracy, in sense of conformity with reality due to the precision of data, is improved only in a limited fashion. Despite increased efforts, the

information quality of sustainability reports still only moderate. Thus, the intrinsic dimension seems to be satisfied except for the criterion of limited accuracy.

Contextual information quality. Previous attempts to improve contextual information quality have been less successful. Similarly, *sustainability committees*, *NGO cooperation*, and *internal audits* strengthen sustainability reports. Due to the increase of expertise in the sense of competence and suggested neutrality, the criteria of completeness and appropriate amount of data improve. However, we question the satisfaction of the criteria due to the discovered quality deficiencies. In addition, the limited impact of *external audit* methods, high-quality *auditors*, and *stakeholder involvement* can be expected only to lead to a limited increase in relevancy and timeliness. The criterion of added-value seems to be of lesser importance as it has not been considered so far. Thus, the contextual dimension does not even seem to satisfy one criterion in its entirety.

Addressing the deficits. Due to the number of deficits in both dimensions, we limit ourselves to and, thus, focus on a selection of meaningful criteria. Therefore, we have used the GRI v4 guidelines as the most commonly used framework of sustainability reporting worldwide (de Boer et al. 2013, p. 12) for prioritization. Their recommendations demand stakeholder inclusiveness, sustainability context, materiality, completeness, balance, comparability, accuracy, timeliness, clarity, and reliability (GRI 2016, pp. 9-18). Related research has shown that stakeholder inclusiveness, sustainability context, balance, comparability, and clarity of presented information can be regarded as part of the dimension of *intelligibility* and that reliability can be achieved through *external audits.* The criteria of materiality, completeness, accuracy, and timeliness remain problematic.

Three of the four criteria of GRI (GRI 2016, pp. 9-18) are consistent with those from Wang and Strong (1996) as found in Table 11 *Materiality* is exclusive to GRI and provides recommendations for the prioritization of topics in reports (GRI 2016, p. 11f). At first sight, this might suggest a trade-off with the criterion of *completeness*. Yet, it is not, as completeness has to be understood as scope, boundary, and time of the report incorporating the measure of prioritization as well as the practices of information collection (GRI 2016, p. 12f & 17). Therefore, it is a prioritization principle that is applied when compiling the measures to include in the report. It does not affect the information quality of the reported measure once they has been selected. Hence, we refrained from including materiality as a criterion.

The importance of the three remaining criteria of *timeliness*, *completeness*, and *accuracy* is supported by a survey of Michnik and Lo (2009), p. 852). The author examined the relevance of the above-mentioned four-dimensional representation of information quality and their criteria for data users. Therefore, we adopt *timeliness*, *completeness*, and *accuracy* as criteria for the representation of information quality.

3.1.4.2 Potential of Improvement with Big Data Analytics

The basic assumption is that credible perception correlates with the quality of information. As argued, this in turn is dependent on the quality of data. It allows us to conclude that there is potential for improvement through effective and efficient data processing. Due to the emergence of data identified as of big data, there is now a major trade-off between size, time, quality, and cost of information generation that cannot be dealt with in terms of traditional business intelligence capabilities (Schön 2016, p. 19f) and may even lead to a situation where companies are confronted with a data deluge (Müller et al. 2018,

p. 489). Thus, we assume that the perception of information in sustainability reports can be improved through big data analytics.

Characteristics of big data. Ylijoki and Porras (2016), p. 74 & 79) provide an extensive, up-to-date survey of big data definitions. They identified 17 interpretations from a total of 479 scientific articles. The result confirms the importance of three characteristics: *Volume* (95 %), *Variety* (89 %) and *Velocity* (74 %). *Volume* denotes an unusually large amount of data (Géczy 2014, p. 98; Tole 2013, p. 32). *Variety* covers the diversity of data sources and formats and in particular enables the processing of unstructured data (Géczy 2014, p. 98f; Tole 2013, p. 33). *Velocity* refers to the speed of data modification and evaluation (Géczy 2014, p. 98; Tole 2013, p. 32). In the following, we use the term *data work* to describe different types of processing in big data analytics (e.g., in scope and frequency) leading to sustainability reports.

Van Altena et al. (2016) come to the same conclusion. Deviations can be found in the dimensions *Veracity* (23 %) and *Value* (27 %). These appear predominantly in newer interpretations and should therefore be taken into account. *Veracity* includes the reliability of data through extensive testing routines (Schön 2016, p. 304; Van Altena et al. 2016, p. 9). *Value* refers to the value of the use of technology from an economic point of view (Tole 2013, p. 32f; Van Altena et al. 2016, p. 9).

Reviewing the characteristics of big data, the size of the data set is not the defining criterion for big data. However, at least one of the three main characteristics (i.e., volume, variety, velocity) should be linked to its economic use.

Big data analytics. Big data requires "the use of powerful computational techniques to unveil trends and patterns within and between these extremely large socioeconomic datasets" (George et al. 2014, p. 321). We term these techniques *big data analytics*. Big data analytics provides a physical (hardware technology) and digital (software technology) materiality representing stable properties across contexts and time. Examples for physical technologies include in-memory databases (chiefly volume, velocity) or in general contemporary compute, storage, and network capabilities. Examples for software are more diverse and include NoSQL databases such as Apache Cassandra or Amazon Dynamo (volume), event stream processing engines such as Esper (velocity), or statistical software such as R (variety). They provide affordances as potentials for action to process data and create comprehensive information for media such as sustainability reports (Lehrer et al. 2018, p. 428f). A further overview of exemplary physical and digital technologies can be found in Lehrer et al. (2018).

Big data analytics, for instance, can give real-time access to analytics of trace data using sensor networks, scalable in-memory access to large amounts of data points, or text and sentiment analysis of heterogeneous external reports or online conversations such as opinions or feedback. Considering all of these applications, big data analytics offer diverse opportunities for innovation and business transformation. To capitalize on these affordances, one needs to use big data analytics appropriate to one's context.

Summarizing, the core aim of big data analytics is to improve insight, decision-making, and process automation from the analysis of (complex) data sets under economically feasible conditions. Technological choices must be made according to one's context and the extraction of the intended data value must be carried out while ensuring high data quality. In term of sustainability reports, the result is an

increase in information quality through extensive data work in any or multiple of the mentioned dimensions, which leads to an improved truth value of the content. This in turn should improve credibility.

3.1.5 Research Methodology

Due to the lack of scientific knowledge and novelty of the topic, we chose the survey of experts with IT- and data-affine persons as the method of investigation (Przyborski and Wohlrab-Sahr 2014, p. 124ff). For its development, we carried out a quantitative and qualitative survey and evaluation. We used the quantitative survey to pinpoint to what extent there is an agreement on the perception of the credibility of recipients of sustainability reports with regard to information quality criteria. The qualitative survey supported the item selection of the survey.

Statistical evaluation. We chose the causal analysis for the statistical evaluation. It allows the investigation of collected data sets for suspected cause-effect relationships. Mathematically, this is based on a combination of three statistical approaches: factor and path analysis and multilinear regression (Kühnle and Dingelstedt 2014, pp. 1017-1028). We used the variance-analytical approach for the estimation of the structural equation model with its multi-variable system of equations. The model is highly prognosis-oriented, with the aim of explaining latent and/ or associated indicator variables. Both reflective and formative measurement models can be used for the model structure (Chin and Newsted 1999, p. 314). This allows us to prove the assumed interrelationships and assess potential improvements through big data analytics.

We selected the partial least squares (PLS) as the statistical evaluation method. This method is suitable due to its focus on predictions, lack of well-founded measurement and construct theories, and a lack of covariance-based independence of the observed values (Chin and Newsted 1999, p. 314). The use of PLS requires seven steps (Weiber and Mühlhaus 2014, p. 325): hypothesis and modeling, construct conceptualization, construct operationalization, evaluation of the measurement models, model estimation, evaluation of the overall model, and result interpretation.

Progression of research. First, we derived hypotheses and justified them based on the information quality criteria presented above. We processed cause-effect relationships with the latent and manifest variables in a structural equation model. Subsequently, we determined suitable indicators for all not directly observable latent variables and, thus, for all theoretical constructs, which represent them in the best possible way and which can be observed and evaluated. The operationalization of the latent variables was done by recording and measuring the hypothetical constructs based on indicators and measurement rules. For this purpose, we generated a rough classification of potential measurement indicators, defined the measurement concept, and designed the measurement specifications. We then tested the measurement models for their quality based on several reliability and validity tests. For the model estimation, we first cleaned the empirical data obtained during the main investigation and then applied it to the structural equation model using SmartPLS. Reliability and validity of the overall model were again tested to ensure a sufficient model fit. Finally, we examined the a-priori hypotheses on basis of the empirically collected data and interpreted them.

3.1.6 Perceived Credibility of Corporate Published Information in Sustainability Reports

3.1.6.1 Hypothesis Determination and Derived Structural Equation Model

In the following, we examine whether it is possible to improve the perception of the objective truth of published sustainability report information by the means of big data analytics. As indicated by our own analysis so far, the improved representation of reality should lead to an improved objective truth and, thus, an improved perceived credibility by the recipient. Nevertheless, the question remains to what extent the limited rationality of human action in perceiving sustainability reports supports or refutes this assumption. For the examination, we developed the following hypotheses for the selected criteria of timeliness, completeness, and accuracy. The items are based on the above findings from research on information quality as well as mathematical terms for their calculation from the field of data quality (for more detail see the Appendix III). All of our hypothesis aim to improve the perception of objective truth by the recipient as (a) we cannot observe and measure objective truth itself and (b) a true report, which the recipient does not consider credible, is futile.

Timeliness. The common ground of measurement methods for determining the validity of data can be found in the application of probability theory (Heinrich and Klier 2015; Hinrichs 2002). The value of data decreases exponentially over time (Heinrich and Klier 2015, p. 91f). The timeliness of data remains dependent on the time of delivery to the respective recipient. Consequently, this can only be validly determined by the recipient (Wang and Strong 1996, p. 7). This leads to the following hypothesis H1: '*The better the expected timeliness of data, the better the perceived objective truth*.'

Velocity. Due to changes in the environment (Seufert 2016, p. 40) an increase of data value volatility can be observed. This means that there is a reduced half-life of data. This increases the technical speed requirements for the underlying data work (Seufert 2016, pp. 41 & 48-54; Vargas-Solar et al. 2016, pp. 2-12). A high up-to-date value implies new hardware and software technologies as promised by big data analytics. Velocity is necessary per a certain level on the timeliness of data resulting in hypothesis H2: '*The greater the need for the big data characteristic velocity, the better the expected timeliness of the data.*'

Completeness. A value for the completeness of data compared to reality can be determined at the level of the database (Aljumaili et al. 2016; Heinrich and Klier 2015). Incomplete entries represent unknown or missing data (Batini et al. 2009, p. 7). Completeness represents an expected extent to which relevant data for a specific scope of application is available for big data analytics (Aljumaili et al. 2016, p. 244). Conversely, we can assume as well that the more comprehensive the analysis and assignment of data values, the better its completeness. Again, the quality can only be determined by the recipient (Wang and Strong 1996, p. 7). Consequently, hypothesis H3 is defined as follows: '*The better the expected completeness, the better the perceived objective truth*.'

Volume. Nowadays, large amounts of data have to be evaluated (Seufert 2016, p. 40f). This cannot be realized in an economic fashion with traditional IT standards. Physical and digital big data analytics technologies based on volume promise a remedy. Based on this, we formulate hypothesis H4: '*The greater the need for the big data characteristic volume, the better the expected completeness*.'

Variety. In addition to the amount of data, the origin and structure of data changes. Nowadays, more and more video and audio material, browser data, simulations, or gyroscopic data has to be evaluated (Vargas-Solar et al. 2016, pp. 2-12). In the past, IT methods have not been implemented for this purpose and reach physical and economic limits. Problems arise primarily with regard to the evaluation of semi- and unstructured data, which necessitates complex pre-treatments (Schön 2016, p. 298). More and more information is becoming available, which calls for innovative technologies (Seufert 2016, p. 48ff). Physical and digital big data analytics technologies catering for the characteristic of variety promise a solution to this (Seufert 2016, p. 53f). We derive the following hypothesis H5: '*The greater the necessity of the big data characteristic variety, the better the expected completeness*.'

Accuracy. To determine the value of accuracy, one can compare data from an information system with a data entity *x* assumed to be free of errors to the modelled reality (Aljumaili et al. 2016; Heinrich and Klier 2015; Hinrichs 2002). Accuracy data denotes sufficient detail and exactness in the measurement and retrieval of data as well as validation routines (Aljumaili et al. 2016, p. 243f). However, this is also depending on the individual decision, as a (subconscious) validation process takes place due to information asymmetries (Shankaranarayan et al. 2003, p. 9). Therefore, the recipient must determine the value. This leads to hypothesis H6: '*The better the expected accuracy, the better the perceived objective truth*.'

Veracity. Due to a multitude of new data sources and data creators, the origin of data becomes increasingly questionable (Lukoianova and Rubin 2014, p. 4f). It is also important to avoid the challenges of internal and external manipulation attempts (Kepner et al. 2014, p. 1). This makes the process of matching reality enormously difficult. Therefore, the necessary effort for technical reconciliation and validation is growing (Schön 2016, p. 304). It can only be done economically justifiable on the basis of random checks (Hinrichs 2002, p. 87). Again, new hardware and software technologies for big data analytics promise improvements, which are reflected in the characteristic of veracity. We derive hypothesis H7 accordingly: '*The greater the need for the big data characteristic veracity, the better the expected accuracy*.'

The hypothesis results in the following structural equation model:

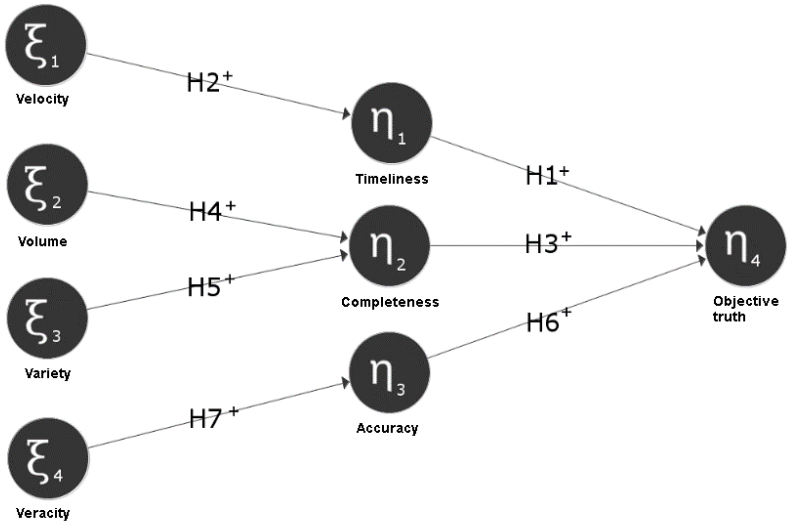


Figure 16: Derived structural equation model without measurement criteria

Equation model. The dependencies of the perception of the *objective truth* on the information quality criteria of *timeliness*, *completeness*, and *accuracy* are our starting points (H1, H3, H6). We can also assume that they can be improved by improvement of information quality through big data analytics (represented here through its characteristics) (H2, H4, H5, H7). According to these assumptions, all links shown in Figure 16 have a positive effect. For clarity reasons, the residual variables and the 'place-holder variables' for the path strengths were not included in the figure.

3.1.6.2 Construct Conceptualization

For the subsequent operationalization, we first describe the latent variables and define them as precise as possible (Weiber and Mühlhaus 2014, pp. 95-102). A summary overview of the latent variables of the structural equation model can be found in Table 12.

Table 12: Brief descriptions of the latent variables

Latent variable	Explanation
Objective truth	Assumed current state of reality
Timeliness	Contemporary mapping of the properties of the object
Completeness	Coverage of information reach and detail
Accuracy	High value of data, comparison of correct reality representation
Velocity	Speed of data processing within data work
Volume	Unusually large amounts of data
Variety	Diversity of (new) data sources and formats
Veracity	Tested reliability of the (comprehensive) data

Construct decision levels. For the three central levels according to Rossiter (2002), p. 309), the following decisions were made in our own investigation:

1. *Subject level* (target persons): Target persons for the survey are employees up to 60 years of age and/ or knowledge of sustainability reports. We justify this by the fact that many respondents will become potential recipients and possible decision-makers in the next few years. We have also selected test persons with a uniform cultural background due to the findings in section 3.1.3.1.
2. *Objective level* (carrier of the assessment): Participants assess the perceived information quality and perceived objective truth of different forms of big data analytics data work based on extracts from sustainability reports.
3. *Attribute level* (object properties of the appraisal): Participants assess the changed conditions of the selected information quality criteria in conjunction with the perceived objective truth-value.

3.1.6.3 Construct Operationalization

A data quality framework from the health sector (Canadian Institute for Health Information 2009) and topic-related mathematical calculation models (see Appendix III) were used to pre-operationalize the theoretical constructs for the selected criteria of *timeliness*, *completeness*, and *accuracy*. Cf. Table 13 for the derived measurement indicators and their explanation.

Table 13: Derived measurement indicators of the information quality criteria

Dim.	*Measurement indicator*	*Explanation*	*Ø app.*	*Ø wei.*
Timeliness	Update frequency (U_frequen)	Time interval between measurements	94 %	34 %
	Ageing rate	Data validity period as defined by data experts and users	63 %	-
	Data age (D_age)	Time between data collection and information delivery	100 %	44 %
	IT-speediness (IT_speed)	Time required for data processing	75 %	22 %
Completeness	Amount of data (S_volume)	Total number of included data records	100 %	37 %
	Sources considered (S_consid)	Data sources for dataset generation	100 %	36 %
	Formats considered	Data formats for dataset generation	25 %	-
	Attributes considered (A_consid)	% coverage of most important attribute values	81 %	27 %
	Coverage ratio	% coverage of relevant real world scenario	63 %	-
Accuracy	Precision (Precision)	Precision of measures and stored data values	100 %	39 %
	Validation level (V_level)	Scope of data and source validation	94 %	23 %
	Validation frequency (V_frequen)	Frequency of validation methods	81 %	17 %
	Error ratio (E_ratio)	Ratio of incorrect/non-existent data attributes to error-free data attributes	88 %	22 %
	Importance measure	% validity rate of important attribute values	63 %	-
	Deviation from reality	Missing/NULL values compared to reality	63 %	-

Expert survey. To validate the identified measurement indicators, a qualitative expert survey was conducted with a total of 16 participants. After explaining topic and intention, a questionnaire was sent to the experts to validate the suitability of the initial measurement indicators, to determine their weighting for the respective theoretical construct, and to make proposals for further indicators. The results are also included in Table 13, where 'Ø-weighting' is the mathematically calculated average score when 'Ø-approval' is ≥ 75%. This ensures that the majority of experts support the need and legitimacy of the respective measurement indicators.

Expert discussion. Only two experts made further proposals to supplement missing measurement indicators. The proposals themselves (source reliability, non-redundancy, consistency) were thoroughly reviewed, but had to be rejected due to duplication, as they are already covered by other indicators (sources considered, validation level).

Big data analytics value determination. For the characteristics of big data analytics, no suitable studies could be found to derive measurement indicators. Therefore, we did not carry out a separate expert survey. The value determination for the individual big data analytics characteristics within the survey are based on previous academic findings (Géczy 2014; Schön 2016; Van Altena et al. 2016; Vargas-Solar et al. 2016) and an expert survey according to Seufert (2016). Furthermore, due to the lack of a complete reflectivity of the theoretical constructs, the measurement concept was uniformly defined to be formative.

Operationalized equation model. As the result of operationalization, the structural equation model is extended to include measurement indicators and their weighting for the underlying latent variables. The result is shown in Figure 17.

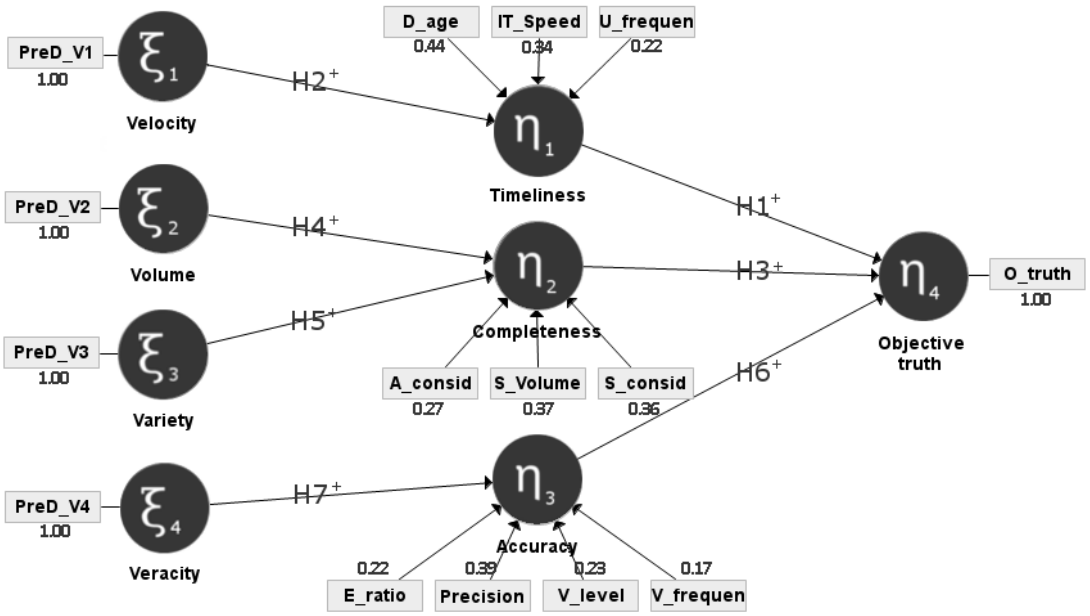


Figure 17: Derived structural equation model with measurement criteria

For the big data characteristics "PreD_V1" to "PreD_V4" a predefined value is specified. The weighting is therefore "1.00" each. The *objective truth* also receives "1.00", since it contains only one measuring indicator. The respective weighting of the other variables is based on the expert survey. The designations can be found in Table 13 as "Ø wei(ghting)".

The residual variables and placeholder variables for the path strengths have been omitted again for clarity reasons. Due to mathematic rounding, summations may result in values ≠ 1.

3.1.6.4 Evaluation of the Measurement Models

Ultimately, we conducted a quantitative survey to examine the extracted structure equation model. Therefore, a six-tiered (Trommsdorff 1975, p. 93ff) Likert-scale was used as the measuring method (Weiber and Mühlhaus 2014, p. 43). Thus, there is a forced decision of the respondents on their tendency, which prevents undetectable reasons for the choice of averages (Weiber and Mühlhaus 2014, p. 42). For the grading, terms “very good” to “very bad” were used.

Survey setup. The survey itself was carried out using two questionnaires of the same type (group A and B) with different extracts from sustainability reports. A uniform language was chosen to counteract the falsification due to cultural influence (see section 3.1.3.1). The questionnaire was therefore conducted in German language. As participants, employees were acquired from six companies (A = 3; B = 3). The sample *n* before adjustment was 68 (A = 37; B = 31). Exclusions of age 60+, lack of knowledge about sustainability reports, and detected anomalies in the response behavior resulted in a final sample *n* of 44 (A = 26; B = 18).

Survey content. As the basis for our questions, we used excerpts from actual sustainability reports by Volkswagen AG and Henkel AG & Co. KGaA (see the Appendix III for details). We used these excerpts to ask questions about our variables in all three dimensions. For each dimension we formulated a text paragraph with a scenario description and asked about our variables on the aforementioned Likert scale.

Once all three dimensions had been answered, we closed with a summative question on the perceived truth value. In total, we asked each question thrice varying the data work involved to generate the report. For example, concerning timeliness of data we use the following three scenarios:

(1) *"We update our data weekly, data is evaluated every month and takes two days to process."*

(2) *"We update our data monthly, data is evaluated every three months and takes six weeks to process."*

(3) *"We update our data quarterly, data is evaluated every six months and takes twelve weeks to process."*

Then, we asked for the recipient's perception on the adequateness of the measurement indicators for update frequency, data age, and IT speediness.

We have varied the sequence of the data work scenario questions in the survey. Concerning completeness and accuracy, we created similar scenarios using the other indicators of Table 13: *"we cover x as data sources with an inclusion of x % of possible attributes, and a total amount of x rows of data"* and *"we validate aspect x with a precision of x decimal places every x time units, our validation has a maximum error rate of x %"*.

The respondents evaluated their perception with the varying data work. In the same way, we examined an overall perception of *objective truth* throughout the questionnaire. Reliability and validation measures were used to ensure the consistency of the measuring instrument (Weiber and Mühlhaus 2014, p. 169f).

Survey validation. Forecast validity was used in the examination at indicator level. The permissible value range is a regression coefficient of ≥ 0.5 (Diamantopoulos and Riefler 2008, p. 1189). The calculated forecast values are available in Table 14.

Table 14: Results from the forecast validity of the measurement indicators

Latent variable	Measurement indicator	Forecast value
Velocity	PreD_V1	1.000
Timeliness	D_age	0.878
	IT_speed	0.931
	U_frequen	0.701
Volume	PreD_V2	1.000
Variety	PreD_V3	1.000
Completeness	A_consid	0.862
	S_volume	0.900
	S_consid	0.583
Veracity	PreD_V4	1.000
Accuracy	E_ratio	0.600
	Precision	0.844
	V_level	0.855
	V_frequen	0.596
Objective truth	o_truth	1.000

The result shows a high quality of the individual criteria. There are anomalies only with two measurement indicators: sources considered (S_consid = 0.583) and validation frequency (V_frequen = 0.596). However, these remain within the defined approval range and have been confirmed by the expert survey.

At the construct level, the validity of convergence, discrimination, and nomological validity were examined. AVE ≥ 0.5 (Fornell and Larcker 1981, p. 46) indicates the threshold value for good reliability in convergence validity. Values that have an average variance ratio with the latent construct that is lower than the latent construct with its own indicators (AVE (ξi) > $\Phi^2 ij$ ∀ *i*, *j*) (Fornell and Larcker 1981, p. 46) are considered to be permissible values for the discriminant validation.

Table 15: Results of the testing measures for the formative measurement models

Latent variable	**AVE**	**Fornell-Larcker criterion**							
		Tim	Velo	Com	Volu	Vari	Acc	Vera	oT
Tim	0.698	0.836							
Velo	1.000	0.621	1.000						
Com	0.631	0.603	0.715	0.794					
Volu	1.000	0.621	1.000	0.715	1.000				
Vari	1.000	0.562	0.961	0.710	1.000	1.000			
Acc	0.540	0.594	0.668	0.650	0.668	0.640	0.735		
Vera	1.000	0.621	1.000	0.715	0.961	0.961	0.668	1.000	
oT	1.000	0.658	0.779	0.760	0.779	0.739	0.801	0.779	1.000

Legend: Tim = Timeliness; Velo = Velocity; Com = Completness; Volu = Volume; Vari = Variety; Acc = Accuracy; Vera = Veracity; oT = Objective truth; AVE = average variance extracted; values are mathematically rounded

As shown in Table 15, all constructs have a permissible dispersion when computing the respective AVE. Therefore, we consider convergence validity to be assured. The value of accuracy is relatively low, but nevertheless permissible (Acc = 0.540). One possible explanation is the high number of four measurement indicators.

In the case of discriminant validity, in addition to the fixed values for the characteristics of the big data properties allocated ex-ante, there is also an abnormality in the accuracy (Acc = 0.735). This shows a critical overlap with the construct of *objective truth*. One possible reason could be the sequence of the survey. Possibly, respondents are influenced by the evaluation of the measurement indicators of the preceding accuracy when grading the objective truth. The construct of objective truth is again delimitable from the other constructs. Except for the low value on the criterion of accuracy, discrimination seems to be valid.

3.1.6.5 Model Estimation and Evaluation of the Overall Model

The estimation of the structural equation model was done with the help of the adjusted empirical data from the quantitative survey. We performed an intermediate step using the bootstrapping method (Weiber and Mühlhaus 2014, pp. 173-198 & 323-342) due to the missing numerical values, an thus, distributions of the latent variables.

Survey reliability. The coefficient of determination (R^2) was used for checking at indicator level. The range of values is declared with [0;1] and should be ≥ 0.19 in accordance with Chin (1998), p. 325). The

thresholds are confirmed by Hansmann and Ringle (2005), p. 227), who make a further subdivision. They declare the range $0.19 \leq R^2 < 0.33$ as weak, $0.33 \leq R^2 < 0.67$ as medium and $R^2 \geq 0.67$ as substantial. Considering the sources, a value from $R^2 \geq 0.33$ should be considered acceptable for our work.

As shown in Figure 18, all latent variables are adequately covered by the measurement indicators assigned to them. Each of the values is ≥ 0.33. This confirms it as a reliable structural equation model.

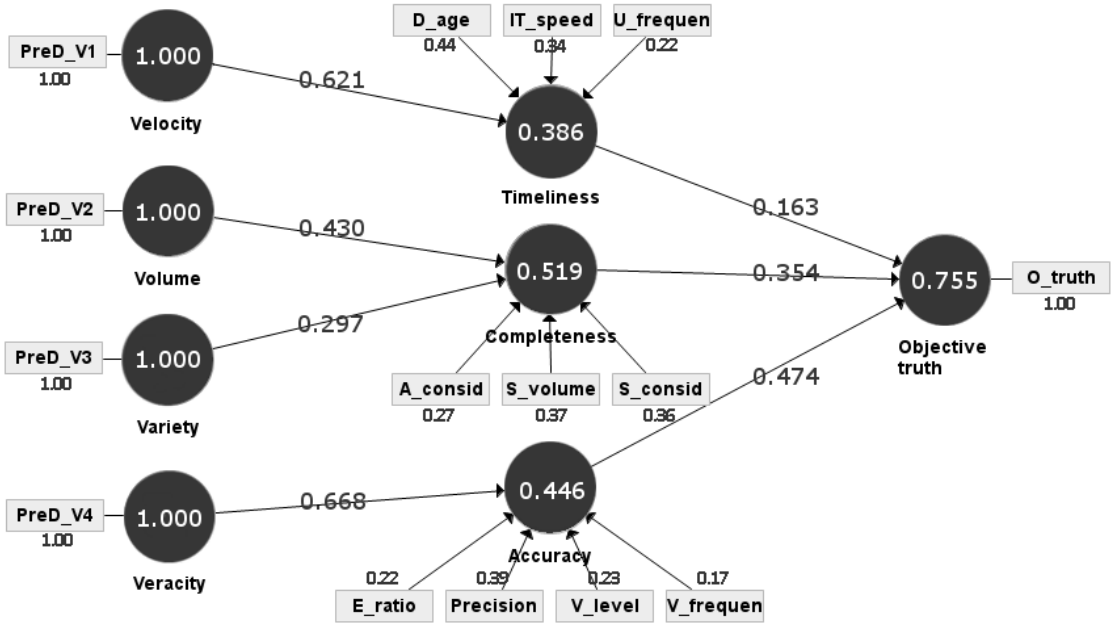


Figure 18: Calculated structural equation model

Survey results. Subsequently, the nomological validity was assessed at the construction level. For the proof of respective hypothesis, its path coefficient has to differ significantly from 0 (≥ 0.3) and must correspond to the a-priori assumed direction of action (Weiber and Mühlhaus 2014, p. 265). Results are shown in Table 16 and correspond to the values in Figure 18.

Table 16: Result of the hypothesis test by nomological validity

No.	*Predication in short*	*From*	*After*	*Value*	*Yes?*
H1	Expected timeliness of the data on perceived objective truth	Tim	oT	0.163	-
H2	Necessity of the big data property velocity to expected timeliness	Velo	Tim	0.621	(x)
H3	Expected completeness of the data on perceived objective truth	Com	oT	0.354	x
H4	Necessity of the big data property Volume to expected completeness	Volu	Com	0.430	x
H5	Necessity of the big data property Variety to expected completeness	Vari	Com	0.297	-
H6	Expected accuracy to perceived objective truth	Acc	oT	0.474	x
H7	Necessity of the big data property Veracity to expected accuracy	Vera	Acc	0.668	x

There is no assumed increase in the perceived objective truth through an increase in data timeliness (H1 = 0.163). Despite reaffirmation of an improvement in timeliness by velocity (H2 = 0.621) no increase in perceived objective truth, and thus credibility, can be achieved through reporting speed for sustainability reports. For completeness (H3 = 0.354) there seems to be a (low) increase. Therefore, an

improvement of the objective truth by the connected criterion volume (= 0.430) can be assumed. However, this does not apply to variety (= 0.297). On the other hand, accuracy has a positive effect on objective truth (= 0.474). The criterion veracity leads to an increase in accuracy (= 0.668) and therefore to an increase of the credibility as well.

3.1.7 Discussion of Results, Limitations and Further Research

The perceived credibility of sustainability reports has been a subject in research for years known as the *credibility gap*. We have devised an approach incorporating the conflict between the (ir)rationality of decisions in business and the limited rationality of human action to optimize the perception of sustainability reports, in particular in the perception of the dimension of objective truth. Despite the obvious connections between the psychological construct of credibility and the quality of the information provided, the direct impact of big data analytics remained questionable due to the limited rationality of the recipient to appreciate higher quality data. Our results indicate that the perception of sustainability reports can be improved generally with big data analytics. In doing so, we incorporate both, the communicator-centered view stating that credible communication is improved by passing on superior information and the recipient-centered view stating that credible communication is based on the recipient appraisal of the information.

Discussion. As big data analytics covers a diverse range of physical and digital technologies, their use has to be optimized for the application context. In the following, we discuss our findings on how to improve sustainability reports using big data analytics. We have found that the *timeliness* of data seems to have only a very small effect on the perception of truth by the recipients of sustainability reports. There does not seem to be any improvement in sustainability reports from big data analytics technologies such as in-memory or event processing in the *velocity* area. We assume that this is due to the fact that sustainability reports are typically periodical publications and the implementation as an updated real-time report does not provide substantial added value. Consequently, the value of real-time data for sustainability reports should always be very critically reflected and general reports are unlikely to benefit. Nevertheless, there may be niche applications where real-time data may be valued more. In contrast, the criterion of *completeness* has a measurable impact on perception. Big data analytics with the characteristic of *volume* such as physical storage technologies or NoSQL databases improve this criterion. Recipients seem to value comprehensive data sets and analysis. *Variety*, on the other hand, as expressed through innovative data mining tools does not seem to result in a significant increase for sustainability reports. As discussed below, we assume this to be due to the area of application. Sustainability reports are based on defined measurements and performance indicators of limited variety. Recipients apparently do not value an increase of those. The criterion of *accuracy* shows the highest influence on the perception of credibility. This can be further increased by big data analytics using comprehensive and reproducible algorithms to improve the *veracity* of big data.

Our results do not confirm the assumptions of Natarajan et al. (2017) who expects that *variety* is the most significant factor of big data analytics. Natarajan et al. (2017) has made these assertions in the context of medical information quality. It is conceivable, that for medical decisions a variety of information, which points to the same diagnosis, is more important than volume or accuracy of individual data points due to the issue of differential diagnoses. Consequently, and as indicated earlier, it is

important to clearly define the context in which big data analytics is employed to ensue maximal value in the delivery of information.

Limitations. There are limitations to our process of investigation during the quantitative questioning and to its scope. During the determination of the values per survey cycle, we provided explicit information on the data work undertaken for each section of the sustainability report we presented. In practice, this information typically is not available or only available to a very limited extent. Validations with other target groups also seem to be advisable to ensure that the information provided is of generalizable nature.

The Habermas Theory of Communicative Action assumes idealized conditions of discourse (i.e. an ideal speech situation) which is then immunized against repression and inequality in a special way. We have used this theory to analyze the impact of big data analytics on information quality and, thus, on the dimension of objective truth. Using the instrument of a survey, we have not analyzed the impact of further influencing factors that are inherent to our imperfect world. Hence, it is conceivable that other factors impact the recipient's perception of sustainability reports such as current (negative) media reports involving the respective companies or internet trolling.

Conclusion. We conclude that an improvement of the perceived credibility of sustainability reports is generally possible with help of big data analytics. As a recommendation to creators of sustainability reports, a focus should be placed on the information quality criteria of *completeness* and *accuracy*. Similarly, further improvement measures through future physical and digital technologies of big data analytics seem to be possible primarily with technologies that focus on the characteristics of *volume* and *veracity*, as this seems to promote the truth perception of published information in sustainability reports.

To further close the credibility gap, we suggest addressing all gaps identified by the objective truth in Habermas theory as an ideal-typical implementation of sustainability report content. Further investigations should focus on the criteria of *appropriate amount of data*, *value-added*, and *relevancy* of the contextual dimension of information quality.

3.2 Model Performance and Model Explainability

Abstract. Numerous machine learning algorithms have been developed and applied in the field. Their application indicates that there seems to be a tradeoff between their model performance and explainability. That is, machine learning models with higher performance are often based on more complex algorithms and therefore lack interpretability or explainability and vice versa. The true extent of this tradeoff remains unclear while some theoretical assumptions exist. With our re-search, we aim to explore this gap empirically with a user study. Using four dis-tinct datasets, we measured the tradeoff for five common machine learning algorithms. Our two-factor factorial design considers low-stake and high-stake ap-plications as well as classification and regression problems. Our results differ from the widespread linear assumption and indicate that the tradeoff between model performance and model

explainability is much less gradual when considering end user perception. Further, we found it to be situational. Hence, theory-based recommendations cannot be generalized across applications.[7]

3.2.1 Introduction

Today, intelligent systems based on artificial intelligence (AI) technology primarily rely on machine learning (ML) algorithms (Janiesch et al. 2021). Despite their prediction performance, there is a noticeable delay in the adoption of advanced ML algorithms based on deep learning or ensemble learning in practice (Wanner et al. 2020a). That is, practitioners prefer simpler, shallow ML algorithms such as logistic regressions that exhibit a higher degree of explainability through their inherent interpretability (Rudin 2019).

In contrast, much of the current AI research focuses on the performance of ML models (La Cava et al. 2021) and data competitions are dominated by deep learning algorithms such as artificial neural networks (ANN) that outperform shallow ML algorithms (e.g., Hyndman 2020). However, the processing of these algorithms is practically untraceable due to its complex and intransparent inner calculation logic. This renders it impossible for humans to interpret an ANN's decision-making process and prediction results, making it a black box.

This results in a tradeoff between performance and explainability which is not yet sufficiently understood. The uncertainty and lack of control due to a lack of explainability can fuel algorithm aversion of the end user. The aversion describes a phenomenon where users prefer humans over machines even when the performance of the machine is superior to the human (Burton et al. 2020). In contrast, recent work by Logg et al. (2019) implies that for some situations when performance is communicated, humans may prefer machines resulting in algorithm appreciation. A better understanding of the tradeoff can help to reduce algorithm aversion and may even foster algorithm appreciation from an end user perspective.

While the performance of an algorithm can be estimated by common performance indicators such as precision, recall, or the F-score, it remains unclear, which ML algorithm's inherent interpretability is perceived as more explainable by end users. However, this is crucial as the perceived explainability of a prediction determines the effectiveness of an intelligent system. That is, if the human decision maker can interpret the behavior of an underlying ML model, he or she is more willing to act based on it (Ribeiro et al. 2016b) – especially in cases where the recommendation does not conform to his or her own expectations. As a consequence, intelligent systems without sufficient explainability may even be inefficacious as end users will disregard their advice.

In scholarly literature, several theoretical considerations on the tradeoff of performance and explainability exist (Angelov and Soares 2020; Arrieta et al. 2020; Dam et al. 2018; Gunning and Aha 2019;

[7] This paper is published within the 20th IFIP Conference on e-Business, e-Services, and e-Society as 'Stop Ordering Machine Learning Algorithms by their Explainability! An Empirical Investigation of the Tradeoff between Performance and Explainability' (Wanner et al. 2021). The conference paper was invited for a special issue of the International Journal of Information Management (IJIM).

James et al. 2013; Nanayakkara et al. 2018; Yang and Bang 2019), yet a scientific investigation or even an empirical proof is still missing. We formulate our research question accordingly:

"How do machine learning models compare empirically in the tradeoff between their performance and their explainability as perceived by end users?"

These insights have a high potential to better explain AI adoption of different ML algorithms contributing to a better understanding of AI decision-making and the future of work using hybrid intelligence. That is on the one hand, the results can help us to understand to what extent various ML algorithms differ in their perceived explainability from an end user perspective. This allows us to draw conclusions about their future improvement as well as about their suitability for a given situation in practice. On the other hand, the results can help us to understand how much performance end users are willing to forfeit in favor of explainability. Ultimately, Rudin (2019)'s call to avoid explaining black-box models in favor of using inherently interpretable white-box models could be better approached if the tradeoff was sufficiently understood from a social-technical perspective.

In the following, Section 3.2.2 introduces fundamentals of ML and the state-of-the-art of existing ML tradeoff schemes concerning model performance and model explainability. In Section 3.2.3, we describe our methodology before we outline preparatory work comprising the datasets and algorithms. The section also comprises the technical realization of the algorithms, the measurement for comparison, and the survey design. In Section 3.2.4, we discuss the results of the empirical comparison. We close by summarizing our results and pointing out limitations of our study in Section 3.2.5.

3.2.2 Fundamentals and Related Work

3.2.2.1 Machine Learning Algorithms

ML focuses on algorithms that are able to improve their performance through experience. That is, ML algorithms are able to find non-linear relationships and patterns in datasets without being explicitly programmed to do so (Bishop 2006). The process of analytical modeling building to turn ML algorithms into concrete ML models for the use in intelligent systems is a four-step process comprising data input, feature extraction, model building, and model assessment (Janiesch et al. 2021).

Each ML algorithm has different strengths and weaknesses regarding their ability to process data. Many shallow ML algorithms require the feature selection of relevant attributes for model training. This task can be time-consuming if the dataset is high-dimensional, or the context is not well-known to the model engineer. Common shallow ML algorithms are linear regressions, decision trees, and support vector machines (SVM). ANNs with multiple hidden layers and advanced neurons for automatic representation learning provide a computation- and data-intensive alternative called deep learning (Janiesch et al. 2021). These algorithms can master feature selection on increasingly complex data by themselves (Schmidhuber 2015). In consequence, their performance surpasses shallow ML models and even exhibits super-human performance in applications such as data-driven maintenance (e.g., Wang et al. 2018a). On the downside, the resulting models have a nested, non-linear structure that is not interpretable for humans, and its results are difficult to reproduce.

In summary, while many shallow ML algorithms are considered interpretable and, thus, white boxes, deep learning algorithms tend to perform better but are considered to be intransparent and, thus, black boxes (Adadi and Berrada 2018).

3.2.2.2 Interpretability and Explainability in Machine Learning

Explanations have the ability to fill the information gap between the intelligent system and its user similar to the situation in the principal-agent problem (Wanner et al. 2020a). They are decisive for the efficacy of the system as the end user decides based on this information whether he or she integrates the recommendation into his or her own decision-making or not. The question of what constitutes explainability and how explanations should be presented to be of value to human users fuels an interdisciplinary research field in various disciplines, including philosophy, social science, psychology, computer science, and information systems.

From a technical point of view, explainability in intelligent systems is about two questions: the "how" question and the "why" question. The former is about global explainability, which provides answers to the ML algorithm's internal processing (Dam et al. 2018; Rudin 2019). The latter is about local explainability, which answers the ex-post reasoning about a concrete recommendation by a ML model (Dam et al. 2018). To form a common understanding for our research artifact, we define explainability as "the perceived quality of a given explanation by the user" (Adadi and Berrada 2018).

In this context, as noted above many shallow ML models are considered to be white boxes that are interpretable per se (Arrieta et al. 2020). In contrast, a black-box ML model is either far too complicated for humans to understand or opaque for a reason and, therefore, equally hard to understand (Rudin 2019). Consequently in this research, in line with Adadi and Berrada (2018)'s argument we consider a model's explainability as its innate interpretability by end users not using any further augmentations.

3.2.2.3 Related Work on Machine Learning Tradeoffs

Considerations about the (hypothesized) tradeoff between model performance and model explainability have been the subject of discussion for some time. Originating from theoretical statistics, a distinction for different ML algorithms was first made between model interpretability and flexibility (James et al. 2013). More recently, this changed towards a comparison between model accuracy and interpretability (e.g., Arrieta et al. 2020; Yang and Bang 2019) or algorithmic accuracy and explainability (e.g., Angelov and Soares 2020; Dam et al. 2018). However, all tradeoffs address the same compromise of an algorithm's performance versus the algorithm's degree of result traceability.

Overall, in the field many subjective classifications of this tradeoff exist (Angelov and Soares 2020; Arrieta et al. 2020; Dam et al. 2018; Gunning and Aha 2019; James et al. 2013; Nanayakkara et al. 2018; Yang and Bang 2019). These subjective classifications of the different authors show great similarities but also some dissimilarities. We summarize the related work and their classifications (left side) in Figure 19 illustrating a high conformity between all authors. The resulting Cartesian coordinate system (right side) shows five common ML algorithms ordered by their common performance (*y*-axis) and their assumed explainability (*x*-axis). Grey-box models (i.e., ex-post explainers) are only subject of few

studies (e.g., Angelov and Soares 2020; Nanayakkara et al. 2018), hence we have not included them in our considerations.

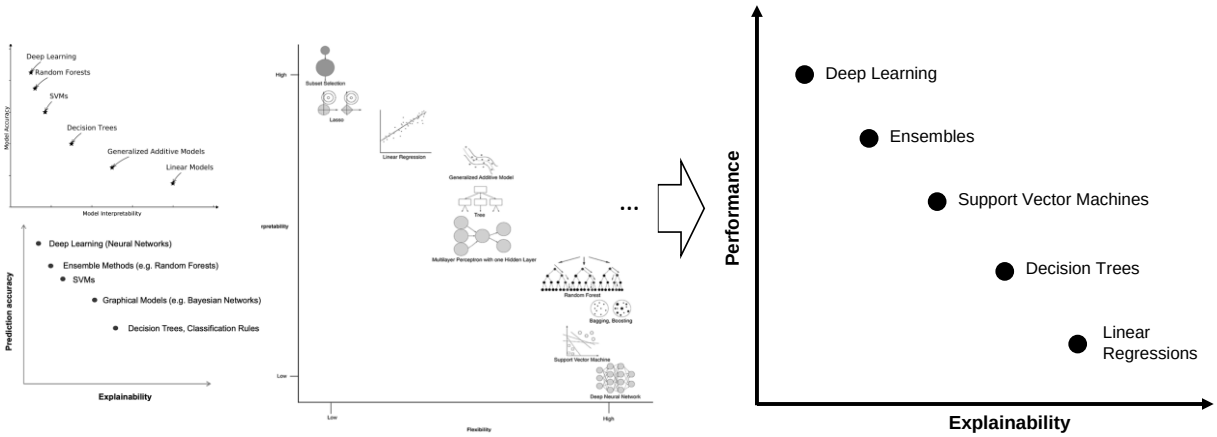


Figure 19: A Synthesis of Common ML Algorithm Classification Schemes

While there is a general agreement on key ML algorithms, there are some differences on their placement and the granularity of representation. The general notion is that with a loss of performance, algorithms provide better explainability in a more or less linear fashion. That is, deep learning algorithms or ANNs are categorized as the most powerful with the least degree of model explainability, followed by ensemble algorithms, which consist of multiple ML models. Third in performance, SVMs serve as a large margin classifier based on data point vectors. Fourth, decision trees use sorted, aligned trees for the development of decision rules. Finally, linear regressions are considered of least performance, yet straightforward to interpret (Goodfellow et al. 2016). Some authors have chosen to classify certain ML algorithms closer to each other to arguably represent better their assumed true position in the tradeoff (e.g., Dam et al. 2018; Gunning and Aha 2019; Guo et al. 2019b).

In essence, these theoretical classification schemes represent a hypothetical and data-centered view on the tradeoff of model accuracy vs. model interpretability. They have neither yet been validated for specific applications based on real data, nor with end users in a user-centered approach to unearth their true pertinency to represent said tradeoff of performance vs. explainability. Despite this obvious deficiency, they are commonly referenced as a motivation for user- or organization-centered XAI research or intelligent system deployment (e.g., Asatiani et al. 2021; Guo et al. 2019b; Rudin 2019).

Thus, in summary it remains unclear how the end users perceive explainability and how this is in line with these tradeoff considerations. In our work, we focus on the tradeoff between performance and an ML models inherent explainability to avoid biases introduced by model transfer techniques from the field of explainable AI (XAI), which aims at providing more transparent ML models that have both, high model performance and high explanatory power (Gunning and Aha 2019).

3.2.3 Methodology

Our research methodology uses four main steps: research question, data collection, data analysis, and result interpretation (Müller et al. 2016). They are depicted in Figure 20.

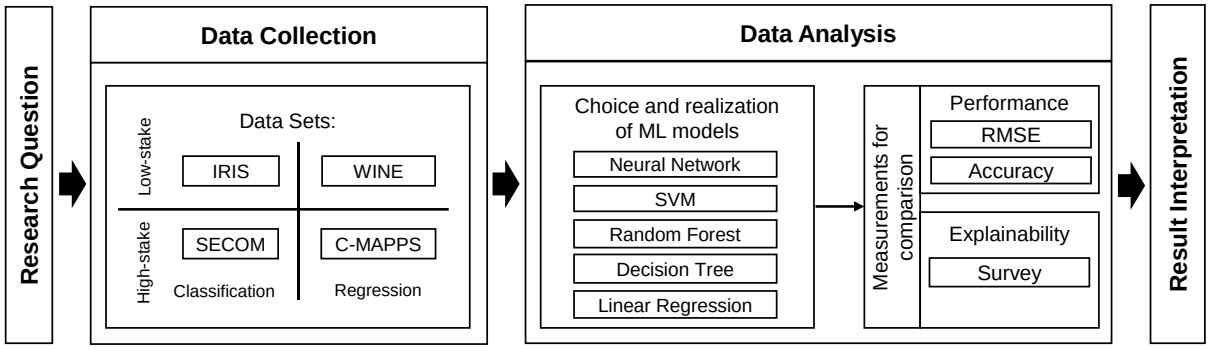


Figure 20: Overall Methodology

We started by formulating our RQ with the aim to shed light on the similarities and differences between different ML algorithms in terms of their tradeoff between performance and explainability. We verified the relevance of our RQ by a theoretical review of existing contributions and pointed out the research gap (cf. Section 3.2.2.3).

As we expect the tradeoff to be moderated by the underlying criticality of the task (low stake vs. high stake) and the type of the task (regression vs. classification), we employ a two-factor factorial design with four treatments using four different publicly available datasets. See Table 17 for an overview of the datasets.

To test the tradeoff empirically, we trained five ML models using common ML algorithms present in the aforementioned theoretical tradeoff schemes for the four treatment datasets using scikit-learn. We performed common data cleansing steps prior to model training. See Table 18 for an overview of the implementations.

Table 17. Overview of Datasets.

Dataset	Treatment	Description
IRIS (Marshal 1988)	Low-stake classification	IRIS is well known and has a low complexity. It contains 150 observations of 4 different features about the shape of iris flowers as well as their classification into one of 3 distinct species.
WINE (Cortez 2009)	Low-stake regression	The WINE quality dataset consists of 11 different features describing red Portuguese "vinho verde" wines. The dataset includes 1599 wine samples that are ranked in their quality from 0 to 12.
SECOM (McCann Michael 2008)	High-stake classification	SECOM includes use data from a semi-conductor manufacturing process. It contains data of over 590 sensors tracking 1567 observations of single production instances as well as the classification of semi-conductor production defects.
C-MAPSS (Saxena and Goebel 2008)	High-stake regression	C-MAPSS provides turbofan engine degradation sensor data. It is based on a modular aero-propulsion system simulation about the remaining useful lifetime using different operational conditions. It contains simulation data from 93 turbines with 50 cycles per turbine and 25 sensors measurements per cycle.

To evaluate the performance of our models, we used two different measurements due to the type of problem (i.e., regression vs. classification). For the evaluation of the regression-based predictions, we applied the root mean square error (RMSE). For the evaluation of the classification-based predictions, we calculated the model's accuracy.

Table 18. Overview of ML Algorithm Implementations.

ML Algorithm	Implementation
Linear Regression	Due to data preprocessing, we skipped default normalization and used the default settings. For the non-centered datasets such as SECOM, we included the intercept of the model.
Decision Tree	We did not restrict the models by regulations such as the minimum sample split numbers of the estimators. The resulting trees have a depth of five or six, depending on the treatment.
SVM	For all datasets, we applied an SVM using a radial basis function as kernels.
Random Forest (ensemble)	We used the bagging algorithm random forest as proxy for ensembles. Random forests consist of 100 estimators each and their complexity was not restricted (see decision tree).
ANN	For C-MAPSS, we used an ANN with six alternating hidden layers consisting of LSTM and dropout layers. For the other datasets, we applied a multi-layer-perceptron with six hidden layers including dropout layers.

While a model's performance can be evaluated independently of the user, its explainability depends on the perceptions of its users (Miller 2019). Therefore, we evaluated the users' perceived explainability by conducting a survey to account for the subjective nature of the perception of the ML models. We used the platform prolific.co using a monetary incentive. We did not limit the participation by factors such as the experience with AI or data science skills to receive broad feedback. For reasons of duration and repetitiveness, we designed two separate studies that were assigned at random: a classification study and a regression study, each containing a low-stake and high-stake case. The procedure within each variant was identical.

In the survey, we first collected demographics, prior experience with AI, as well as the participant's willingness to take risks. In the second part, we provided them with an introduction to the concepts of either regression- or classification-based ML, typical data processing steps, and general information about the visualization of ML predictions.

Second, we presented the use case for each treatment: The interviewees were asked to assume the role of an employee confronted with a decision situation. We provided a task definition and information about the process. Further, we explained that the task should now be performed by an intelligent system. For each case, we provided the criticality of wrong decisions.

Third, we evaluated their explainability based on the propositions by Hoffman et al. (2018). To survey global explainability, we provided the participants with descriptions of the employed ML algorithms. To survey local explainability, we provided the participants with a graphical visualization of specific predictions. The participants did not receive any information about the performance of the ML to avoid biases. For each ML model, the participants had to rate their overall perceived explainability of the model on a five-point Likert-scale. The models were presented in random order to avoid sequence bias.

We received responses from 204 participants (112 classification, 92 regression). After processing multiple exclusion criteria (duration, lazy patterns, control questions), we could use 151 surveys (117 male, 34 female). Most participants (≈45%) were between 20 and 30 years old, followed by 31-40 (≈28%). ≈75% were from Europe, while ≈23% were from North America and only ≈2% from other regions. Half of the participants (≈52%) had no experience in AI, while ≈33% used AI for less than two years and only ≈15% had more than two years of experience with AI. ≈13% of the participants would describe

their willingness to take risks as very low, while ≈46% would classify themselves as medium and ≈41% as high to very high.

3.2.4 Results

3.2.4.1 Result Comparison

Performance. In general, the performance results confirm the theoretical ordering in Figure 1 (*y*-axis). Nevertheless, the relative performance differs. Especially, the difference between random forest and SVM is smaller than assumed. In our case, this may be due to the datasets and the ensemble algorithm, but it reveals that the ordering of algorithms by their performance is hardly deterministic. Further, the performance difference between shallow ML algorithms and deep learning can be almost neglectable in scenarios with low complexity such as IRIS. Still, linear regression constantly performed worst while ANN performed best in comparison to the other models. Table 19 illustrates the results of our performance evaluation.

Table 19. Performance Results of ML Models.

	Classification in Accuracy*		Regression in RMSE**	
Model	IRIS	SECOM	WINE	C-MAPSS
Linear Regression	81.59	68.70	1.05	59.39
Decision Tree	85.95	83.50	0.85	55.60
SVM	92.10	94.46	0.81	53.03
Random Forest	92.90	94.92	0.79	42.31
ANN	**94.21**	**95.20**	**0.77**	**38.56**

* higher = better, in %; ** lower = better, in total values

Explainability. We present the perceived level of explainability from the conducted survey for each algorithm in Table 20. We follow the recommendations of Boone and Boone (2012) and applied a mean calculation for the Likert-scale data. The standard deviations appear normal with no discernible anomalies.

Table 20. Comparison of Mean Explainability and Standard Deviation.

	Mean Explainability*				SD Explainability**			
	Classification		Regression		Classification		Regression	
Model	IRIS	SECOM	WINE	C-MAPSS	IRIS	SECOM	WINE	C-MAPSS
Linear Regression	3.30	3.04	3.13	2.97	0.85	0.93	**0.86**	**0.85**
Decision Tree	**3.53**	3.34	**3.17**	**3.41**	**0.79**	0.83	0.88	0.90
SVM	3.29	3.12	2.88	3.03	0.96	0.89	0.90	0.85
Random Forest	3.38	**3.42**	3.32	3.32	0.91	**0.75**	0.87	0.90
ANN	3.07	3.25	2.92	2.95	1.02	1.01	1.00	0.98

* mean of five-point Likert scale; 1,00 = very low; 5,00 = very high; ** standard deviation of five-point Likert scale

Across all treatments, random forests and decision trees achieved the highest or second-highest ratings. Decision trees are considered highly interpretable by humans in terms of their global and local explainability, since it is possible to follow a path of variables from the root node to a leaf node containing the final decision (Arrieta et al. 2020). This explainability by design makes the model itself (global) as well

as every prediction (local) transparent. Random forests use multiple decision trees with a majority vote or averages on the predictions from the decision trees resulting in a single prediction. This could explain their comparably high scores. The perception of explainability varies across the remainder of models as discussed in the following.

3.2.4.2 Discussion

Low- and high-stake classification. For the low-stake classification treatment IRIS, the models' explainability were generally well-received and perceived as more similar. They reflect the theoretical ordering of explainability in Figure 19 (*x*-axis) quite well. IRIS represents a case of low algorithmic involvement with good accuracy values resulting in the low distances between the models. The case is straightforward with only few variables on flower properties such as sepal width. Hence, any participant should have been able to grasp the features relevant to fulfill this task in its entirety.

For the high-stake classification treatment SECOM, we found large performance differences as the case is more complex with more input variables, which is reflected by the poor performance of the shallow ML models such as linear regression. In addition, we found that the explainability of models, which can be visualized for simple cases in a straightforward way, loose their explanatory value for end users in this treatment.

We also found that the user's preference shifts from single decision trees to the majority vote of random forests. We assume that human biases may be at work more prominently in high-stake scenarios. This is also mirrored by the higher explainability scores of ANN for SECOM even though – objectively – the global and local explainability should be non-existent as ANN is a black-box model.

Low- and high-stake regression. The regression datasets also highlight the divergent perception regarding the different stakes. In the low-stake WINE treatment, the results mostly fit the theoretical assumption. In contrast, in the high-stake C-MAPSS treatment, the explainability score for ANN is higher than for SVM and linear regressions. Furthermore, linear regression received low scores for explainability in strong contrast to theory. A possible rationalization is the difficulty of the participants to grasp the nature of regression altogether since it is not as naturally understood as classification. This may highlight the importance of some data science skills at the human user's end in order for the explanations (also in the context of XAI) to have any meaningful impact on the (hybrid) decision-making.

In general, the random forest seems to master the tradeoff between performance and explainability particularly well in relative comparison to the other ML models. Except for decision trees, there is also a shift of the user's favor from shallow ML models to deep learning models when the stake rises.

Generalization of tradeoff. For the generalization of our findings and analysis of the tradeoff, we merged the data of the four treatments. In order to enable this merge, we normalized the data to the range of 0 to 1 to allow for relative comparison of the ML algorithms regarding the different use cases, tasks, and performance measurements. For the factor regression, we inverted the performance scale of RMSE since smaller values indicate better predictions, inversely to accuracy for classification. We transferred it into a Cartesian coordinate system similar to Figure 19. We used mean values to yield a position for each algorithm. Figure 21 shows the resulting averaged scheme calculated from the data in Tables 19 and 20.

The hypothetical simple linear relation between ML model performance and ML model explainability assumed theoretically by prior research does not hold across our user-centered treatments. While we can confirm some tendencies mostly concerning ML model performance, reflected by accuracy and RSME, a few things are notably different from the theoretical proposition.

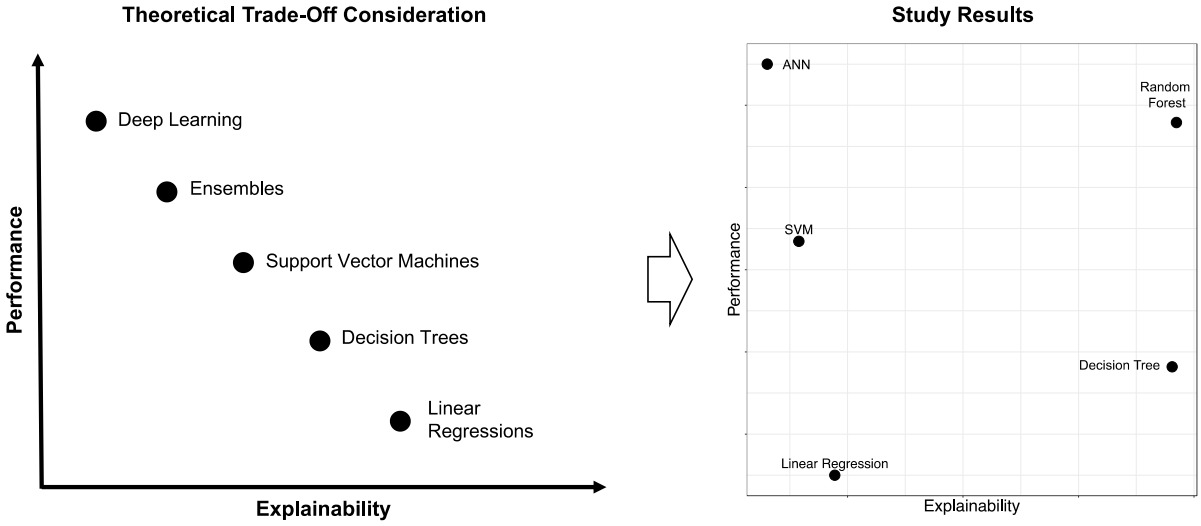


Figure 21: Theoretical vs. Empirical Scheme for the Tradeoff of Performance vs. Perceived Explainability in Machine Learning

We find that the tree-based models decision trees and random forests are perceived to provide the best explainability of the five ML models by far from an end user's perspective. We assume that this is most likely due to their intuitive transparency with regard to global explainability (Mohseni et al. 2021), which may indicate that these two tree-based algorithms do not invoke the same degree of algorithm aversion associated with the remainder of ML algorithms. Contrary to our expectations, we could not substantiate that a single decision tree is perceived as more explainable than a random forest consisting of many unbalanced decision trees. We assume that this may be since we did not present all resulting trees of the random forest to the participants for review.

3.2.4.3 Implications

Our observations enable us to suggest theoretical and practical implication. They are important to consider when assessing how people respond to algorithmic advice as they hold implications for any decision maker or organization using intelligent systems.

Biases hinder objective measurement. It is possible that participants were biased in their judgement by the perceived capability or promise of an algorithm and therefore assumed a higher value (Hilton 1996). That is, shallow ML algorithms such as SVM and linear regression offer a form of internal explainability. Hence, they were supposed to result in a better perceived explainability than black-box models with no internal explainability such as ANN. However, we found that there is hardly any difference in their perceived explainability by end users. This may be due to participants who were not able to understand the presentation of SVM and linear regression as they lacked prior knowledge (Amershi et al. 2019), which may be a practical problem in real-life cases as well. In contrast, simpler models

seem to be especially good in explaining more straightforward scenarios. Consequently, due to high valuation in one category (performance), end users may attribute higher scores in another category (explainability). This is called halo effect.

Interpretability does not entail explainability. The discrepancy between theory and our empirical findings can be explained at least partly by the nature of our observations. While theoretical contributions look at the algorithmic and mathematical description of objects (data-centered perspective), we have employed a socio-technical and thus user-centered perspective. That is, in our study, we targeted the naturally biased perception of end users of an ML algorithm directly and found that the difference between performance and explainability is not linearly increasing. Rather, we found that linear regression's and SVM's (and ANN's) explanatory value is far from tree-based algorithms in most situations. While our results do not allow to uniformly rank and rate explainability for ML decisions (and were not expected to), they add to the growing evidence that there is more to model explainability than transparent mathematical parameters and good intentions. Moreover, ordering ML algorithms by their assumed data-centered interpretability is not helpful as it is constantly being misinterpreted and misused in socio-technical settings. In contrast, socio-technical aspects stand out as important for the efficacious use of ML models and explainability may be the key factor for their acceptance by end users (Cramer et al. 2008; Lee 2018). According to our research, in non-augmented form decision trees and random forests are currently the most suitable options to engage with end users.

3.2.5 Conclusion, Limitations, and Outlook

Albeit its fundamental importance for human decision-makers, empirical evidence regarding the tradeoff between ML model performance and explainability is scarce. The goal of our research was to conduct an empirical study to determine a more realistic depiction of this relationship and subsequently compare the placement of common ML models to the existing theoretical propositions.

We found that the explanatory value of decision trees and random forests constantly dominates other ML models. Comparing averages, we could not find noteworthy differences in the perceptions of explainability of SVM, linear regression, and even ANN. We did notice though that explainability was generally better received for more straightforward cases such as low-stake classifications.

In summary, we found existing theoretical propositions to be data-centered and misleading oversimplifications when compared to our user-centered observations. Our study shows that when explanations are put to use, socio-technical factors of user perception dominate well-intended analytical considerations concerning the goodness of visualizations by ML experts.

As with any empirical research, our study faces some limitations. First, our study was an online survey with benchmarking datasets. While we only allowed for participants with a certain background, participants may have been exposed to the scenarios and several of the ML algorithms for the first time. Hence, we measured an *initial* explainability. Second, there was no time restriction for viewing and assessing an explanation. We expect results to differ in a high-velocity treatment. Third and last, we compared inherently interpretable shallow ML algorithms and ANN without further augmentations. We assume that XAI augmentations will affect explainability positively. In contrast, other more diverse ensembles than random forests may perform worse.

Concluding, we identified socio-technical aspects as highly important for the perception of explainability and therefore further user studies with varying skill levels and cultural backgrounds are necessary to better understand the biases at work. Further, explainability does not entail understandability. If explainability only contributes to more trusted decision-making but not to a better understanding, research into XAI may be on the wrong track and ultimately only lulls users into a false sense of security by adding fancy yet inefficacious visualization.

3.3 Model Explainability and Model Comprehension

Abstract. In explainable artificial intelligence (XAI) researchers try to alleviate the intransparency of high-performing but incomprehensible machine learning (ML) models. This should improve their adoption in practice. While many XAI techniques have been developed, the impact of their possibilities on the user is rarely being investigated. It is neither apparent whether an XAI-based model is perceived to be more explainable than existing alternative ML models nor is it known whether the explanations actually increase the user comprehension of the problem, and thus, his or her problem-solving performance ability. In an empirical study, we asked 165 participants about the perceived explainability of different ML models and an XAI augmentation. We further tasked them to answer retention, transfer, and recall questions within three use cases of different stake. The results reveal high comprehensibility and problem-solving performance of XAI augmentation compared to the tested ML models.[8]

3.3.1 Introduction

Artificial intelligence (AI) based decision support systems (DSS) are increasingly being transferred in research and practice to support humans in various areas of daily life and business (Zhang et al. 2018a). Thereby, AI describes a concept of data-driven problem solving using multiple mathematical algorithms, often related to the research subset of machine learning (ML) (Goodfellow et al. 2016). During the decades, several types of ML models have been developed, with different kinds of calculation logic (Bishop 2006). In practice, it is noticeable that low-complex ML models, i.e., models that are transparent from a user's perspective, are often preferred over high-complex ML models that lack traceability even though they may outperform their counterparts (Adadi and Berrada 2018; Rudin 2019). That is, users prefer *white-box ML models* over *black-box ML models*. The reason is assumed to be that AI-based DSS users would have to trust the recommendation of a black-box ML model without understanding what is going on. Such a circumstance holds several dangers for decision-makers, such as legal issues regarding general data protection regulation (GDPR) (Goodman and Flaxman 2017).

The research domain of explainable AI (XAI) deals with this issue by developing solutions to overcome the intransparency of black-box ML models while maintaining their high model performance (Gunning

[8] This paper is published within the 29th European Conference on Information Systems as 'I DON'T GET IT, BUT IT SEEMS VALID! THE CONNECTION BETWEEN EXPLAINABILITY AND COMPREHENSIBILITY IN (X)AI RESEARCH' (Herm et al. 2021).

and Aha 2019). Despite that there are already some XAI transfer techniques for transferring black-box models to white-box models (Wanner et al. 2020c), they are heavily criticized. This is, two independent models with their related complexity are trained instead of using a white-box ML model from the very beginning and improve it iteratively to achieve a comparable performance (Rudin 2019). However, since the performance power of black-box models is not to be dispensed with, more research is being done on ex-post explanatory approaches. These are referred to as *grey-box ML models* (Gunning et al. 2019). Through XAI augmentation techniques, methods are applied to the trained model to make its internal logic or result computation transparent (Slack et al. 2020). There are first positive implications already (Lundberg et al. 2020). Nevertheless, on the one hand, scientists claim that these methods are only an approximation and, therefore, inherently inaccurate (Rudin 2019). On the other hand, little is known about how users perceive (X)AI explanations (Adadi and Berrada 2018).

XAI research should therefore address both points of criticism to resolve best the trade-off given (Doran et al. 2017; Gilpin et al. 2018; Guidotti et al. 2018a). A particular problem seems to be that an AI-based DSS's high performance is still associated with a high decision quality. However, the decision quality only becomes effective, if the user of the system includes the recommendation of the algorithm in the decision process, which requires a credible perception (Nawratil 2006). Existing XAI research shows that this depends heavily on the extent to which a person understands the behavior of a model (Ribeiro et al. 2016b). Therefore, the given information gap between the AI-based DSS and its user must be closed by appropriate explanations (Cui et al. 2019; Dam et al. 2018; Gilpin et al. 2018).

Further, research demonstrates that a hybrid intelligence consisting of humans (here: system users) and machines (here: AI-based DSS) can be considered state-of-the-art to accomplish tasks (Dellermann et al. 2019). What seems to be problematic is that precise explanations are often not easy to interpret for humans, and conversely, understandable explanations often lack predictive power (Doran et al. 2017; Gilpin et al. 2018; Guidotti et al. 2018a). In addition to an explanation that is perceived as interpretable, the question arises, to what extent the user really comprehends what the system explains to be able to act as a validator and form a functional hybrid intelligence (Futia and Vetrò 2020).

As current XAI research focuses primarily on solving the trade-off between model performance and model explainability from a feature perspective, we are trying to understand the correlation between perceived explainability and subsequent comprehensibility. To do so, we ask ourselves to what extent this circumstance already exists in today's ML model types as the backbone of an AI-based DSS and to what extent a popular XAI augmentation (feature influence method) can compete with those or even surpass them. Thus, we first try to determine if and to what extent an (X)AI explanation is perceived as explainable by system users. Following that, we examine if the perceived explainability improves the comprehensibility for problem-solving. Thus, we formulate the following research question:

***RQ**: What is the relationship between the perceived explainability and comprehensibility of predictions for the user of AI-based DSS and what influence do XAI augmentations have on this?*

To answer the RQ, we structure our paper as follows: In Section 3.3.2, we present the theoretical background and the related work based on (XAI) dimension and interrelation, as well as a structured literature review. Section 3.3.3 describes our research design, including the methodology, the theoretical derivation of the research model, the scenarios, technical realization, and the survey design. In Section 3.3.4

we describe the survey results. We critically discuss these in Section 3.3.5, including the own implications. Concluding in Section 3.3.6, we describe limitations, and provide an outlook for future research.

3.3.2 Theoretical Background and Related Work

3.3.2.1 Artificial Intelligence

AI in the Information Systems (IS) discipline research is a generic term for 'intelligent agents'. These agents pursue a specific goal, which they try to maximize by perceiving and interacting with the environment (Poole et al. 1998). To do so, they need cognitive abilities of learning and problem solving, which can be compared to intelligent abilities that resemble a human being (Nilsson 2014). In recent years, for practitioners' use especially ML is of great interest. It is the science of mathematical models and algorithms improving their performance through experience (Goodfellow et al. 2016). This enables them to learn iteratively from empirical data, allowing them to find non-linear relationships and complex patterns without being explicitly programmed to do so (Bishop 2006).

The current focus of ML research is on the optimization of the model performance. More specifically, deep learning (DL) models regularly outperform other types of ML models. Thereby, DL models, represent a specific type of ML algorithms, by using (deep) artificial neural networks (ANN) (Janiesch et al. 2021). These models are especially good at analyzing highly complex datasets (Zhang et al. 2018a). However, due to their complex structure, they are intransparent. Thus, a user often understands neither inner model logic nor specific decision making (Ribeiro et al. 2016b). Therefore, these models are black boxes that face the problem of a lack of trust, which reduces the willingness of users to accept the recommendations of such a system (Adadi and Berrada 2018).

3.3.2.2 Explainable Artificial Intelligence

Since complex deep learning models tend to outperform lower complexity models, they are considered to have the greatest potential for further optimization (Rudin 2019). The research area of XAI tries to develop methods to explain these black-box models by converting them into comprehensible 'grey-box models' (Gunning et al. 2019), while preserving their high model performance (Lundberg et al. 2020). Here, comprehension refers to the ability to understand a decision logic within a model and therefore the ability to use this knowledge in practice (Futia and Vetrò 2020). Therefore, grey-box models should enable users to understand two different components of the model (Lipton 2018): the inner logic (global explainability) and the reasoning for a specific result (local explainability).

Multiple XAI techniques have been developed. On the one hand, there is the option of XAI model transfers. Here, a second, white-box model, that is a model that is perceived as per-se explainable (global), is used to explain the black-box model (Adadi and Berrada 2018). On the other hand, there are XAI augmentations calculated on top of the black-box model (local). Therefore, multiple augmentation techniques are used, such as explanation by simplification, visualization, knowledge extraction, or influence methods. In terms of influence methods shapley additive explanations (SHAP) is a commonly used XAI tool (Lundberg et al. 2020). These toolsets estimate the influence of a single feature on a specific prediction post-hoc. By iterative manipulation of the feature values, the tools analyze how these

features truly influence the prediction or the overall model's decision behavior (Ibrahim et al. 2019). However, many researchers, such as Rudin (2019) claim that these explanations are only a mathematical approximation to the actual values and thus inferior as the techniques are insufficiently detailed to enable users to use the AI as a DSS (Hoffman et al. 2018). Aggravating this issue, there is no shared understanding of how a proper explanation should look like to ensure explainability and also comprehensibility (Miller 2019).

3.3.2.3 (X)AI Dimensions and Interrelations Artificial

The trade-off that XAI research tries to solve in the best possible way is between model performance and model explainability (Adadi and Berrada 2018; Angelov and Soares 2020; Arrieta et al. 2020; Dam et al. 2018). It can be assumed that these two dimensions are related to the comprehensibility of the explanation for the AI-based DSS user. He or she acts as a validator (cf. Table 21).

Table 21: Dimensions of XAI research

Dimension	Description	Reference(s)
Performance	Accuracy of an AI model regarding its predictions.	Arrieta et al. (2020)
Explainability	Perceived quality of a given explanation by the user.	Adadi and Berrada (2018)
Comprehensibility	Degree of user understanding of the explanation enabling the user to apply the information for new tasks.	Fürnkranz et al. (2020)

Many authors have tried to classify different types of ML models according to the trade-off between model performance and model explainability. Typically, a two-dimensional grid is used for this purpose. Commonly classified ML models here are support vector machines (SVM), linear regressions, rule set algorithms, decision trees, ensemble learning, and ANNs (Arrieta et al. 2020; Dam et al. 2018; Luo et al. 2019; Morocho-Cayamcela et al. 2019). SVMs are a margin-based classifier for datapoint vectors. Decision trees are sorted decision rules, which are aligned in a structured tree hierarchy. Ensemble learning models are a combination of different ML models combined with a majority voting. An ANN consists of many (hidden) computational layers and perceptrons. Input is processed through these layers and their perceptrons using mathematical operations. Linear regression is a popular statistical technique included in these comparisons, aiming to find a linear function to describe a dependent variable according to one or more independent ones (Goodfellow et al. 2016). We did not include rule sets in our analysis as they are rarely used in practice nowadays (Nosratabadi et al. 2020) and they were examined already by Fürnkranz et al. (2020).

The left side of Figure 22 illustrates this trade-off by a cross-section of the authors' classification. We further integrated the classification advances by Angelov and Soares (2020) and Nanayakkara et al. (2018) who also consider XANN. The y-axis represents the performance scoring, as an accuracy-based metric used, of a model compared to the other models mentioned. The x-axis represents the relative explainability scoring. The authors' classification entails that complex models achieve higher performance compared to less complex models, but at the cost of explainability (Arrieta et al. 2020; Dam et al. 2018; Duval 2019; Gunning and Aha 2019; Luo et al. 2019; Morocho-Cayamcela et al. 2019; Salleh et al. 2017; Yang and Bang 2019).

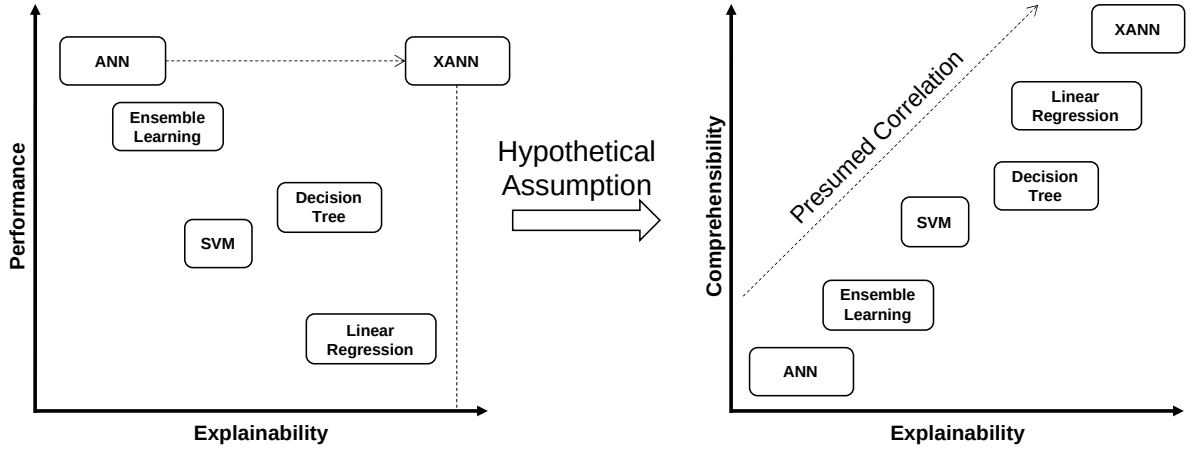


Figure 22: Relation of Performance, Explainability, and the Presumed Comprehensibility

Despite the authors' predominant agreement on the trade-off classification of existing ML model types, the suitability of the explanations for the users has not been evaluated yet. Hence, we need to verify if a higher perceived model explainability also results in higher comprehensibility, and thus, problem-solving performance. Several contributions theoretically assume that there is a linear correlation between explainability and comprehensibility (Blanco-Justicia and Domingo-Ferrer 2019; Došilović et al. 2018; Futia and Vetrò 2020; Holzinger et al. 2019; Páez 2019). This leads to the hypothetical assumption of certain comprehensibility levels for the different ML models (cf. Figure 22, right side). Here, the y-axis represents the achieved comprehensibility scoring, while the x-axis represents the explainability scoring.

3.3.2.4 Preliminaries and Research Gap

To investigate whether empirical user-based studies about the correlation between perceived model explainability and user comprehensibility of (X)AI models already exist, we conducted a structured literature review according to Webster and Watson (2002). We focused on the Computer Science related databases IEEE Xplore and ACM Digital Library. Further, we queried relevant Information Systems databases: AIS eLibrary, Science Direct, and Web of Science. Due to the novelty of the subject, we did not restrict our search to (journal) rankings. We used the following pseudocode for our search term: "*((Expla* | Interpreta* | Comprehensib* | Decision Quality | Black box | Blackbox) AND (Machine Learning | Artificial Intelligence | AI | Deep Learning | Neural Net* | ANN) AND (XAI) | Explainable Artificial Intelligence)*". Through the extension of a forward and backward search, we identified 12,321 publications. After an abstract and keyword analysis, and full-text analysis, we considered n=42 publications to be relevant.

Theoretical Contributions. Most preliminary work (n=26) is about the theoretical evaluation of the usefulness criterion of (X)AI explanations. In particular, authors try to theoretically assess factors that affect the perceived model explainability, such as explanation fidelity (e.g., Guidotti et al. 2018b), trust (e.g., Guo 2020), effort (e.g., Calegari et al. 2020), privacy (e.g., Ras et al. 2018), and interpretability (e.g., Tjoa and Guan 2020). The factor of user comprehension is examined only to a limited extent so far. Research has attempted to derive measurements and influences for AI explanations by using literature from related topics such as Cognitive Science (Arrieta et al. 2020; Schneider and Handali 2019). Often, the term interpretability is used instead of comprehensibility (e.g., Freitas 2014).

Empirical Contributions. A few contributions (n=16) already evaluated their findings of (X)AI empirically. Here, different contributions examined the influence of fidelity and interpretability (Lakkaraju et al. 2019), trust (Weitz et al. 2019), effort (Wang et al. 2019a) as well as privacy (Pereira and de Carvalho 2019). Furthermore, authors such as Förster et al. (2020) compare different XAI methods to reveal key criteria for XAI augmentations' adaption. Likewise, a large stream of research investigates the willingness to adopt different (X)AI explanation in practice, such as, for example, in medicine (Gale et al. 2019), industrial maintenance (Wanner et al. 2020a), or education (Putnam et al. 2019). Two contributions investigate the influence of comprehensibility within a rule-based system (Fürnkranz et al. 2020) and decision trees (Huysmans et al. 2011). Contrary, comprehensibility within (X)AI-based systems is only proposed to be examined by Kuhl et al. (2019) who plan to do an exploratory study to analyze the task-solving performance of AI models through the influence of the compliance with (X)AI learning algorithms and explanations.

Summary and Research Gap. Research on the perceived explainability of X(AI) models and the resulting user comprehension has so far been theoretical rather than practical in investigation. Further, we did not find any contributions dealing with the comparison of XAI comprehensibility with other AI models by using augmentation techniques.

3.3.3 Research Design

3.3.3.1 Methodology Overview

To ensure the quality of our research, we follow the methodology according to Müller et al. (2016). This methodology is divided into four steps: (1*) Research Questions*, (2) *Data Collection*, (3) *Data Analysis*, and (4) *Results Interpretation*. We explain the steps in Figure 23 and briefly below.

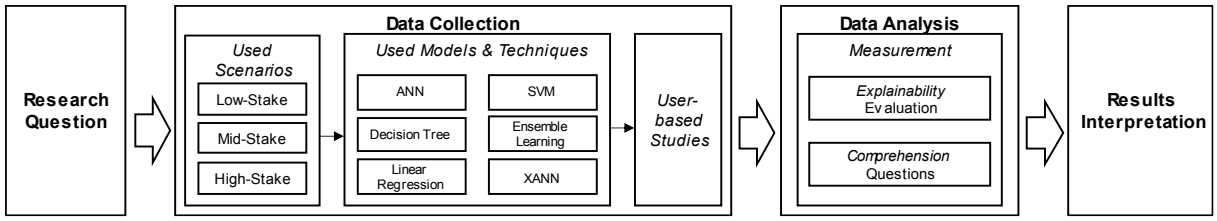


Figure 23: Research Methodology according to Müller et al. (2016)

*(1) Research Question***.** We identified a research gap through a structured literature review: First, we want to investigate how users perceive the level of explanation of different types of ML models and an XAI-transferred ANN (XANN) augmentation. Second, we want to check whether higher perceived explainability leads to better problem-solving performance, requiring explanation comprehension.

(2) Data Collection. We perform an empirical study to answer the question of interest. Further, we use different scenarios with different stakes to enable result generalization. *(3) Data Analysis*. After steps of data preprocessing, we apply various quantitative as well as qualitative analyses for knowledge discovery. *(4) Results Interpretation*. In the last step, we analyze our data and make apparent the relation between the perceived level of explainability and users' comprehension regarding the different ML models and scenarios. Finally, we discuss our findings in comparison to existing research and theories.

3.3.3.2 Measurement Model

We developed a corresponding measurement model through theoretical research before we conducted the survey to investigate the assumed connection between the two dimensions.

Variables and Dependency. The theoretical relationship between the (perceived) model explainability and the related user comprehension can be found in explanation and ML theory (cf. Section 3.2). So, explanations that are perceived as more complex are assumed to decrease user comprehension (Futia and Vetrò 2020). Especially for users that are inexperienced with AI systems, this might negatively impact their acceptance of AI-based DSS as they do not comprehend the results (Došilović et al. 2018). Nevertheless, Blanco-Justicia and Domingo-Ferrer (2019) recommend further investigation since an XAI-surrogated model, and thus theoretically explainable but not comprehensible model, can confuse users since many XAI researchers build XAI augmentations for their own purposes rather than for the intended system user (Miller et al. 2017). Therefore, we assume a linear relationship between both variables, whereby a misapprehension may exist.

Stake of Scenario. It has been shown that people act differently in terms of their decision-making behavior, depending on the criticality of the scenario they are confronted with (Arnott and Pervan 2005). We therefore assume that criticality (i.e., *stake of scenario*) has a moderating effect on the connection between the perceived explainability and subsequent user comprehension. Here, low-stake scenarios describe user decisions that have only minor (cost) effects. In contrast, high-stake scenarios are associated with user decisions that may even potentially cost human lives (Kunreuther et al. 2002).

Measurement Method. The *explainability* of a model is a sociological measure and must therefore be approximated, and thus objectivated, by user perceptions toward the presented explanations of an ML model (Hoffman et al. 2018; Miller 2019). The *comprehensibility* of ML model explanations can be measured by user questions related to the given use case and results (Lage et al. 2018; Poursabzi-Sangdeh et al. 2018). Based on the Cognitive Theory of Multimedia Learning, our examination uses three types of tasks: retention, transfer, and recall. Retention is about understanding the prediction of the model, and thus what the AI model presents to the employee. Transfer is about the employee's ability to use the knowledge gained, e.g., to process further tasks based on the AI model's decision. Finally, recall tests the ability to reproduce the knowledge. This tests whether participants have difficulties remembering the information due to limitations in the employee's cognitive abilities regarding the given explanations (Mayer 2005). We used a group interaction calculation to measure the influence of the *stake of use case* on the relationship between explainability and comprehensibility. We divide the test sample into groups per use case so that the answers can be calculated separately. This allows post-hoc comparability of the group results (e.g., Tausch et al. 2007). We present the final measurement model in Figure 24.

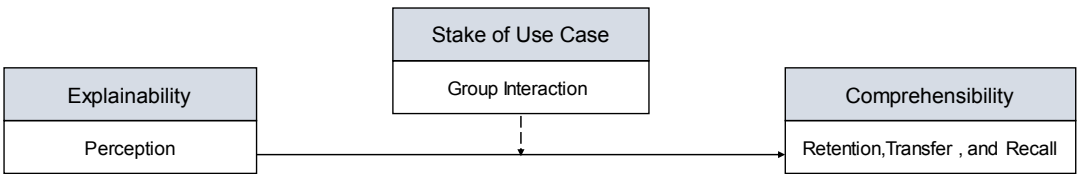


Figure 24: Measurement Model

3.3.3.3 Scenario Selection and Technical Realization for Survey

To enable a generalization of our findings, we use three different regression scenarios. These three scenarios differ in their stake (low; medium; and high) and are described in the following. Further we describe the technical realization of our model implementations.

Dataset WINE. We used the dataset on WINE quality from the UCI machine learning library for our low-stake scenario (Cortez 2009). We consider it low stake since a wrong prediction only results in falsely predicted wine quality. The dataset consists of 11 different features describing different "vinho verde" wines from Portugal. For our approach, we have used the red wine dataset only. This dataset includes 1599 wines, which are ranked numerically between 0 to 12 in their quality level.

Dataset Bakery. We cooperated with a local German bakery retailer to obtain sales data from 40 stores over the last 3.5 years. In total, we used 11 different features, such as weather data, past sales, or school holidays, to predict the sales quantity for the next day. Since wrong order decisions reduce the company's profit, we used this dataset as our medium-stake scenario.

Dataset C-MAPSS. We use the regression dataset modular aero propulsion system simulation (C-MAPSS) from the NASA Prognostic Center of Excellence as our high-stake scenario (Saxena and Goebel 2008). The dataset contains simulation data from different turbofan engines. The simulation of each turbofan is tracked by 25 sensors and contains over 93 turbines on 50 simulation cycles each. After each cycle, the remaining useful lifetime (RUL) is verified. A wrong decision and, thus, a turbine failure can lead to the loss of human life. Hence, we consider the scenario to be of high stake.

Technical Realization. Starting with data processing, we stick to the recommendation of García et al. (2016) and deleted any incomplete observations and outliers as well as applied a feature selection and normalization. Subsequently, we have implemented the different ML models for each scenario described in Figure 23. For the implementation of the models, we use the python package scikit-learn and keras as well as the package SHAP for the XAI augmentation. We selected the parameters through hyperparameter tuning using scikit-learn's GridSearch. Further, each result presentation is set in the same color scheme. Further information about the technical realization is shown in Herm et al. (2021a).

3.3.3.4 Survey Design

To evaluate the three use cases chosen (cf. Section 3.3.4.1), we set up three separate surveys (cf. Section 3.3.3.3). Further, each survey is divided into three parts: i) demographics and introduction, ii) perceived model explainability, and iii) examination of the user comprehensibility.

Demographics and Introduction. First, we examined the participants' demographics. In addition to gender, age, and location, we asked them whether they already have had experience with AI systems and whether they were willing to adopt them. Subsequently, we presented the procedure of the survey. We also gave an introduction to AI to ensure a shared understanding of the necessary knowledge.

Perceived Model Explainability. Second, we examined the users' perceived explainability of the implemented ML models (cf. Section 3.3.4.1). We started with a description of the respective scenario. This includes information about the use case, the dataset, the task objective, and the criticality of wrong decisions. Afterward, we presented a prediction of a particular observation for each of our five ML

models to the participants. To avoid bias, the order of the models presented was randomized. Also, we gave the instruction that for all models the same model performance should be assumed to avoid a performance bias. First, we explained the algorithm itself theoretically to ensure an understanding of its general global explainability. Also, where technically applicable, we include an average feature importance or feature impact calculated by the trained model (partial dependence plot) as well as the local explanation of the calculated result by the ML model (visualization). An example is shown in Figure 25 by a SHAP-based XANN for the scenario of WINE. Based on this information, we asked the user to rate the statement "The presented explanations are good" on a seven-point Likert-scale (*strongly disagree to strongly agree*) (Joshi et al. 2015). This kind of question is based on the recommendation for XAI-based studies by Hoffman et al. (2018) and Luo et al. (2019). The complete questionnaire is available at Herm et al. (2021a).

Examination of User Comprehensibility. Lastly, we performed a review of user comprehension based on the given explanations to examine the effect of the AI model support (Miller 2019). Therefore, we asked the participants to choose their preferred explanation from the five ML models. The remainder of the survey is conducted based on the comprehensibility of the selected explanation. Based on Mayer's Cognitive Theory of Multimedia Learning (Mayer 2005), we examined user comprehension by asking three types of questions for retention, transfer, and recall. An example from the WINE dataset for retention is "*Does the pH level have a significant influence on the quality of the wine relative to the other features?*" We provided single choice options as answers. To examine the ability to transfer, we asked for example "*Explain the influence of the sulfate level on the quality of the specific wine in comparison to the other wines*". These questions had to be answered as open text. To test the recall of users, by using cloze questions, we asked for example "*The explanations of the models show how the different [features] influence the [quality] of the wine*". Here, the complete sentence with the missing words was presented at the beginning of the survey and can be reconstructed from the tasks conducted during the investigation.

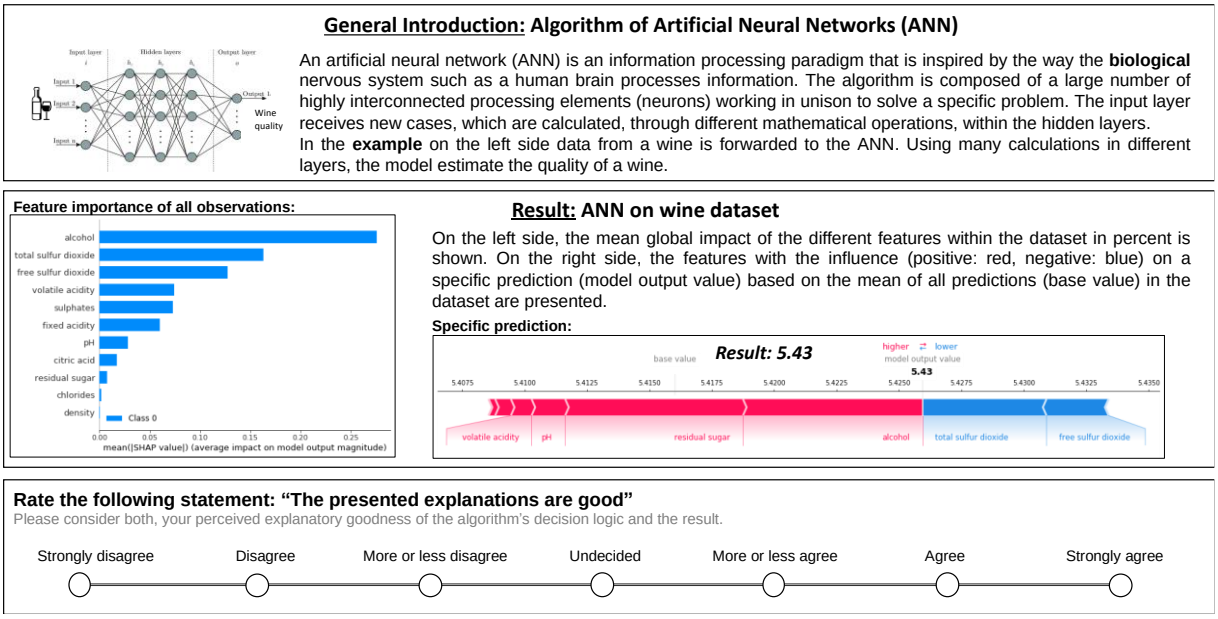


Figure 25: Example Introduction to the XANN Model and Prediction

3.3.4 Data Analysis

3.3.4.1 Survey and Demographics Overview

We used the platform *Prolific.co* to recruit our participants, granting them a monetary incentive of £10 per hour. The platform allows specifying one's target group by characteristics and abilities to achieve valid results within research tasks (Peer et al. 2017). In this way, we have ensured that we survey appropriate experts for each use cases and further knowledge in AI. We received feedback from n=175 participants. To ensure the data quality of the answers, we further used several validating checks, looking for randomly filled questionnaires, lazy patterns, failure in answering control questions, and time constraints. Subsequently, we used the feedback from n=165 participants (WINE n=55, Bakery n=53, C-MAPSS n=57). The survey data is available at Herm et al. (2021a). Out of those n=165 participants, n=98 are male, while n=66 are female and n=1 diverse. Most of the participants are of age between 20 and 30 (≈58%) or between 31 and 40 (≈24%.). Most answers came from Europe (≈89%). Overall, on a five-point Likert-Scale, the participants shared a medium (median) willingness to accept AI at their workplace and a medium (median) trust in AI.

3.3.4.2 Result Analysis

In the following, we present the survey results according to the study structure. First, we detail the results of the participants' perceived explainability per model. This is followed by the selection of the interviewees' preferred ML model to solve problems. Finally, we discuss the comprehension tasks (retention, transfer, and recall). The calculated results can be found in Table 22. They are presented per scenario, ML model and question, subdivided into perceived explainability, retention, transfer, and recall. Furthermore, the table includes standard deviations, aggregated, mean and min-max-normalized results to support generic insights according to the theoretical assumption (Boone and Boone 2012).

Table 22: Results of Explainability and Comprehensibility

Case	Model	Perceived Explainability / Standard Dev. [1)]	Comprehensibility / Accuracy of Answers [2)]						
			Retention		Transfer		Recall		Overall / Standard Dev.[3)]
			RT1	RT2	T1	T2	RC1	RC2	
WINE	*ANN*	4.00 / 1.63	0.13	0.25	0.00	0.38	0.63	0.63	0.34 / 0.19
	XANN	6.00 / 0.97	0.64	0.71	0.86	0.86	0.93	0.86	**0.81** / 0.19
	Ensemble Learning	5.00 / 1.15	1.00	1.00	0.00	0.67	0.67	0.67	0.67 / 0.16
	Decision Tree	5.00 / 1.46	0.58	0.83	0.83	0.67	0.83	1.00	0.79 / 0.29
	SVM	5.00 / 1.37	0.25	0.33	0.33	0.75	0.83	0.83	0.55 / 0.20
	Linear Regression	5.00 / 1.14	0.50	0.67	0.50	0.67	0.67	1.00	0.67 / 0.14
Bakery	*ANN*	3.00 / 1.38	0.71	0.43	0.29	0.86	0.43	0.86	0.60 / 0.19
	XANN	6.00 / 1.41	0.93	0.93	0.79	1.00	0.79	1.00	**0.91** / 0.24
	Ensemble Learning	6.00 / 1.45	0.88	0.63	0.50	0.75	0.50	1.00	0.71 / 0.34
	Decision Tree	5.00 / 1.46	1.00	0.82	0.45	0.91	0.55	0.91	0.73 / 0.29
	SVM	5.00 / 1.48	1.00	0.50	0.50	1.00	0.50	1.00	0.38 / 0.23
	Linear Regression	5.00 / 1.47	0.36	0.55	0.73	0.91	0.73	1.00	0.71 / 0.20
C-MAPSS	*ANN*	3.00 / 1.72	0.50	1.00	0.00	0.00	0.50	0.50	0.42 / 0.11
	XANN	5.00 / 1.23	0.95	0.95	0.95	0.82	0.91	0.82	**0.90** / 0.17
	Ensemble Learning	5.00 / 1.47	1.00	0.89	0.56	0.78	0.67	0.89	0.80 / 0.20
	Decision Tree	4.00 / 1.40	1.00	0.00	0.50	1.00	1.00	0.00	0.58 / 0.35
	SVM	5.00 / 1.36	0.78	0.33	0.33	0.78	1.00	0.89	0.69 / 0.16
	Linear Regression	5.00 / 1.28	0.92	0.38	0.46	0.62	0.92	0.92	0.70 / 0.16
Overall [4)]	*ANN*	0.00	0.45	0.56	0.10	0.69	0.52	0.66	0.00
	XANN	**1.00**	0.84	**0.86**	**0.87**	**0.89**	**0.88**	0.89	**1.00**
	Ensemble Learning	0.86	**0.96**	0.84	0.35	0.73	0.61	0.85	0.60
	Decision Tree	0.57	0.86	0.55	0.59	0.86	0.79	0.64	0.60
	SVM	0.71	0.68	0.39	0.39	0.84	0.75	0.91	0.43
	Linear Regression	0.71	0.59	0.53	0.56	0.73	0.77	**0.97**	0.51

Legend: *1) Perceived Explainability* by median / *Standard Dev.; 2) Comprehensibility / Accuracy of Answers* by relative number (number correct answers / total number of answers); *3) Overall* as average of Comprehensibility / Accuracy of Answers per model and Standard deviation of Overall; *4) Overall* as normalized average for explainability and comprehensibility per scenario and tasks types

Explainability. First, it is noticeable that the ANN model solution is perceived worst across all scenarios and in relative comparison to all other ML models tested (0.00). However, if an XAI augmentation (here via SHAP) is used, the user's perception changes profoundly. Across all scenarios that we tested, the XANN was perceived to be highly explainable. In relative comparison, XANN even scored best (1.00). However, the perception seems to decrease with an increasing stake. The relative positioning of decision tree, SVM, and ensemble learning between 0.57 and 0.86 is generally consistent with the theoretical assumption across the different stakes and complexities. However, our results contradict theory with regard to ensemble learning's positioning within this group. The assumption was that a single decision tree is better explainable than a complex ensemble learning model. In our case, participants preferred ensemble learning to a decision tree in terms of explainability.

Choice for Best Model. Following the presentation of the scenario and ML models, the participants had to choose their preferred model for solving different comprehension evaluation questions. We present the selection results per scenario in Figure 26. The ratings of the participants' perceived explainability per ML model and scenario are given in Table 22. As expected, there is a strong correlation between evaluating the participants' perceived explainability and their best model choice for solving the problem. In each scenario, XANN was rated best in explainability and is accordingly also most frequently selected (n=50). On the contrary, we could confirm that the ANN was selected least as the model with the worst perceived explainability (n=17). Furthermore, decision trees were chosen primarily for scenarios with a lower stake (n=12, n=11), whereas they do not seem to be an alternative for high-stake scenarios (n=2). This is also in line with their perceived explainability scoring. The results for the decision tree is contrary to the choice of linear regression. Here, users seem to prefer its option with an increasing stake (n=6, n=11, n=13). Similarly, there is a similar tendency in the choice of random forest as the best model (n=3,

n=8, n=9). However, the selection of SVM seems to depend strongly on the respective scenario (n=12, n=2, n=9).

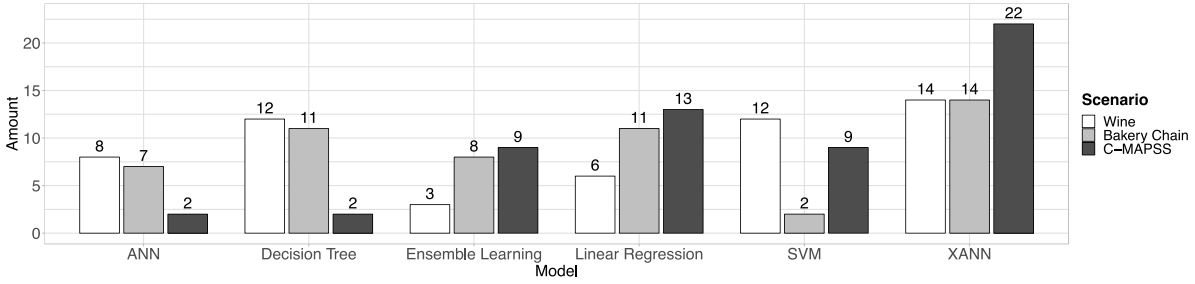


Figure 26: Choice of Preferred ML Model for Problem-Solving

Comprehensibility. The examination of the users' comprehension of the ML model explanations shows similar results regarding the perceived explainability. Again, the results of the ANN are worst (0.00) and those of the XANN are best (1.00). The understanding even seems to increase with an increased stake. XANN seems to support users well, especially for transfer tasks in comparison to other ML models. On the other hand, ensemble learning seemed particularly useful in supporting users for retention tasks, but lack in transfer tasks. In a relative comparison, decision trees show equally good user comprehension (0.60). These, on the other hand, are characterized by an excellent balanced rating across the comprehension evaluation categories, but do not stand out in any of them. SVM (0.43) and linear regressions (0.51) perform worst except for ANN for comprehensibility. Yet, they scored higher in perceived explainability than decision trees. Nevertheless, both were helpful in answering recall questions.

Further, Figure 27 provides an overview of the distributions based on the relative number of correct answers per model across all scenarios as the number of correct answers relative to the six questions. Overall, as expected ANN has the lowest and XANN the highest median compared to the other models. Decision tree, linear regression, ensemble learning, and SVM share roughly the same median. Nonetheless, the top quartile of the decision tree is much higher in comparison to these models.

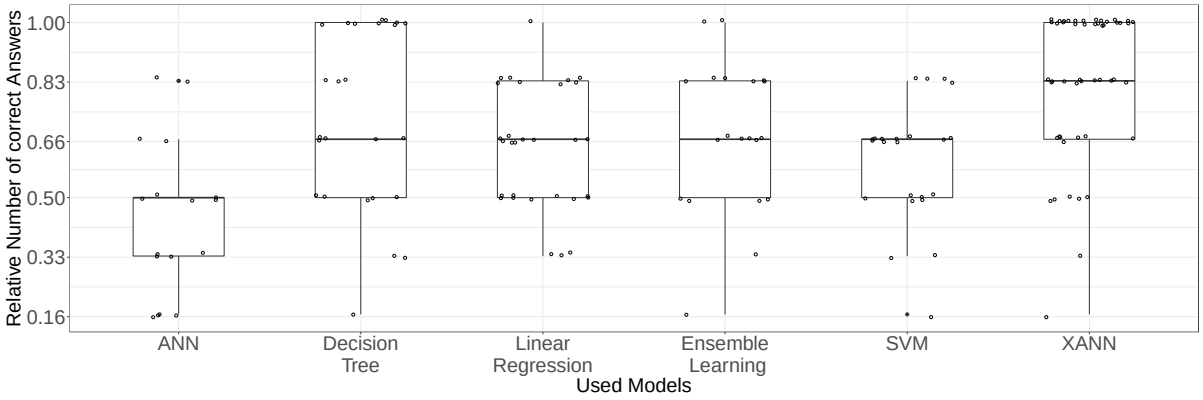


Figure 27: Boxplot on the Relative Comprehensibility per Model across All Scenarios

3.3.5 Discussion and Implications of Findings

3.3.5.1 Discussion of Findings

To investigate the correlation between the perceived ML model's explainability and ML model's user comprehension, we plotted the results into a two-dimensional grid presented in Figure 28.

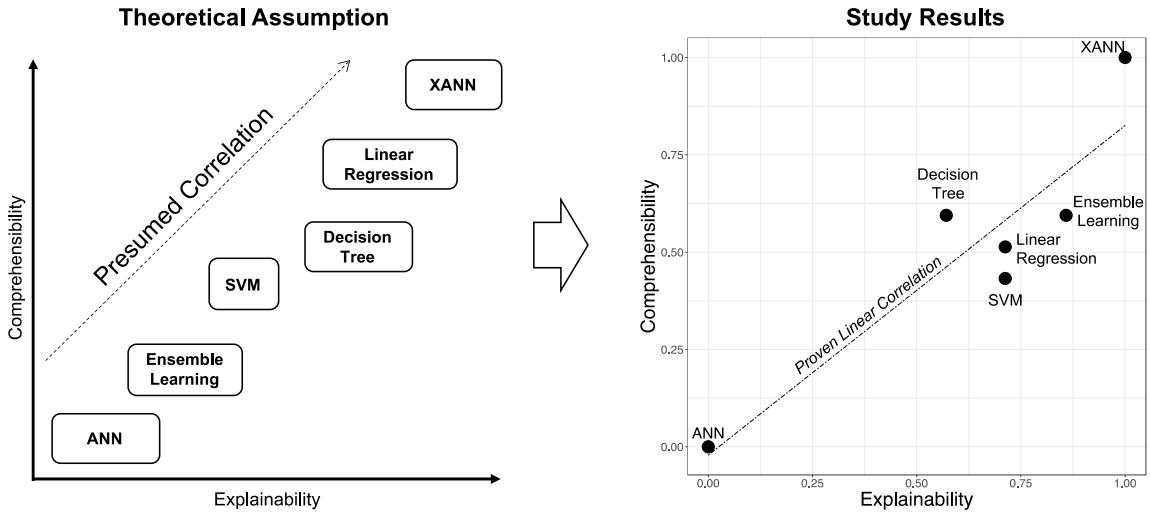


Figure 28: Theoretical Assumption of Explainability and Comprehensibility vs. Study Results

The left part of Figure 28 shows the hypothetical assumptions (see Section 3.3.3.2). The right part of the figure shows the empirical results of our survey. For the sake of generalization, we merged the results of the different scenarios. By doing so, we enable more general claims across criticalities as well as the associated complexity of the scenarios, as described in literature. Furthermore, we used the normalized results of the two dimensions to compare the theoretical assumption within Figure 23 and our results (cf. Table 22). To prove the presumed linear correlation, we followed Meng et al. (1992) and applied a linear correlation between both dimensions using Pearson's r (p-value: 0.01; corr: 0.91).

General Correlation. As we can see, the results, especially considering Pearson's linear correlation, show a high agreement with the theoretical assumptions from the preliminary work of various authors such as (Blanco-Justicia and Domingo-Ferrer 2019; Holzinger et al. 2019). We also have to agree with Páez (2019) describing that explanations focusing on the post-hoc interpretability (XANN) lead to a better task solving performance comparing a model's 'own transparency' (e.g., linear regression). Further, we can also validate the assumptions from Freitas et al. (2008) and Verbeke et al. (2011) that models such as decision trees are more comprehensible in comparison to non-linear-models such as ANN or SVM. Likewise, Ribeiro et al. (2016a) assume black-box ANNs as the worst explainable models. Nonetheless, we also found discrepancies in our results: Futia and Vetrò (2020) indicate that comprehensibility for users should correlate with the focus on user-centered explanations. They claim that interactive explanations are necessary for problem-solving. This contradicts our results, since our participants were able to solve the different tasks (locking at retention and transfer). Therefore, this assumption can instead be linked to the willingness to accept (X)AI-based DSS (Burton et al. 2020). We see that even the user's perceived model explainability does not perfectly transfer to the actual user

understanding, but both dimensions share a high correlation, and thus, a strong dependency. Since, we conducted a study with experts, the results may differ in comparison to non-experts (Castelo et al. 2019).

Model Specifics. We show that especially the decision tree ML model offers above-average comprehensibility. Ensemble learning also scored above the presumed expectations in our study. We concluded that the choice of using a random forest algorithm might have influenced this, as it allows for similar interpretability as the decision tree model. These findings are discussed in Subramanian et al. (1992). Following them, these representations lead to the ability to show decision patterns for the data more clearly than other ML models. Nonetheless, we also recognized different levels of task performances and thus a high standard deviation within the group of participants who chose decision tree and random forest. Referring to Huysmans et al. (2011), we assume differences through users' preexisting knowledge in AI and, thus, their understanding of the explanation representation (Amershi et al. 2019). Further, it is noticeable that users perceive the ensemble behavior as more explainable than the individual tree. One possible explanation is that users often expect that a model perceived as more complex should provide a more precise prediction (Nawratil 2006; Pratt and Zeckhauser 1985). Likewise, the influence of the factor trust concerning the model's complexity through the applied majority or average vote can lead to those user rankings (Guo 2020; Tintarev and Masthoff 2012). However, looking at the transfer questions answers, it appears that participants using decision trees perform better in reusing the given information compared to ensemble learning. A further indication of this can be seen in comparing the SVM model and the linear regression model. Both models are perceived as equally good in their explainability. However, linear regression models had better user comprehension. A possible explanation of the result is that the intuitiveness of those models for a human decision-maker may be increased due to preexisting knowledge (Narayanan et al. 2018; Weld and Bansal 2019). Nonetheless, keeping the clarity and theoretical considerations (cf. Figure 2) of linear regression models in mind, they perform worse (transfer), we assume this, due to the resulting complexity of many features in real-world data. Further we assume, due to the good recall performance, that linear regression does not overload the cognitive abilities of the participants.

XANN Specifics. For XANN, it is noticeable that it has shown the best performance in both dimensions (explainability=1; comprehensibility=1). Thus, the XAI augmentation improved the worst perceived and performance-solving ANN model (explainability=0; comprehensibility=0) substantially (cf. Figure 27). The high appropriateness is also reflected in the users' choice of the best model to support comprehension tasks (cf. Figure 26). This corresponds with the theory regarding the overload of user's cognitive capacity having inappropriate explanations (Grice 2019). Fürnkranz et al. (2020) argue that there must be an appropriate way to explain the user's prediction. Due to relatively low standard derivation of comprehensibility of XANN (compared to the other models), we assume that most participants were able to use these explanations. Further, we noticed, that the color scheme of SHAP and therefore the style of presentation can cause misunderstandings since the participants were not familiar with the explanation type and a uniform and standard definition seems therefore necessary for adoption (Förster et al. 2020; Schneider and Handali 2019). Looking at the transfer-questions of the high-stake scenario, we noticed a strong primary use of local explanations by the participants instead of the global explanation. This is in line with Wolf and Ringland (2020) stating that the importance of local explanations helps solve tasks correctly in real-world scenarios and understanding the overall decision logic becomes less relevant for the respective decision instance. This goes in line with our findings, where XANN also performs good

at retention questions. The high potential of XANN for problem-solving seems to be particularly evident in high stake scenarios (cf. Table 22) and is also recognized by the users (cf. Figure 25). Both findings stand in contrast to the recommendations from Rudin (2019). However, in the low-stake scenario, the XANN shows weaknesses in the area of retention. Also, the average overall result also shows further potential for increasing the comprehensibility dimension. Nonetheless, it showed that XANN scored best overall in comparison to the other common ML model types (cf. Table 22). Thus, we assume that a personalized explanation, as Schneider and Handali (2019) suggested, can further increase the XANN's comprehensibility.

3.3.5.2 Implications of Findings

Theoretical Implications. We noticed a lack of knowledge regarding the tested comprehensibility at (X)AI models. While contributions such as (Fürnkranz et al. 2020) already describe the importance of comprehensibility in theory and Kuhl et al. (2019) intend to investigate this in future research, we aimed at closing this gap. Due to the participants ability to choose their model for task solving on their own, the sample size for specific models is relatively low. Thus, using statistical tests indicate misleading results. Nonetheless, our results provide a first overview of participants' task-solving performance on common (X)AI models and also highlight user preference based on scenario stake clearly. Following that, future research can use our findings to concentrate on promising models and also test the significance in more detail. Further, our findings provide a first insight, where models explanations are lacking in terms of user's comprehensibility and stake. Nonetheless, further investigation is needed regarding different dataset types and XAI augmentation techniques, as we only used SHAP. Similarly, we assume that the differences between perceived explainability and tested comprehensibility often result from different factors such as trust. Therefore, further research methods such as technology acceptance models may be necessary to better understand perceived explainability.

Practical Implications. Likewise, due to the proven correlation, we were able to suggest the commonly used SHAP-based XAI augmentation technique for task solving. However, this recommendation has to be taken with a grant of salt, since this approach consists of a post-hoc trained grey-box. Therefore, in many cases, using white-box models decision trees is necessary, due to regulations (Rudin 2019). While literature stated linear regression as most explainable model, we noticed the lagging of comprehensibility. In contrast, within our study the decision tree performed well. Nonetheless, the use of decision tree requires skilled employees, due to the data-centered and thus complex representation of decision logic (Subramanian et al. 1992).

3.3.6 Conclusion, Limitation, and Outlook

While, it is assumed that the perceived explainability of a model depends on the perceived information asymmetries (Pratt and Zeckhauser 1985), a high perceived explainability does not necessarily require a good user understanding and vice versa (e.g., Gilpin et al. 2018). Thus, past research has shown that comprehensibility is of enormous importance to form an effective hybrid intelligence that outperforms man and machine separately (Dellermann et al. 2019). Therefore, we wanted to understand the extent to which current XAI augmentation techniques, as a promising subfield of XAI research (Lundberg et al.

2020), compete with existing ML models in user comprehension at real-world scenarios. Thus, we applied the commonly used XAI augmentation SHAP.

We performed an empirical study, including different stakes and complexities to do so. Our results indicate that grey-box XAI explanations achieve the best results and are perceived to be even superior to white-box ML models. One explanation seems to be that local explanations are more helpful in solving tasks correctly, while understanding the overall decision logic becomes less relevant for the respective decision instance. This entails that the need to explain the decision logic within a black-box ANN seems to be less critical than representing the approximated impact of the features on a decision. The results of the decision trees showed that the importance of user-centered rather than data-centered explanations are related to good user comprehension of the results. Likewise, our results reveal that XANN models perform best in users' perceived explainability. We also show that there is a good correlation between the perceived explainability and the associated user comprehension across all other ML models, and thus, problem-solving performance. Subsequently, we have shown that there is a *linear correlation between perceived explainability and comprehensibility* of the models, with decision trees and XANNs being most consistent. However, while XANN's perceived explainability excelled in low- and medium-stake scenarios, it decreased with high-stake scenarios, which underlines Rudin (2019)'s call for the use of (new) white-box models rather than developing new XAI augmentations.

There are some limitations to our contribution. We implied a correlation between scenario complexity and scenario stake. A further isolated observation with more observations seems necessary. In addition, our literature review revealed additional factors for the usefulness of (X)AI explanations such as explanation fidelity, that we did not (yet) examine. Lastly, we also have to consider several XAI augmentation techniques to examine influences such as the cognitive load within these augmentations. Likewise, using XAI augmentations for e.g., image classification can produce different results.

Looking forward, we thus intend to investigate the perceived level of comprehensibility within different XAI augmentation techniques as well as overcoming the lack of design principles for (X)AI in practical use. Further research also needs to extend our study and give user-centered, socio-technical recommendations for the development and sophistication of XAI frameworks to overcome the issue of "inmates running the asylum" in XAI research (Miller et al. 2017).

4 (X)AI DSS Adoption

Table 23: Research summary of Chapter 3

Research objectives		
RO3	Adoption factors of (X)AI-based DSS in Industry 4.0	
3a	Weighting of factors for users' selection of an appropriate DSS tool	
3b	Evaluating the relative importance of adoption factors for users	
3c	Testing the effects of (X)AI augmentations on human decision-making	
Reference to original work		
Wanner, Heinrich, Janiesch, et al. (2020)	Publication 7	Chapter 4.1
Wanner, Popp, Heinrich, et al. (under review)	Publication 8	Chapter 4.2
Wanner (2021)	Publication 9	Chapter 4.3

Intelligent DSSs promise great potential in data-driven environments. They permit the rapid evaluation of complex issues (Arpaia et al. 2020; Hu et al. 2020). Despite the advantages, however, their effectiveness is crucially dependent on whether the user accepts the system. This is a prerequisite implying that he or she will consider the system's recommendations in the decision-making process. This problem has intensified as, due to enormous progress in the field of DL, these models often outperform other ML models and humans in many use cases, such as in the area of (smart) manufacturing (Khan and Yairi 2018; Wang et al. 2018a). However, they have the decisive disadvantage of being incomprehensible for humans.

This lack of comprehensibility becomes a problem especially when such a system is used in areas where humans cannot adequately cope with the amount of data without system support and therefore depend on intelligent decision support (Raouf et al. 2006b). On the other hand, according to current research, it is essential for humans to know when a system is wrong in order to match the common cause and decision situation with the system's evaluation logic. Only through positive validation can humans trust the system and consider its advice when making decisions (Miller 2019). Thus, from a problem perspective, an intelligent DSS must be both accurate and transparent. This represents the research subject of XAI.

XAI research assumes a trade-off between model explicability and model performance that needs to be resolved in the best way possible (Gunning and Aha 2019). In order to develop adequate XAI measures and techniques, it is necessary to have a better understanding of the actual relative importance of the dimensions from the user's perspective. Relatedly, it is crucial to understand the importance and interrelations of factors that influence the user's willingness to adopt such systems. In addition to performance and explainability, other factors – such as effort (Clancy 1995) and trust (e.g., Dam et al. 2019) – seem to be crucial in a practical context. Besides, even if XAI researchers find ways to induce broad adoption of these former black-box AI models, it will be critical to ensure a high ultimate decision quality. At best, this is achieved through an effective hybrid intelligence of man and machine

(Dellermann et al. 2019). However, there is still debate as to whether this is the most powerful form or whether man and machine separately outperform the hybrid one (Lai and Tan 2019; Zhang et al. 2020).

A better understanding of the adoption factors of (X)AI-based DSSs is necessary (RO3, cf. Table 23). Chapter 4 explores the significance of individual factors in relation to the readiness of system users to adopt. On the one hand, this will be done in the respective industry context on the basis of a selection of concrete AI-based DSS prototypes (3a). It is also important to understand the other influential factors that condition such a system selection and the associated readiness to adopt. This also implies the necessity of understanding whether there are indirect links between the factors in order not to derive false conclusions (3b). Furthermore, it is important to clarify the extent to which such (X)AI-based DSSs bring about an actual change in human decision-making and with what consequences in terms of decision quality (3c).

4.1 Decision Factors for AI-based DSS Adoption

Abstract. Artificial intelligence (AI) based on machine learning technology disrupts how knowledge is gained. Nevertheless, ML's improved accuracy of prediction comes at the cost of low traceability due to its black-box nature. The field of explainable AI tries to counter this. However, for practical use in IT projects, these two research streams offer only partial advice for AI adoption as the trade-off between accuracy and explainability has not been adequately discussed yet. Thus, we simulate a decision process by implementing three best practice AI-based decision support systems for a high-stake maintenance decision scenario and evaluate the decision and attitude factors using the Analytical Hierarchy Process (AHP) through an expert survey. The combined results indicate that system performance is still the most important factor and that implementation effort and explainability are relatively even factors. Further, we found that systems using similarity-based matching or direct modeling for remaining useful life estimation performed best.[9]

4.1.1 Introduction

In 2017, Gartner declared 'Artificial Intelligence (AI) everywhere' a mega-trend and called it the most disruptive class of technologies over the next decade and its hype as well as its promise has not faded since (Panetta 2017). A major reason is today's ubiquitous use of IT and enhanced sensor technology that facilitate the generation of large amounts of data, providing an ideal starting point for knowledge discovery and improved decision support (Carvalho et al. 2019b; Zschech et al. 2019). This new way of gaining knowledge holds great potential especially in critical areas such as cancer diagnostics in medical science, machinery and vehicle maintenance, or in autonomous driving.

[9] This paper is published within the 41st International Conference on Information Systems (ICIS) as 'How Much AI Do You Require? Decision Factors for Adopting AI Technology' (Wanner et al. 2020). The paper won the Best Student Paper Award of the track 'IT Implementation and Adoption' and was nominated as Best Student Paper of the 41st ICIS conference.

To process the data and to gain new insights, advanced AI capabilities are used that are based primarily on algorithms from the field of machine learning (ML). Here, artificial neural networks (ANN) are particularly promising as they are able to identify complex nonlinear relationships within large datasets based on flexible mathematical models (Miller and Brown 2018). Especially in tasks related to high-dimensional data, such as classification and regression, ML algorithms show good applicability. By learning from previous computations and extracting regularities from given examples, they can produce accurate models and repeatable decisions. On the downside, AI-based decision support systems (AI DSS) have the disadvantage that the processing mechanisms and their results are often difficult to reproduce as ML algorithms usually show black-box characteristics (Miller and Brown 2018). Thus, decision support based on a 'black box' AI model might not be fully explained or understood (Siau and Wang 2018). This could lead to users not accepting the system and consequently, not using it (Dam et al. 2018). Still, in domains where a lot of input information needs to be processed for decision making, experts have to rely on automated, intelligent decision support (Raouf et al. 2006a). As a result, humans need to align their common cause and effect evaluation of the decision situation with the assessment reasoning of the system to accept the decision of the AI system (Miller 2019). This creates a dilemma between the demand for accurate vs. transparent DSS, which is the object of research on explainable AI (XAI) (Wanner et al. 2020c). Consequently, XAI aims at a high degree of model explanation while maintaining the best performance possible (Gunning and Aha 2019).

While research focuses on these two areas, practical issue such as environmental constraints and individual user preferences seem to be ignored. In particular, only cost and time seem to be considered as crucial in (IT) projects (Clancy 1995; Lech 2013). Hence, today, we observe rather isolated research on either model accuracy or model explainability. Yet in contrast, decisions towards adopting complex technologies are very complex and are subject to a range of cognitive bias, especially for applications that involve high-stake decisions and therefore are of high criticality (Das and Teng 1999). We understand high-stake decisions as those where a wrong or late decision can result in the loss of human lives.

With this research, we want to explore the human factor in AI adoption. We aim to understand the variables influencing the decision of choosing a particular AI technology for decision support in applications involving high-stake decisions (Stefani and Zschech 2018). Consequently, our research question is as follows:

RQ: *Which factors are of importance when choosing an AI DSS for high-stake decisions, and how can we characterize the trade-off between different AI DSS implementations?*

In order to answer this question, we derive *decision factors* and from the related domains ML, XAI, and IT project management. Then, we propose observable measurements for those factors. After modeling the decision as a hierarchy of decision factors and superior *decision categories*, we gather judgements on factor importance from a survey. Lastly, we simulate the decision process for the case of a high-stake maintenance scenario and weigh the proposed decision factors as a result of the survey.

Our research yields several contributions: First, we derive a theoretical construct of measurement variables from the interdisciplinary field of AI adoption, which is based on well-founded scientific theories of Information Systems and Business Research and can also form the basis for further AI research. Second, our research involves the derivation and implementation of best practices of AI DSS for the case of high-stake maintenance, which are highly relevant for practical application. Third, our end-user-

based study results allow for a better understanding of the significance of decision criteria for AI adoption. On the one hand, this benefits research, which can focus on promising approaches in addition to further evaluation possibilities, and on the other hand, practice benefits from the decision model and proposed measurements for implementing their own decision process.

Our paper is structured accordingly: In the next section, we present the theoretical background and derive evaluation factors in terms of decision and attitude factors for AI-based system adoption. Subsequently, we depict our research methodology and describe the use case, followed by the introduction of a measurement model for the decision factors as well as the high-stake maintenance case. We then proceed to introduce the decision model, describe the survey setup, and present our results. In the last section, we summarize our contribution, discuss limitations, and present an outlook of further research opportunities.

4.1.2 Foundations, Related Work and Derivation of Evaluation Factors

4.1.2.1 AI-based Decision Support Systems

From an economic point of view, a decision is an intellectual effort to make the best possible choice to given circumstances. For a decision maker, information is the key to understand these circumstances and make the best possible judgement. Due to the increasing use of information systems in daily business, both the complexity and the amount of available information is growing (Bonczek et al. 2014). Research on decision support tries to address this by providing support for the decision-maker using modern techniques and optimization theory. To be more specific, a decision support system encapsulates complexity and allows combining personal assessments about a necessary decision (problem) with computer output in a user-machine interface. In this way, it produces meaningful information for support in a decision-making process (Simonovic 1999). Through the years, these systems have developed into ‘intelligent’ systems called AI DSS (Bonczek et al. 2014). AI DSS are able to iteratively learn from empirical data, allowing them to find non-linear relations and complex patterns without being explicitly programmed (Bishop 2006).

Beyond the possibilities, however, there is the problem that decision makers must adopt and use the system and its underlying information for its advice to be effective. This leads to the research area of technology acceptance. A key construct of the related Unified Theory of Acceptance and Use of Technology (UTAUT) model is the user’s performance expectancy. It is defined as the degree to which an individual perceives that using an information system will help him or her to attain an increase in his or her job performance (Venkatesh et al. 2003). AI research, as the backbone of AI DSS, is therefore concerned with the continuous improvement and expansion of algorithms. The basic quality of an AI algorithm is measured on two kinds of indicators: *prediction value (PV)* and *inference time (IFT)* (e.g., Lane et al. 2016). The former refers to the prognostic power of the algorithm model. The latter is defined as the trained model’s delay in the calculation of a new data input in practice. Both can lead to consequential costs.

Thus, recent research efforts are particularly directed towards the development and application of ANN with increasingly deeper architectures often summarized as deep learning (DL) (Zschech et al. 2019). These show a high prediction value with parallel low inference time. Their multi-layered architecture

allows them to be fed with high-dimensional raw input data and then automatically discover internal representations at different levels of abstraction (LeCun et al. 2015). DL approaches currently outperform traditional models for most applications, which constitutes them as state-of-the-art in the field of data-driven practical ML implementation, for example in the field of (smart) maintenance (Khan and Yairi 2018; Wang et al. 2018a).

4.1.2.2 Demand of Explainable AI-Systems

The high performance of ML and especially DL models comes at certain costs, as their nested, non-linear structure creates a lack of transparency by constructing internal high-degree interactions between input features, which are difficult to disaggregate into a human-understandable form. In other words, it is not clear what information in the input data drives the models to generate their decisions. Therefore, they are typically regarded as 'black boxes' (Samek et al. 2017). Although not every practical task might require an explainable decision model, because it may be more important, for example, to prevent a failure than to understand its cause (Dragomir et al. 2009), the lack of explainability still poses problem for accepting an AI decision support system. For human intelligence, it is generally an important aspect to be able to explain the rationale behind one's decision, while simultaneously it can be considered as a prerequisite for establishing a trustworthy relationship (Samek et al. 2017).

Trust issues in the context of an agency theory setup can result from the information asymmetry between the AI DSS (agent) and its user (principal) (Kleine 1995). Due to the absence of knowledge about the inner functions of the AI DSS, the user cannot effectively validate whether the system operates within his interests or if is the subject of adversarial alteration (Heinrich et al. 2020). The missing observability of the decision process as a property of black-box models renders it difficult to detect possible deviations from the user's expectations. While a black-box AI DSS has no ability to 'act in its own interest' as it lacks an own agenda, its decision making process is not observable on its own, resulting in issues comparable to a moral hazard that can be avoided by increasing observability through measures of algorithmic self-signaling by the AI DSS. This call for improved observability of the inner decision logic of an AI DSS is in line with the XAI community's demand for explainable models while maintaining a high degree of model predictability (Gunning and Aha 2019).

In this case, explainability is about the understanding of the reasoning behind a decision by a human observer (Dam et al. 2018). Thus, the degree of model explainability remains dependent on the respective end user. However, there is a distinction between two types of explanation: global explanation and local explanation (Dam et al. 2018). The former offers a *causal explanation (CE)*. It is about the process of making an AI-based decision traceable by providing transparency into the decision model, its components such as parameters, or its algorithm (Ras et al. 2018). For this purpose, the causal model of the algorithm is of great importance. Local explanation is about a post-hoc interpretability of an AI-based decision recommendation through textual explanations, graphical presentations, or examples (Lipton 2018). It aims at an appropriate type of *visual explanation (VE)* for intended users (Heinrich et al. 2019; Miller 2019).

4.1.2.3 (X)AI-based Projects in Practice

IT projects are said to fail particularly often (Lech 2013). In order to identify the failing causes and derive success factors of IT project management, there is a long-term study of the Standish Group called the 'CHAOS-study'. It was first published in 1994 and since then is continuously updated, with a total dataset of over 40.000 individual projects that have been scientifically investigated. The study distinguishes between successful, partially successful, and unsuccessful projects by measuring the compliance of three criteria: budget, time, and planned functionality (Clancy 1995). This is also confirmed by the empirical study of Lech (2013).

At the beginning of a project, at the stage of project planning, it is particularly important to define the envisaged framework of the three criteria. It has been shown that uncertainties, changing environmental factors, or dependencies result in non-compliance with budgets and schedules influence projects (Lech 2013). These should therefore be minimized as far as possible through a comprehensive understanding of the project intent and influencing factors. Regarding scientific theories, the technology acceptance theory and the theory of transaction costs are particularly important. The construct of user's effort expectancy of the UTAUT model of the technology acceptance theory addresses this. It is defined as the degree of ease associated with the use of an information system (Venkatesh et al. 2003). Referring to Ghalandari (2012), effort expectancy has a strong link between the effort, its achieved performance, and the rewards resulting. From a project management point of view, it is therefore particularly important during project planning to understand the effort required and the resulting performance benefits for a potential solution and its alternatives. In addition, considering the many extensions of the acceptance theory, we can identify two potential attitude factors that could alter a ranking of decision factors: *risk attitude* and technology anxiety, which in our case would be reflected by the *willingness to use an AI system* (Yang and Yoo 2004).

With regard to the future AI DSS, effort for the decision logic of the AI algorithm results from the *implementation time (IMT)* and the associated resource intensity, which depends on the *training time (TT)* of the AI model (Lane et al. 2016). Further, it is also important to understand the extent to which the project team has the *required skill level (RSL)* to be able to realize the potential implementation or if acquisition of external expertise is necessary. In general, the decision to outsource capabilities and resources is grounded, among other factors, in transaction cost theory (Alaghehband et al. 2011). More specifically, the RSL of an AI DSS acts as an effort indicator to be compared with the firm's capabilities and, therefore, can act as a proximity factor for costs.

We summarize the derived decision and attitude factors in Table 24 to complete *step (a)*.

Table 24: Evaluation Factors of AI DSS for High-stake Decisions

Decision Factors			
Research Domain	*Category*	*Factor*	*Kernel Theory*
Machine Learning	Performance	Prediction Value (PV)	Technology Acceptance Theory
		Inference Time (IFT)	
Explainable AI	Explainability	Causal Explanation (CE)	Agency Theory
		Visual Explanation (VE)	
IT Project Management	Effort	Implementation Time (IMT)	Technology Acceptance Theory; Transaction Cost Theory
		Training Time (TT)	
		Required Skill Level (RSL)	
Attitude Factors			
Risk Attitude		Willingness to Use AI	

4.1.3 Methodology and Use Case

4.1.3.1 Research Methodology

As outlined above, we focus on the selection problem of AI DSS motivated through three domains: IT project management, ML, and XAI. We approach the problem with an experiment based on three kernel theories: transaction cost theory, technology acceptance theory, and agency theory. Specifically, to gain insights into the user's decision rationale when choosing an AI DSS, we model the decision as a hierarchy of the decision factors using the Analytical Hierarchy Process (AHP) method by Saaty (2008). The complete research methodology is depicted in Figure 29. We apply the method to compare *m* variations of the domain-specific AI DSS for high-stake maintenance.

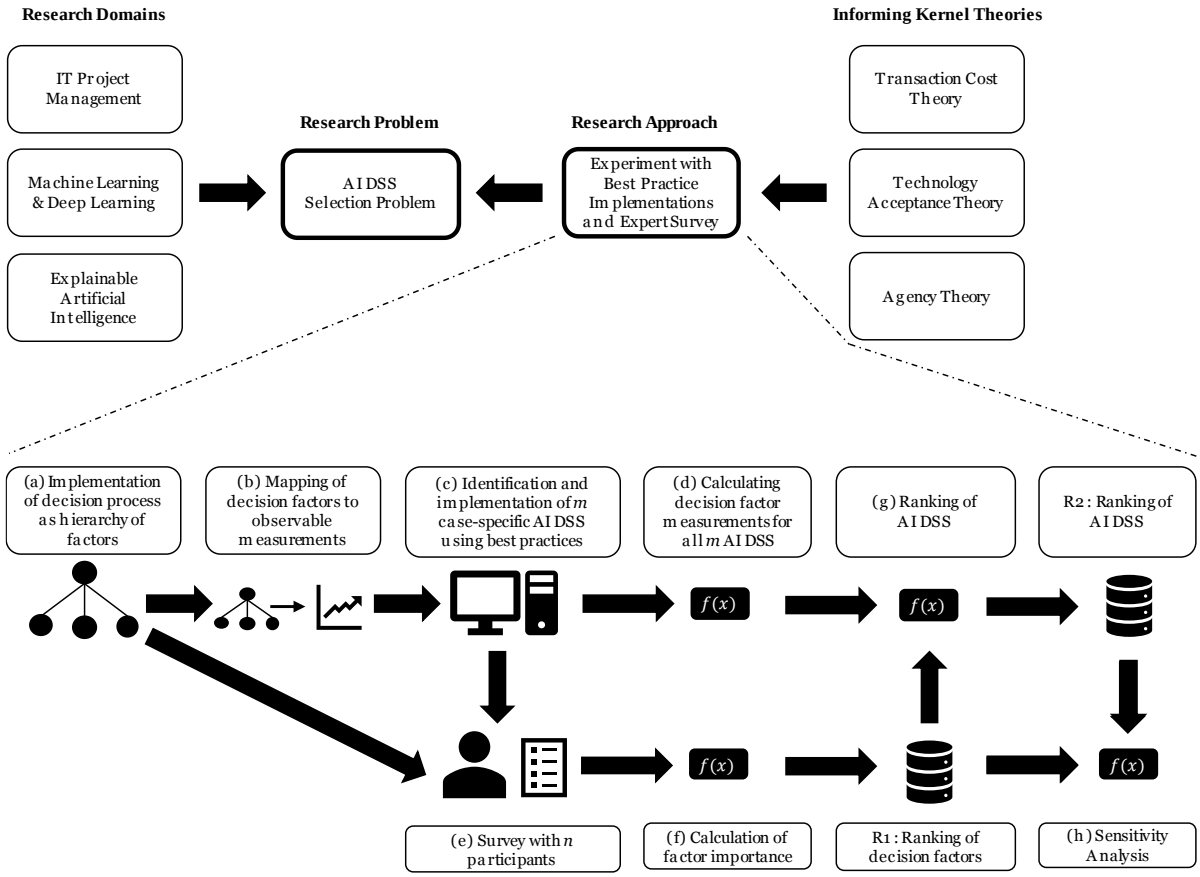


Figure 29: Research Methodology

Our general research approach using the AHP methodology is as follows: We (a) model the decision factors in the form of the hierarchy given in Table 24 (e.g., 'inference time' is a decision factor subordinate to the category 'performance'). Afterward, (b) the criteria on the lowest level are mapped to observable measures for a specific case (e.g., inference time is measured by the time it takes the algorithm to complete the classification of one element). After (c) implementing *m* variations of the AI DSS using best practice approaches, (d) the measures are calculated for every variation.

In parallel, we (e) use consistency-controlled pairwise comparisons between the decision factors from a survey to (f) obtain a transitive ranking of influence factors. In order to ensure the results are valid, we implemented a consistency check, as suggested by Saaty (2008), to ensure transitivity for every

participant and his or her set of pairwise comparisons. The pairwise comparisons are carried out by presenting a questionnaire to *n* potential expert users of the AI DSS using the nine-point Saaty scale (1=equal importance, …, 9=extreme importance). As a result, we yield weights between 0 and 1 for the decision factors and the superior decision categories. In order to observe the moderating effects summarized in Table 1, we additionally included an item for each attitude factor using a five-point Likert scale.

Using the decision weight factors calculated in (f) and the measurements calculated in step (d), we can (g) calculate an overall rating of the *m* AI DSS. As a result of the AHP approach, we yield a first ranking (R1) of decision factor importance and, subsequently, a second ranking (R2) for the *m* AI DSS implementations. Finally, we conduct (h) a sensitivity analysis to explore the stability of the respective decisions and weights regarding the individual attitude variables. In addition, we point out that step (d) is independent of the use case so that the mapping can be adopted for other application areas that use AI DSS.

4.1.3.2 Use Case of High-stake Condition-based Maintenance

Industrial maintenance is intended to maintain and restore operational readiness of machinery to keep opportunity costs as low as possible. Related activities can be performed either i) after a break-down occurred, ii) in periodic cycles, or iii) in a condition-based manner. As unplanned downtime costs up to $250,000 per hour (Koochaki et al. 2011), or, in our specific case of high-stake maintenance cases, can even put human lives at risk (Raouf et al. 2006a), a proactive condition-based maintenance (CBM) strategy seems to be the most useful approach (Kothamasu et al. 2006). For this purpose, comprehensive data collections are gathered and processed by a CBM system to assess the current state of the equipment and derive recommendations for the optimal time of intervention (Jardine et al. 2006; Veldman et al. 2011). In contrast to reactive strategies, divergent machine behavior can be detected and classified at an early stage by means of diagnostic techniques to avoid unnecessary work. Furthermore, by using suitable indicators and prognostic techniques, it is possible to determine a machine's future state or its remaining useful life (RUL), which is often referred to as predictive maintenance (Elattar et al. 2016; Peng et al. 2010).

To support CBM prognostic tasks, corresponding DSS can be based on different principles and approaches. This includes physical models, knowledge-based approaches, statistical methods, or AI-based approaches (Zschech 2018). Physical models are mathematical representations of physical processes, such as specific degradation laws. They can provide accurate health information, as the remaining quality of the component or system of interest, but they also require a thorough understanding of underlying mechanisms. Knowledge-based approaches are built on experiences from human experts. They can be formalized, for example, by means of domain-specific rules or heuristics, which, however, are difficult to obtain and hardly transferable to new contexts (Peng et al. 2010). Statistical methods, such as regression models, multivariate methods, and state-space models, use collected data observations to identify and model relationships for prognostic purposes. They are useful to assess risks quantitatively, but also heavily rely on assumptions of distributions, which in many real-world cases cannot be verified as fulfilled (Peng et al. 2010; Zschech et al. 2019). AI-based approaches cover a variety of ML techniques, such as support vector machines or different kinds of decision trees and ANN. They have the advantage of automatically exploiting hidden insights in vast amounts of observed data records (Elattar et al. 2016).

Given the technological possibilities to collect large and multifaceted data assets in a simplified manner, AI-based approaches using ML can currently be considered as the most promising candidate for CBM decision support (Carvalho et al. 2019b).

4.1.4 Measurement Model

In order to determine the overall decision, we need to map the decision factors to observable measures (in *step (b)*) and later calculate them for each of our *m* AI DSS (in *step (d)*).

Effort. Two characteristics can be quantified to approximate the effort of an algorithmic ML model: i) *implementation time* and ii) *training time*. The former calculates the time required to implement the selected algorithm, which is determined by the average of an estimation of several ML experts. This includes both preliminary steps, which we summarize as pre-processing, and the algorithmic realization, including re-engineering until a satisfactory solution is available. We define the implementation time (IMT), measured in person hours, by equation (1):

$$IMT = \sum_{i=1}^{n}(PP_i + AR_i) * \frac{1}{n} \quad (1)$$

averaging over all estimations n of the necessary time for pre-processing PP_i and the time needed to realize the algorithm AR_i itself over all experts i.

The algorithm's training time, on the other hand, indicates the resource intensity of a model for training. Training time (TT) is measured in seconds and determined by equation (2):

$$TT = \sum_{e=1}^{m}\sum_{b=1}^{n}|(tr_{ebt} - tr_{ebt+1}) + (te_{ebt} - te_{ebt+1})| \quad (2)$$

adding up the times needed to perform all training epochs e over all batches b as the number of samples given to the model before model's parameter updating, measured by the difference between the training's start time (tr_{ebt}) and end time (tr_{ebt+1}), and its related times needed to test the result ($te_{ebt} - te_{ebt+1}$).

A further characteristic that has a significant effect on the effort when implementing algorithms is the iii) required skillset (RSL). This cannot be quantified directly and, thus, needs to be substituted for measurement. We use the required training as a proxy variable to do so and obtain the values based on the training courses on the platform *datacamp.com*. These courses were analyzed by data science experts that beforehand were familiarized with the prognostic approaches to filter out the courses of interest. Thus, we received a dictionary mapping the course short name and time to complete each of them (equation (3)):

$$RSL_c = \{\text{R}|\text{python basics}: 8, \text{ML basics}: 8, \text{ML regression}: 4, \text{DL}: 12, \text{Bayesian modeling}: 8\} \quad (3)$$

We then accumulated the number of hours of all courses that would be necessary for a computer science student with no particular data science knowledge to implement the respective AI DSS, referred to as

the choice c. We used the implementations and source code provided by the authors of the respective prognostic approaches identified in the next section[10].

Performance. Two characteristics quantify the performance of an algorithmic model: i) *prediction value* and ii) *inference time*. Prediction value (*PV*) refers to the prognostic power of an algorithm. We identified two measures, which are used in RUL data challenges: the '*PHM08' score* and the *root mean squared error* (RMSE) (Zschech et al. 2019). 'PHM08' prefers an early prediction to a late one. Thus, the scoring is asymmetric around the true time of failure, and late predictions are penalized more. The penalty itself expands exponentially with increasing error (Saxena et al. 2008). Equation (4) and (5) describe this:

$$s = \sum_{i=1}^{N} s_i \qquad with \quad S_i = \begin{cases} e^{\frac{d_i}{13}} - 1 \; for \; d_i < 0 \\ e^{\frac{d_i}{10}} - 1 \; for \; d_i \geq 0 \end{cases} \tag{4}$$

$$d_i = \hat{L}_i - L_i^T \tag{5}$$

with s being the calculated score, N the number of units to be maintained and d_i the deviation of the estimated RUL $\hat{L}_i$ against the real RUL L_i^T. The preference for premature predictions corresponds to a risk-averse attitude and forces a high sensitivity to outliers in the exponential curve. A disadvantage is that the prognostic distance is not included in the scoring evaluation and algorithms are preferred that intentionally underestimate the RUL (Lim et al. 2014).

Thus, the RMSE is often used in parallel to measure the accuracy, punishing intentionally underestimated RUL, and in this way, it allows for a critical sub-evaluation. It is calculated using equation (6):

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)^2}{n}} \tag{6}$$

adding all $(\hat{y}_i - y_i)^2$ squared differences of the real values against the calculated values in relation to the given sample size of n. The root obtains the actual deviation distance as the total error.

The inference time (IFT) describes the delay in the calculation of an algorithmic model in practical use. Thus, it is defined as the time a model takes between the input of new data and its calculated result, representing its real-time ability. It is measured in microseconds. IFT can be formulated using equation (7):

$$IFT = \sum_{i=1}^{n} |t_i - t_{i+1}| * \frac{1}{n} \tag{7}$$

averaging over all time differences between the beginning of the calculation as the time of reading the new data t_i and the time the algorithm finished calculating the results t_{i+1}, which in turn represents the start time of the new calculation process.

[10] As a result, we found that every AI DSS implementation would require a basic set of courses in either R or Python (8 hours). Further, *similarity-based matching* ($AI\ DSS_3$) and *direct RUL* ($AI\ DSS_1$) require basic ML skills (4 hrs.), while *direct RUL* requires ($AI\ DSS_1$) at least two additional courses in DL (12 hrs.). *Indirect RUL* ($AI\ DSS_2$) requires Bayesian modeling (8 hrs.) in addition to basic ML course.

Explainability. Both explainability characteristics i) *causal explanation (CE)* and ii) *visual explanation (VE)* can only be measured on an ordinal scale to create a ranking comparing the different solutions.

The former is about the ability of the algorithm to reveal the influence of each input variable with regard to the output. We measure this as a binary function, following the categorization of Yang et al. (2019). We set the measurement *causal explanation*=1 whenever a DL system can provide either a local and/or global intrinsic explanation manner, and we set *causal explanation*=0 when this is not the case.

Since the model visualization quality largely depends on the human's ability to interpret it, we chose to use the model visualizations of the *m* prognostic approaches (cf. next section) to our participants and let them rank the visualizations. Subsequently, we are calculating normalized weight scores for each AI DSS as a measurement for visual explanation.

4.1.5 Identification of AI DSS, Implementation, and Results

4.1.5.1 Identification of Best Practice AI DSS Using Datasets for Predictive Maintenance

In order to decide on the number and types of the *m* AI DSS for implementation, we need to identify best practices or at least promising examples of CBM using AI technology (in *step(c)*). As an AI-based CBM prognostic approach requires sufficiently extensive machinery data including failures to draw conclusions for early indicators, we decided to survey the most widely used datasets for high-stake maintenance decisions to identify the best practices of AI DSS.

We limited of search to predictive maintenance datasets that are publicly available, deal with high-stake maintenance cases, and have been used in a sufficient number of publications. We focused on the identification of existing comparative reviews first. We selected the following databases for our literature review: *IEEE Xplore Digital Library*, *EBSCOhost Academic Search Elite*, *EBSCOhost*, *Business Source Complete*, *ACM Digital Library*, *ScienceDirect*, and *Web of Science* using terminologies from predictive and condition-based maintenance combined with generic terms of datasets, comparisons, and reviews. Further, we have excluded terms from medical science, as these otherwise would have pre-dominated the results. As a result, we identified 25 datasets from five review articles. We used a hit popularity analysis to reveal the most popular datasets in research by the number of downloads and citations.

A closer analysis of the top three datasets highlight that *Turbofan (NASA)* and *PHM 2008* share the same data basis of NASA's Prognostics Data Repository (Elattar et al. 2016; Zschech et al. 2019): The so-called C-MAPSS data simulates large commercial engines (Richter 2012). It represents a high-stake decision case as a failure of engine turbines can lead to a crash of an airplane and related human casualties. To date, however, besides prognostic scoring, user acceptance has not been tested.

Using the taxonomy of Zschech et al. (2019), it is possible to make a distinction between three different data-based prognostic approaches for CBM using the C-MAPSS dataset. Among others, the taxonomy distinguishes the five existing scenarios of C-MAPSS. We consider this an essential limitation to ensure comparability and to identify best practices. For our purpose, we chose the dataset of the 'FD001' scenario as it is most commonly used in 60 out of 106 papers.

We differentiate between i) *direct RUL-mapping* (*AI* DSS_1), ii) *indirect RUL-mapping via health index (HI)* (*AI* DSS_2), and iii) *similarity-based matching* (*AI* DSS_3) (cf. Figure 30). In i) direct RUL-mapping, the training data is transformed into a multidimensional feature space first, using RULs to label the vectors. Then, a mapping between feature vectors and RUL is developed using methods of supervised ML (Ramasso and Saxena 2014). A total of *k*=21 publications of our subset chose this approach. From 2016, the majority apply different types of ANN with a tendency towards deeper architectures (Zschech et al. 2019). For ii) indirect RUL-mapping via HI, two mapping functions are combined. The first one maps sensor values to a HI for each training unit. The second links HI values to the RUL. Thus, a degradation model library is formed that serves as prior knowledge to update the parameters of the model corresponding to the new test instance (Ramasso and Saxena 2014). A total of *k*=28 publications of our subset chose this approach. The types of algorithms used differ. Thus, there is no clear favorite. For iii) similarity-based matching, historical degradation progressions (HI curves) are calculated and stored, forming a library with known failure times first. The RUL of a new instance is then estimated with the help of the most similar stored ones (Ramasso and Saxena 2014). A total of *k*=12 publications of our subset chose this approach. Various distance measures and geometric calculations are used to calculate the assessment of the similarity (Zschech et al. 2019).

In order to derive best practices for the three prognostic approaches, we looked at the performance ranking of the listed publications. Accuracy-based metrics have been used especially in the related data challenges to compare the different algorithm coding. Ordered by the 'PHM08' score, the two highest-scoring publications belong to the category of similarity-based matching with another similarity-based matching paper in the top ten. All other seven top ten publications use direct RUL-mapping. An algorithmic analysis of all publications revealed the technical best practices per prognostic approach: For the i) direct RUL-mapping, using a long-short-term memory network (LSTM) or a convolutional neural network (CNN) seems promising. This is in accordance with four out of the top ten publications by 'PHM08' score, where three are based on an LSTM. Focusing on ii) indirect RUL-mapping via HI, using an extrapolation is a good choice. For iii) similarity-based matching, an LSTM encoder-decoder combined with a curve matching and a similarity-based reasoning with a polygon clipping is favorable. This is in line with the two best-performing contributions (Malhotra et al. 2016; Ramasso and Saxena 2014).

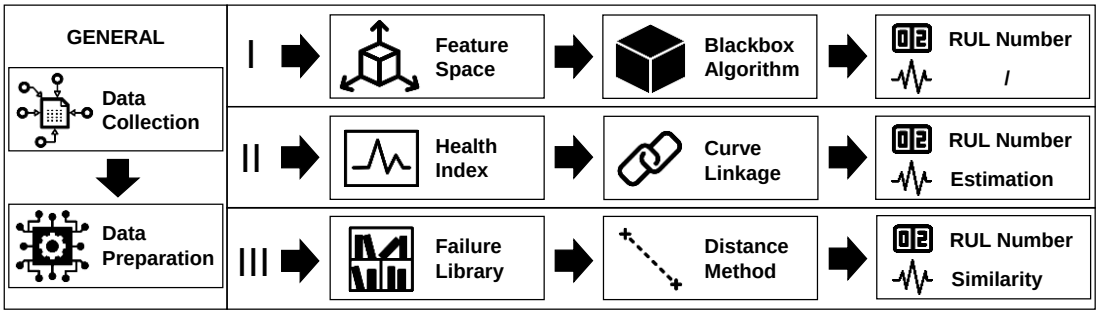


Figure 30: Model Explanation per Prognostic Approach

4.1.5.2 Implementation of Best Practice AI DSS

We have based our own prototypical implementations (in *step (c)*) on these best practices of prognostic approaches. If their documentation was not available in a comprehensible way, we have tried to follow a comparable study. It was particularly important for us to understand the technical challenges that the implementation entails and the opportunities that arise as a result. For the i) direct RUL-mapping approach, we have implemented an LSTM. For ii) indirect RUL-mapping via HI, we have used an algorithm based on extrapolation. The iii) similarity-based matching was reconstructed using a squared polynomial curve fitting. These three approaches represent our m=3 AI DSS for the case of high-stake maintenance.

Direct RUL-mapping. For the RUL target function, we determined the RUL value by the difference between the total runtime of the unit and the individual cycle numbers. This corresponds to a decreasing trend. We set the maximum RUL estimation to 125, in accordance with Zhu et al. (2018a) and Malhotra et al. (2016). The size of the time window is defined by N_{tw}=30 (Li et al. 2018b; Zhu et al. 2018a). This is equivalent to the window size in Zhu et al. (2018a) and has been proven by the results of Li et al. (2018b), who made a comparison of time window sizes for the C-MAPSS dataset. We used the *mean squared error* (MSE) as the loss function and selected all 21 sensors as inputs. The architecture of our artificial network was based on Zheng et al. (2017) as the best ranked LSTM solution according to the 'PHM08' score. We have implemented a total of five layers: two LSTM layers, followed by two full layers and another final full layer. For the parameterization of the LSTM layers, own cross-validation studies have shown that two 64-units layers achieve more robust results than the 64- and 32-unit version of the one in Zheng et al. (2017). The full layers were set to 8-units each. Further, Zheng et al. (2017) mentioned the usage of a dropout rate without specifying its value. Our test set shown the best result for *dropout*=0.2 and a final *dropout*=1.

Indirect RUL-mapping via HI. Our method for the indirect RUL-mapping via HI is based on the work of Coble and Hines (2011). They have proposed a dynamic Bayesian updating procedure that allows a priori information from the training data to be incorporated into the extrapolation procedure of the test data to obtain the model parameters. So, the HI is calculated with linear regression, using the first 10% of training instances as 1 and the last 10% as 0. Comparing different time windows of preliminaries, we settled with N_{tw}=15 (Li et al. 2018b). We smoothed the degradation curve using locally weighted scatterplot smoothing (LOWESS). It assigns the highest weight to the value to be smoothed and lower weights to more distant values. To forecast the RUL, the degradation curve is plotted up to a predetermined limit value indicating the extrapolated error status. We set this limit value to h=0. For the necessary curve fitting, we used dynamic Bayesian updating with a polynomial of the 2nd order. Coble and Hines (2011) proofed that while an exponential polynomial would be physically more useful, a quadratic polynomial is more robust in terms of noise and results in a better fit.

Similarity-based matching. The implementation of our similarity-based algorithm follows the work of Malhotra et al. (2016), who achieved the second-best score for the dataset 'FD001'. First, we built a reference library. Thus, we created one-dimensional degradation curves in the form of HIs from the multidimensional training data. Our implementation of the first similarity-based approach was geared to Wang et al. (2017). We calculated the new HI using linear regression and a squared polynomial for curve matching. The parameters are determined by *least-square fitting*. We calculated the similarity

score using *information fusion* and considering the time lag between training and test data. The weighting parameters μ and θ are determined as μ=0.8 and θ=0.2 (Wang et al. 2017). The maximum RUL estimation is set to 125. Our second implementation was geared to Malhotra et al. (2016). The HI is calculated by linear regression. Here, no curve matching is applied to assign the HI to similar functions of the library. Instead, we smoothed the historical HI degradation progressions using the LOWESS method with a time window of N_{tw}=15 (Li et al. 2018b). In addition, we considered the time lag. We set the maximum RUL estimation to 125 (Malhotra et al. 2016; Zhu et al. 2018a). We calculated the similarity score using Euclidean distance and set the scaling similarity measure to λ=0.0005. We determined the weighting parameters as μ=0.8 and θ=0.2 (Wang et al. 2017).

Results. The quantifiable measures of each prototypical AI DSS solution can be found in Table 25 (completing *step (d)*). All algorithms have been deployed ten times, taking their average values. As hardware backbone, we used an Intel Core i7-6700HQ CPU (4x 2.60 GHz), with an NVIDIA GeForce GTX 960M and 16 GB RAM, operating under Windows 8.1 pro.

Table 25: Measurement Results for High-stake Maintenance AI DSS

Prognostic Approach *(AI DSS)*	**Effort**			**Performance**			**Explainability**	
	IMT	TT	RSL	PHM08	RMSE	IT	CE	VE
Direct RUL	8 hrs	313.9 sec	20 hrs	270	13.51	1562 µsec	No	0.10
Indirect RUL	15 hrs	44.9 sec	16 hrs	775	21.23	6006 µsec	Yes	0.52
Similarity-based	25 hrs	57.2 sec	12 hrs	409	14.17	5345 µsec	Yes	0.38

4.1.6 Decision Model and Results Discussion

4.1.6.1 Decision Model

Following *step (a)*, we first build a hierarchical model of the decision process, where the choices are the *m*=3 AI DSS and the decision factors of Table 24. The hierarchy of factors is depicted in Figure 31. The decision factors are depicted by white filled boxes while the actual choices of AI DSS implementations are depicted as black filled boxes.

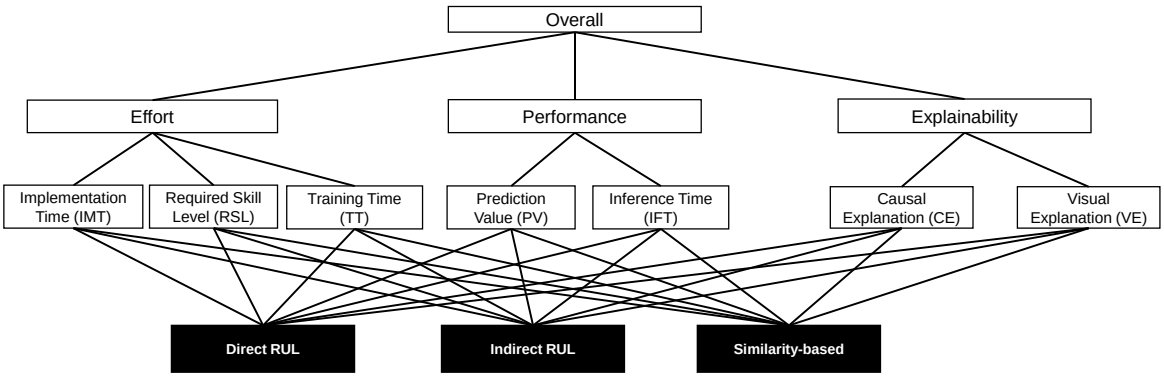


Figure 31: Factor Hierarchy for AHP

The questionnaire (in *step (e)*) started with items regarding basic demographic information about gender, age, region, industry sector experience, company size, current position, and work experience. It also

included views of the two moderating attitude factors (willingness to take risks and AI at the workplace). Then, we introduced the use case of establishing preferences for a future AI DSS at the workplace for high-stake maintenance of airplane turbines. In the second part of the survey, we first asked the participants to rank visual explanations of the *m*=3 AI DSS. Examples of the approaches are depicted in Figure 32.

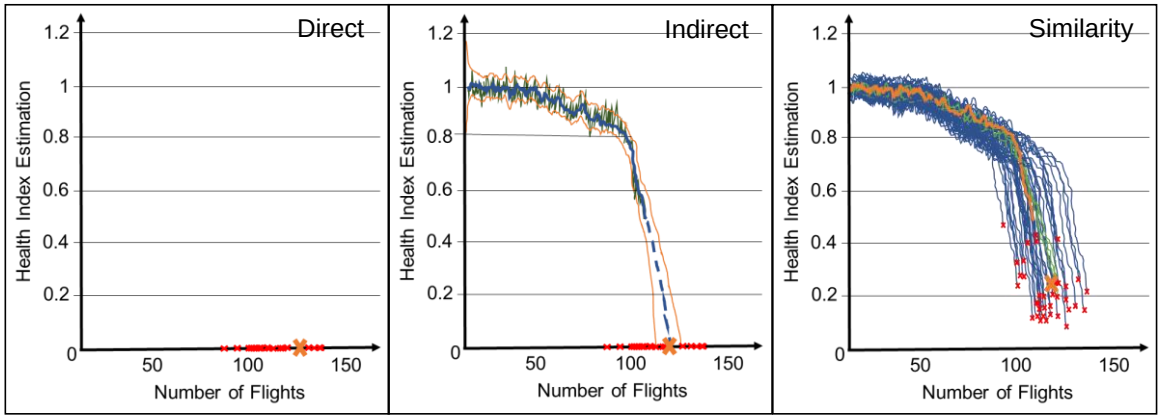


Figure 32: Visual Explanation of Each Prognostic Approach (AI DSS) 11

Second, we asked for pairwise comparisons of the decision factors, and third, we asked for pairwise comparisons of the categories (for both cf. Table 1). For example, we asked whether participants considered the inference time or the prediction value of an AI DSS to be more important and, if so, by how much on the aforementioned nine-point Likert scale. In doing so, we created a weighted hierarchy of decision factors as well as a weighted hierarchy of the summative categories.

Then, we used the platform *Prolific.co* to recruit *n*=165 participants[12]. The platform enabled us to screen for professionals in the fields of manufacturing, aviation, and other related industrial fields. We cross-checked this in the survey using demographic items.

After receiving the initial data, we checked all questionnaires by applying the following inclusion criteria: (i) The participants needed at least 5 minutes to complete the survey (with 5 minutes being the minimum time determined to understand all given information), (ii) the participants had at least 2 years of experience in the field of maintenance, and (iii) the answers were not trivial due to primacy or recency bias or simply carelessness. After applying criteria (i) (-45), criteria (ii) (-47) and criteria (iii) (-0), we ended up with a final sample of n=73 (male=44, female=29; with age of $\bar{x}$=41, *M*=36, *SD*=11). 67% of the participants originated from Europe, 30% came from North America, and only 3% from other continents.

[11] Fig. 3 shows an example for the visual presentation of results of the AI DSS implementations. The *y*-axis represents the health status estimated by the AI system. The *x*-axis indicates the amount of flights of the turbine. Red crosses represent the failures known to the system from the training data, whereas the large orange cross is the calculated failure of the turbine, which implies its RUL.

[12] The financial incentive for complete surveys was approx. $14/hr.

Our verification for experience in industrial maintenance showed a high experience in the topic of interest ($\bar{x}$=10, *M*=8, *SD*=6). The duration to complete the survey was in min. $\bar{x}$=9:28, *M*=7:54, *SD*=6:13. We additionally implemented a consistency check using Saaty's proposed method by calculating the consistency index and removing all judgments with an unacceptable inconsistency rate of >10%. No such inconsistencies were found, which can be explained by the straightforward design of only five and three pairwise comparisons, respectively.

We accumulated the *n* judgments based on the geometric mean approach described by (Dijkstra 2013). Multiplying the weights from R1 with the respective normalized measurements yields the overall rankings R2. Since we have two indicators of prediction value, we use the average of the RMSE and PHM08 as the AHP input for prediction value. We summarize the results in Table 26[13]. In addition, we provide the AHP weights for high- and low-risk attitude as well as high and low willingness to accept AI at the workplace to enable a sensitivity analysis regarding the attitude factors. For the *low* group of the attitude factors, only values 1 and 2 of the Likert scale were selected, while for the *high* group, only values 4 and 5 were selected.

Table 26: Results of the AHP, Including Attitude Effects

		All	*Risk Attitude*		*Willingness to Use AI*	
Category	*Factor*	(n=73)	Low (n=25)	High (n=19)	Low (n=7)	High (n=38)
Decision Factors (R1)						
Effort	IMT	0.22	0.21	0.21	0.36	0.24
	RSL	**0.55**	**0.58**	**0.51**	**0.41**	**0.53**
	TT	0.23	0.21	0.28	0.22	0.23
Performance	PV	**0.87**	**0.92**	**0.70**	**0.84**	**0.90**
	IFT	0.13	0.08	0.30	0.16	0.10
Explainability	CE	0.25	0.37	0.27	0.39	0.21
	VE	**0.75**	**0.63**	**0.73**	**0.61**	**0.79**
Overall (Factors)	Effort	0.19	0.20	0.24	0.27	0.17
	Performance	**0.61**	**0.63**	**0.53**	**0.52**	**0.59**
	Explainability	0.20	0.17	0.23	0.21	0.22
AI DSS Decision (R2)						
Overall (Alternatives)	Direct RUL	0.35	0.35	0.34	0.35	0.34
	Indirect RUL	0.30	0.29	0.31	0.31	0.30
	Similarity	0.35	0.36	0.34	0.35	0.35

4.1.6.2 Decision Model and Results Discussion

R1. Overall (i.e., in *step (g)*), we found that *performance* is the factor that was selected to be most important for the decision which AI DSS to choose. Although this result was expected for a case of

[13] Bold numbers indicate largest decision weights per category. We provide details on our data and calculations as a digital supplement at https://doi.org/10.13140/RG.2.2.18577.45928.

high-stake maintenance, the magnitude of the decision weight was lower than expected in comparison with literature that almost entirely suggests that measures of prediction value (however they might be expressed) along with inference time are the only factors used in evaluation (La Cava et al. 2021).

A detailed look at the performance category shows that measures for system prediction quality (e.g., RMSE) is the main factor. This result holds for low-risk attitude and both willingness attitudes (low and high). However, we discovered a significant change in decision weights when high-risk attitude participants decided which system to use. It shifts from 0.92 (low risk) to only 0.70, giving much more weight to the inference time. We expect this result, as sometimes risk-takers will ignore the probability (risk) that the AI system is wrong to a higher degree than risk-averse persons. Risk-takers gamble for a higher reward and for a situation with high performance, expecting the system still to put out a good-enough value for the maintenance professional to make the right decision at lower inference times and therefore maximizing utility. We see the opposite for risk-averse people, where inference time does not matter at all (only 8% decision weight) compared with the system being able to predict a value close to the true RUL. As mentioned before, we found that *effort* and *explainability* are equally important. While this is surprising from a scientific point of view, it was expected from a practitioner's viewpoint. The theory on explainability of AI DSS and, thus, the need to implement additional XAI algorithms or chose transparent models from the outset while partially ignoring performance, is an isolated viewpoint as is the theory on performance of AI DSS (Rudin 2019). Only very few scientific articles are concerned with the actual cost of AI DSS or the comparison to alternatives (Elliott and Griffiths 1990; González-Rivero et al. 2020; Partel et al. 2019). While research for models to determine the value of an information system is a core IS research task, value, and costs estimates for AI DSS are still scarce (Matlin and Land O'Lakes 1979). This is partially explained by the fact that AI DSS typically introduce some degree of automation within a corporate information system landscape, and therefore it is hard to capture all long term benefits and cost savings. In addition, the recent AI and XAI literature is rarely concerned with value and costs of such systems as a core topic. However, our results reflect that in practice, as expected, this factor is attributed with some importance. Specifically, the required skill level with a decision weight of 0.58 stands out since it is seen as the biggest cost driver apart from implementation and training time, which were found to be approximately equal at 0.20. This can be explained by the fact that these criteria are not necessarily distinguishable by maintenance professionals who are not familiar with the concept of developing and training an AI DSS. We can detect a decision weight increase regarding the factor implementation time for the case of people with a low willingness to use AI. This could be associated with the negative expectation of particularly long implementation times for AI DSS. Among many reasons, this could be caused by own experience with a bad state of facilitating conditions, which, according to Venkatesh et al. (2003), influences the acceptance of the technology.

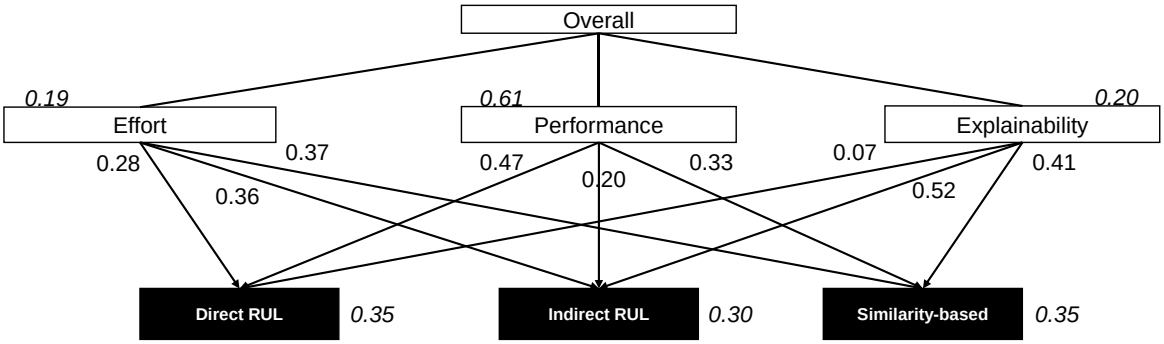


Figure 33: Decision Weights for the AI DSS Decision (all, n=73)

Within the category of *explainability,* we can distinguish between the ability of a model to connect its results to the input variables and therefore the ability to create transparency as to what caused the decision (causal explanation) and the ability to justify the 'correctness' of the results visually incorporating domain-specific knowledge already known to the user due to his or her experience. Surprisingly, the justification of the results seems to be much more important than the causal explanation for the system's output. This could be since the sheer number of sensor input variables specific to our case would overwhelm even expert users, while the visualization gives a clear degradation trajectory that is understood by all maintenance experts. In addition, the indication of variable importance to choose a value A over B expressed by a statistical measure is not the same as identifying a real root cause, which the AI DSS is usually not able to determine since it cannot identify the natural context of the problem and is not expected to do so by its users (Chaczko et al. 2020). We also find that for people with low willingness to use AI, the causal explanation and, therefore, the transparency of the system regarding its decision process is more important than for the other groups. This can be attributed to the fact that among other reasons, those people could have trust issues motivated by either previous experience or biased media exposure. Understanding how the system calculates the RUL and comparing it with their own experience and 'way of doing it', could, therefore, improve this relation and, thus, it is deemed more important by that group (Miller 2019).

R2. We depict the results of the decision process (R2) in the lower part of Table 26 and show that across all attitude variations, direct RUL and similarity-based matching are tied with scores of approx. 0.35 and indirect RUL is inferior with a weight of 0.30.

The choice weights of the overall factors that lead to those final scores R2 are depicted in Figure 33 for all participants (*n*=73). It is clearly shown that the *direct RUL* achieves its score purely by the performance advantage (0.47). This is in accordance with the fact that state-of-the-art black-box models based on DL achieve high task-based prediction values. Improving the explainability of the model with additional XAI algorithms to justify the results and assign input variables weights towards the output would further strengthen this approach. The *similarity-based matching* only achieves mediocre performance but scores high in explainability (0.41) and therefore is tied with direct RUL at a normalized decision score of 0.35. In comparison to the direct RUL, which uses a DL model, the similarity-based approach takes about three times as long to implement than the direct RUL while requiring a lower skill level. The low implementation time of the direct RUL DL model can be attributed to the fact that DL has been gaining a lot of attention from non-AI professionals resulting in a considerable boost of high-level programming packages that can assist in building DL models more quickly. In contrast, the enormous

training time of the direct RUL approach and the rather advanced required skillset explains its low overall score in effort (0.28) and, thus, direct RUL is inferior to the other approaches in terms of effort. Although the *indirect RUL* scores highest in explainability, the overall rather low importance of these factors, according to the survey participants, the low performance and the rather high effort renders it inferior to the other two models. Our results clearly show that the often-proposed trade-off between explainability and performance, while existent, is heavily skewed towards performance in the case of high-stake decisions.

4.1.7 Summary and Outlook

In this paper, we simulated a decision process and implemented an AHP to gain insights into the weights of decision factors for choosing an AI DSS. Therefore, we first derived decision factors from the three domains of ML, XAI, and project management to reflect all aspects of AI DSS applications in the context of a scenario with high-stake decisions where human lives are at risk. Second, we proposed a measurement model for those decision factors. Third, we implemented the decision process for a case of high-stake maintenance, more specifically, a maintenance case in aviation with the goal of preventing airplane turbine failure (called C-MAPSS). Fourth, we conducted a survey to understand the weights attributed to the decision factors and integrated this with measurement results from our implemented AI DSS.

We found that performance is still the overarching factor with effort and explainability tied in second place. In addition, we found that attitude factors influence the importance of decision factors, especially when people show low willingness to adopt AI and therefore have predispositions. For example, risk-takers valued inference time at the cost of prediction value more significantly and risk-averse experts, as well as experts with a low willingness to use AI, valued causal explanations to understand the AI model at the cost of visual explanations of decisions. Further, we found that direct RUL-mapping and similarity-based matching perform best with direct RUL-mapping benefiting from its prediction value and similarity-based matching from its ability to explain decisions.

With this research, we provide multiple theoretical and practical contributions. First, we provide well-founded and operationalized measurement variables for AI adoption that can form the basis for further AI research. Second, we have identified best practices of AI DSS for high-stake maintenance decisions, which yield high practical value. Third, our expert study enables an understanding of the significance of decision factors and attitude factors for choosing an AI DSS or, in general, for AI adoption. Fourth, we were able to draw conclusions, which factors should be focused on when certain risk attitudes and willingness or resistance to use AI can be assumed. This benefits research as scientists can use our results to better understand the trade-off between effort, performance, and explainability and devise further holistic evaluations. Likewise, practice benefits from the decision model and measures when implementing their own decision process.

As with all experimental research, we face some limitations. First, this is merely a descriptive study regarding the case of high-stake maintenance. Although the criticality was emphasized in the study, we cannot guarantee that it was always fully incorporated into the participant's decisions, as it would have if they were faced with a real-world situation. Second, we kept the description straightforward using a general predisposition towards AI systems and avoided adding detailed attitude factors such as fear of AI or AI-independent factors that can be derived from the UTAUT literature such as facilitating

conditions or previous experience alongside hedonic motivation or habit. Third, we were aiming to avoid questionnaire bias from unintended questions regarding the case. Therefore, we set the criticality and the environmental constraints as static factors within the case. However, this removed the ability to implement a group design of experiment to further investigate special trade-offs when criticality changes or other environmental constraints are present.

While we applied the decision process to a specific case to demonstrate it, it can be used for the general problem of choosing an AI DSS for a case with high-stake decisions. The results of this study can be used in both normative and prescriptive decision analysis regarding AI systems as a starting point to investigate the trade-offs of decision factors for specific domains or even domain-independent contexts. Thus, for further generalization, we plan to extend our study to additional settings, such as medical diagnostics and autonomous driving. As such, we want to examine whether our results also apply to similar high-stake decision scenarios. Likewise, we will investigate uncritical environments as a counterpart to isolate the effect of a decision scenario's criticality. For this purpose, our study design provides a sufficiently generic basis to be applied to any conceivable domain and decision context. Furthermore, we plan to extend the study design to include multiple stakeholder groups within an organization by using the methodology of the Analytical Networking Process (ANP), which is an extension of the AHP that allows for consideration of decision clusters (e.g., allowing different stakeholders).

In addition, our study also raises awareness of the preferences of practitioners when it comes to obtaining an AI system. With the large focus on performance, specific issues like AI security and diagnosing failure in critical applications through explainability might need to be communicated more thoroughly through means of IS strategy (e.g., through corporate constraints) to be more resilient when facing these new challenges in the age of AI.

4.1.8 Acknowledgement

This research and development project is funded by the Bayerische Staatsministerium für Wirtschaft, Landesentwicklung und Energie (StMWi) within the framework concept "Informations- und Kommunikationstechnik" (grant no. DIK0143/02) and managed by the project management agency VDI+VDE Innovation + Technik GmbH.

4.2 Adoption Barriers of AI-based DSS in Maintenance

Abstract. Contemporary decision support systems are increasingly relying on artificial intelligence technology to form intelligent systems. These systems have human-like decision capacity for selected applications based on advances in machine learning. In industrial maintenance, among other industries, they already enhance maintenance tasks such as diagnosis and prognosis. However, adoption by end-users remains rather hesitant. At the same time, there is a lack of (guidance for) independent, rigorous studies that investigate this phenomenon. In response, our research is concerned with the application and extension of the established Unified Theory of Acceptance and Use of Technology (UTAUT) to provide a theoretical model that better explains the interaction of end-users with intelligent systems. In particular, we consider the extension by the constructs of trust and transparency, which we consider as major technology acceptance factors due to the black-box nature of many machine learning algorithms.

As a result, we derive an extended theoretical model based on a review of previous extensions for UTAUT. Our model answers several new hypotheses, and our proposed study design includes measurement items for the constructs trust ability, trusting beliefs, and system transparency. It provides the foundation for a better understanding of the human factor in intelligent system acceptance and use.[14]

4.2.1 Introduction

Intelligent systems with human-like cognitive capacity have been a promise of artificial intelligence (AI) research for decades. Due to the rise and sophistication of machine learning (ML) technology, intelligent systems have become a reality and can now solve complex cognitive tasks (Benbya et al. 2021). They are being deployed rapidly in practice (Janiesch et al. 2021). More recently, deep learning allowed tackling even more compound problems such as playing Go (Silver et al. 2016) or driving autonomously in real traffic (Grigorescu et al. 2020) with super-human capabilities. On the downside, the decision rationale of intelligent systems based on deep learning is not per se interpretable by humans and requires explanations. That is, while the decision is documented, its rationale complex and essentially intransparent from the point of human perception constituting a black box (Kroll 2018).

Further, users tend to credit anthropomorphic traits to an intelligent system subconsciously to ascribe the system's AI a sense of efficacy (Epley et al. 2007; Pfeuffer et al. 2019). In this respect, intelligent systems are credited with the trait of agency (Baird and Maruping 2021), creating a situation comparable to the principal-agent problem as their decision logic is self-trained (self-interest) and intransparent to the principal. This results in an information asymmetry between the user (principal) and the intelligent system (agent). This information asymmetry constitutes a major barrier for intelligent system acceptance and initial trust in intelligent systems (McKnight et al. 2002; McKnight et al. 1998), because the system cannot provide credible, meaningful information about or affective bonds with the agent (Bigley and Pearce 1998).

Altogether, this lack of transparency and subsequently trust can be a hindrance when delegating tasks or decisions to an intelligent system (Wanner et al. 2020a). More specifically, the adoption of AI currently remains rather hesitant (Chui and Malhotra 2018; Duscheck et al. 2017; Milojevic and Nassah 2018). The result is observable user behavior, such as algorithm aversion, where the user will not accept an intelligent system in a professional context even though it outperforms human co-workers (Burton et al. 2020). While this can be attributed at least partially to lack of control and the information asymmetry due to its black-box nature, we also observe the inverse, algorithm appreciation, and, thus, acceptance and use of intelligent system in other scenarios (Logg et al. 2019).

This is a crucial point, as intelligent systems can only be effective if users are willing to actively engage with them and have confidence in their recommendations. Consequently, it is of great importance to

[14] This paper is under review at the Journal of Information System Research (ISR) as 'A Theoretical Model for Acceptance and Use of Intelligent Systems' (Wanner et al. 202x). The related supplementary material is given in Appendix III.

understand what the intended users of such systems expect and which influences have to be considered for successful adoption.

Explaining the acceptance and use of technological innovations has been a major area of research and practice in the Information Systems (IS) discipline. Over the last several decades, a multitude of theoretical models has been proposed and used for examination. They offer different explanations for technology acceptance and use based on varying factors. Most notably, Venkatesh et al. (2003) introduced the Unified Theory of Acceptance and Use of Technology (UTAUT), which has been used extensively since. Scientists have proposed several extensions and contextual modifications.

With our research, we expand this area and propose an explanatory model that explores, in particular, the role of transparency and trust in technology acceptance of intelligent systems (e.g., Adadi and Berrada 2018; Miller 2019; Rudin 2019). We do so by extending and modifying the well-known UTAUT model to fit the nature of intelligent systems and to understand the human attitude towards them.

Thereby, we offer two key contributions. First, we provide an extension to the UTAUT model for the context of intelligent system. It can serve as a starting point for research in distinct industries, for example, industrial maintenance. Second, by validating established hypotheses, we provide a better understanding of the actual factors that influence the user's adoption of intelligent systems and explain user behavior towards AI-based systems in general. This allows both the use of this knowledge for the (vendor's) design and implementation of intelligent systems and its use for the (customer's) process of software selection.

Our paper is structured as follows: In Section 4.2.2, we introduce the theoretical background for our research. In Section 4.2.3, we describe our research design. In Section 4.2.4, we describe our research theorizing. This includes the review of existing UTAUT research on trust and system explainability as well as the hypothesis and items of the derived constructs and relationships. In Section 4.2.5, we describe the empirical testing of the theoretical derivations and their results. Finally, we discuss the results in Section 4.2.6. Here, we provide implications of our findings for theory and practice before we summarize and offer an outlook on future research in Section 4.2.7.

4.2.2 Theoretical Background

4.2.2.1 Artificial Intelligence and Intelligent Systems

AI is an umbrella term for any technique that enables computers to imitate human intelligence and replicate or surpass human decision-making capacity for complex tasks (Russell and Norvig 2020).

In the past, AI focused on handcrafted inference models known as symbolic AI or the knowledge-based approach (Goodfellow et al. 2016). While this approach is inherently transparent and enabled trust in the decision process, it is limited by the human's capability to explicate their tacit knowledge relevant to the task (Brynjolfsson and Mcafee 2017). More recently, ML and deep learning algorithms have overcome these limitations by automatically building analytical models from training data (Janiesch et al. 2021). However, the resulting advanced analytical models often lack immediate interpretability constituting an information asymmetry to the user.

Intelligent systems implement ML algorithms to enable decision-making in applications with human-like cognitive capacity. They inherit characteristics associated with new, revolutionary technologies, including technology-related anxiety and alienation of labor through a lack of comprehension and a lack of trust (Mokyr et al. 2015). Hence, when facing these properties, due to effectance motivation, the human has a "desire to reduce uncertainty and ambiguity, at least in part with the goal of attaining a sense of predictability and control in one's environment" (Epley et al. 2007).

4.2.2.2 Transparency and Trust in Intelligent Systems

Trust in the context of technology acceptance has widely been studied and derived from organizational trust towards humans. Notably, besides the core construct of the cognition-based trust in the ability of the system, additional affect-based trust aspects like the general propensity to trust technology and the believed goodwill or benevolence of the trustee towards the trustor (Lee and Turban 2001). While it can be argued that the system has no ill will by itself, in the case of black-box systems, we cannot observe whether it acts as intended, possibly hindering initial trust formation (Dam et al. 2018).

Building trust in new technologies is initially hindered by unknown risk factors and thus uncertainty, as well as a lack of total user control (McKnight et al. 2011). The main factors in building initial trust are the ability of the system to show possession of the functionalities needed, to convey that they can help the user when needed, and to operate consistently (Mayer et al. 1995; McKnight et al. 1998).

For human intelligence, it is generally an important aspect to be able to explain the rationale behind one's decision, while simultaneously, it can be considered as a prerequisite for establishing a trustworthy relationship (Samek et al. 2017). Thus, observing a system's behavior in terms of transparency plays an important role. In IS research, it has been argued that transparency can increase the cognition-based part of trust towards the system (Madsen and Gregor 2000). In addition, system transparency is assumed to have an indirect influence on IS acceptance via trust in the context of recommending a favorable decision to the user (Cramer et al. 2008).

While general performance indicators of ML models can be used to judge the recommendation performance of an intelligent system, the learning process and the inner view of the intelligent system towards the problem can be different from the human understanding, generating a dissonance, suggesting system performance by itself is not sufficient as a criterion (Miller 2019).

Thus, the ML model underlying an intelligent system cannot address these factors itself. Therefore, it is widely suggested that this issue can be alleviated or resolved by providing system transparency by offering explanations of the decision-making process (i.e., global explanations) as well as explanations of individual recommendations (i.e., local explanations) (Adadi and Berrada 2018). The field of explainable AI (XAI) offers augmentations or surrogate models that can explain the behavior of intelligent system based on black-box ML models.

Altogether, the rise of design-based literature on explainable, intelligent systems suggests that the lack of explainability of deep learning algorithms poses a problem for user acceptance, rendering the systems inefficacious (Bentele and Seidenglanz 2015; Nawratil 2006).

It is reasonable to assume that system transparency or its explainability, as well as trust, play a central role when investigating socio-technical aspects of technology acceptance. Furthermore, both seem to be

interrelated to one another. Nevertheless, it is not evident to what extent an increase in the user's perceived system explainability improves the user's trust factor or how this affects the user's technology acceptance of intelligent systems (McKnight et al. 2002; Wang and Benbasat 2016).

4.2.2.3 Technology Acceptance

Technology acceptance has been widely studied in the context of several theoretical frameworks. In its core idea, a behavioral study is used to draw conclusions regarding the willingness of a target group to accept an investigative object (Jackson et al. 1997; Venkatesh et al. 2012).

Davis (1989) utilized the *Theory of Reasoned Action* to propose the *Technology Acceptance Model* (TAM) that explains the actual use of a system through the perceived usefulness and perceived ease of use of that system. It was later updated to include other factors such as subjective norms (Marangunić and Granić 2015). An extension of the theory that includes the additional determinant is the *Theory of Planned Behavior* by Taylor and Todd (1995). As a competing perspective of explanation, the *Model of PC Utilization* includes determinants that are less abstract to the technology application environment, such as job-fit, complexity, affect towards use, and facilitating conditions that reflect on the actual objective factors from the application environment, which can differ largely from case to case. The *Innovation Diffusion Theory* by Rogers (2010) is specifically tailored to new technologies and the perception of several determinants like a gained relative advantage, ease of use, visibility, and compatibility. Furthermore, the *Social Cognitive Theory* was extended to explain individual technology acceptance by determinants like outcome expectancy, self-efficacy, affect, and anxiety (Bandura 2001).

Venkatesh et al. (2003) combined those theories in the *Unified Theory of Acceptance and Use of Technology* (UTAUT). It provides a holistic model that includes adoption theories for new technologies and approaches to computer usage that capture the actual factors of the implementation environment. Here, behavioral intention (BI) acts as an explanatory factor for the actual user behavior. Determinants of *BI* in the UTAUT model are, for example, performance expectancy (PE), effort expectancy (EE), or social influence. UTAUT has been used extensively to explain and predict acceptance and use in a multitude of scenarios (Williams et al. 2015).

Despite the fundamental theoretical foundation, it has become a common practice to form the measurement model for a specific use case given by multiple iteration cycles (e.g, Yao and Murphy 2007). Thus, many authors modify their UTAUT model (e.g., Oliveira et al. 2014; Shahzad et al. 2020; Slade et al. 2015). Typically, an extension is applied in three different ways (Slade et al. 2015; Venkatesh et al. 2012): i) using UTAUT for the evaluation of new technologies or new cultural settings (e.g., Gupta et al. 2008); ii) adding new constructs to expand the investigation scope of UTAUT (e.g., Baishya and Samalia 2020); and/or iii) to include exogenous predictors for the proposed UTAUT variables (e.g., Neufeld et al. 2007). Furthermore, many contributions such as Esfandiari and Sokhanvar (2016) or Albashrawi and Motiwalla (2017), combine multiple extension methods to construct a new model.

Related work of technology acceptance research is primarily focused on e-commerce, mobile technology, and social media (Rad et al. 2018). The intersection with AI innovations is rather small yet. Despite contributions for autonomous driving (e.g., Hein et al. 2018; Kaur and Rampersad 2018) or healthcare (e.g., Fan et al. 2018; Portela et al. 2013), only a few studies exist for industrial applications, such as on

the acceptance of intelligent robotics in production processes (e.g., Bröhl et al. 2016; Lotz et al. 2019). Also, there is the intention to understand the acceptance of augmented reality (Jetter et al. 2018).

Consequently, knowledge about the technology acceptance of intelligent systems is still limited. In particular, *trust* and *system transparency* have not been considered in conjunction as potential factors for technology acceptance of intelligent systems.

4.2.3 Methodological Overview

The focus of our research problem is the adoption of an intelligent system from an end user perspective. It is located at the intersection of two fields of interest: technology acceptance and AI, more specifically XAI.

Figure 34 presents our methodological frame to develop our UTAUT model for the context of intelligent systems. It corresponds to the procedure presented by Šumak et al. (2010), which we modified to suit our objective. We detail the steps in the respective sections.

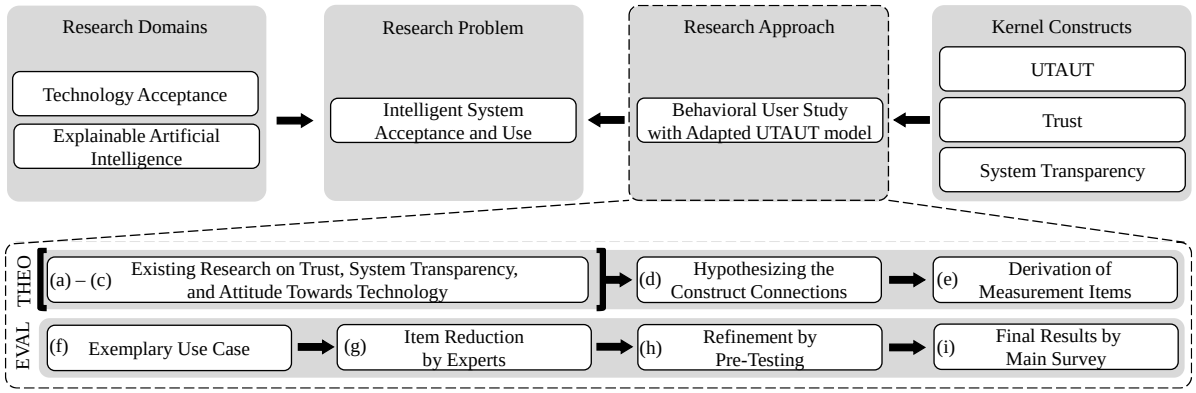


Figure 34. Methodology Overview

The kernel constructs to form our model are derived from the related research on UTAUT, trust, and system explainability. Thus, in the theorizing section (THEO, see Section 4.2.4), we derive a suitable model from existing UTAUT research on (a-c) system transparency, and attitude towards technology. We then (d) hypothesize the derived measurement model constructs and connections based on empirical findings, and we (e) collect potential measurement items.

In the evaluation section (EVAL, see Section 4.2.5), we (f) validate and modify our UTAUT model by using an exemplary application case in the field of industrial maintenance. Further, we (g, h) iteratively adapt it in empirical studies, perform the main study and (i) discuss the results.

As scientific methods, we use empirical surveys (see e.g., Lamnek and Krell 2010) in combination with a structural equations model (SEM) (see e.g., Weiber and Mühlhaus 2014). For the analysis of the SEM, we apply the variance-based partial least squares (PLS) regression (see e.g., Chin and Newsted 1999).

4.2.4 Research Theorizing

In the following, we give an overview of relevant, previous technology acceptance research related to trust and system transparency regardless of its theoretical modeling. This provides us with a wide variety of knowledge to extend UTAUT to the context of intelligent systems in the best possible way.

4.2.4.1 Trust Extensions in UTAUT

While trust has been widely recognized as an important factor in information system usage in TAM theory, the UTAUT model does not account for trust in its original form (Carter and Bélanger 2005). While several extensions of the UTAUT model have been proposed to address this drawback, both the inclusion and definition vary among research contributions (Venkatesh et al. 2016). Table 27 depicts a summary of UTAUT extensions regarding the construct of trust.

We can characterize these extensions by inclusion type regarding the dependent variables, which are affected by the trust construct in the respective UTAUT model. Endogenous inclusion refers to a direct connection between trust and *BI*, while exogenous inclusion refers to an indirect relationship through other variables. Furthermore, we indicate which determinants are included for the trust variable itself.

Table 27. Trust-based UTAUT Extensions

Inclusion Type	Dependent Variables	Determinants	Example References
Endogenous	BI	None	Alaiad and Zhou (2013); Carter and Bélanger (2005); Oh and Yoon (2014)
		Personal Propensity to Trust	Oliveira et al. (2014)
		Trust Integrity, Trust Ability	Komiak and Benbasat (2006)
		Trust Property, Satisfaction	Kim (2014)
Exogenous	PE	Trust Benevolence, Trust Integrity, Trust Ability	Cheng et al. (2008); Lee and Song (2013)
	Perceived Usefulness	Perceived Ease of Use, Consumer Decision Making	Xiao and Benbasat (2007)
	Perceived Risk, Perceived Usefulness	System Transparency, Technical Competence, Situation Management	Choi and Ji (2015)
Endogenous/ Exogenous	Perceived Risk, BI	None	Slade et al. (2015)
	PE, BI	Trust Benevolence, Trust Integrity, Trust Ability	Cody-Allen and Kishore (2006)

In terms of trust-based model components, we found i) several theoretical approaches to describe trust itself; ii) multiple determinants of the embedded trust construct (determinants); iii) several different ways of embedding trust into existing technology acceptance models such as TAM or UTAUT (inclusion type/ dependent variable).

While a majority of contributions (e.g., Oh and Yoon 2014) include trust as a single variable with no determinants in an endogenous manner, other studies (e.g., Cheng et al. 2008) adopted more complex theoretical frameworks. McKnight and Chervany (2000) present a frequently adopted framework. They define a model to represent trusting beliefs by building upon trust perception theory by Mayer et al. (1995). In this model, trust is represented by three variables: *disposition to trust, institution-based trust*, and *trusting beliefs* (TB). Disposition to trust is the general tendency to trust others, in this case, an

intelligent system. Institution-based trust refers to the contextual propitiousness that supports trust, indicating an individual's belief in good structural conditions for the success of the system. *TB* indicates an individual's confidence in the system to fulfill the task as expected (Mayer et al. 1995; Vidotto et al. 2012).

Each of these constructs is then, among other factors, determined by *trust benevolence*, *trust integrity*, and *trust ability* (TA). *TA* refers to the system's perceived competencies and knowledge base for solving a task, that is, trust in the ability of the system. Trust integrity involves the user's perception that the system acts according to a set of rules that are acceptable to him or her. Trust benevolence is indicated to be the belief in the system to do good to the user beyond its own motivation (Cheng et al. 2008; Mayer et al. 1995; McKnight and Chervany 2000).

Considering the problem of a complex, intelligent system that mimics human functions, we adopted the unified model of McKnight et al. (2002) and made several modifications. First, we define trust in the context of intelligent systems as an aggregation of beliefs that allow a professional to become vulnerable to an intelligent system willingly after having considered its characteristics. Second, we solely model *TB* as it is the component that directly measures trust in the system itself rather than environmental factors and personal factors that are covered by facilitating conditions and moderators of the core UTAUT model already. Third, we model *TB* as a direct influence factor of *BI* and as an exogenous factor for *PE*. Last, we omit the determinants trust benevolence and trust integrity, since a system, no matter how many functions or tasks are assigned, has no hidden intention to extend its tasks beyond its programming and cannot change its "promise" by itself.

4.2.4.2 System Transparency Extensions in UTAUT

Especially in recent years, *system transparency* (ST), as the backbone of an XAI's system explainability, has been increasingly integrated into studies of technology acceptance of intelligent systems and seems to have a direct influence on the perceived trust of users (e.g., Nilashi et al. 2016; Peters et al. 2020). Table 28 depicts a summary of UTAUT extensions regarding the construct of *ST*.

Table 28. System-Transparency-based UTAUT Extensions

Inclusion Type	Dependent Variables	Determinants	Example References
Exogenous/ Endogenous	Trust, BI	None	Brunk et al. (2019); Slade et al. (2015); Choi and Ji (2015); Hebrado et al. (2011); Hebrado et al. (2013)
	Trust, BI	Explanation	Nilashi et al. (2016)
	Trust, BI	Accuracy, Completeness	Peters et al. (2020)
	ATT, Trust, BI	None	Shahzad et al. (2020)
	Understanding, BI, Users' Privacy Concerns	None	Zhao et al. (2019)
	TB, Understanding, Competence, Acceptance	None	Cramer et al. (2008)
	TA, Information Satisfaction	Accuracy, Completeness, Time Information Currency	Cody-Allen and Kishore (2006)
	EE, TB	None	Wang and Benbasat (2016)

We can characterize these extensions regarding the dependent variables, which are affected by the *ST* construct in the respective UTAUT model. Again, we found only references for the exogenous/

endogenous inclusion type. Similarly, we indicate which determinants are included for the transparency variable itself.

Among others, Brunk et al. (2019) and Hebrado et al. (2013) define *ST* as a factor to increase the user's understanding of how a system works. It further entails an understanding of the system's inner working mechanisms. That is why specific recommendations were made according to different characteristics and assumptions for a single item (Nilashi et al. 2016; Peters et al. 2020) as well as the system's overall decision logic (Hebrado et al. 2011). Furthermore, *ST* should be used for required justifications (Shahzad et al. 2020).

Nevertheless, the influence of other factors on *ST* differs in these models. While many contributions, such as Brunk et al. (2019) and Peters et al. (2020), take no further factors into account, Nilashi et al. (2016) consider the type of explanation and the kind of presented information. They measure the factor of explanation through the level of explainability according to the user's perception and, thus, how and why a recommendation was made and the interaction level within the recommendation process. For Shahzad et al. (2020), it is about characteristics of the information quality, such as for example accuracy and completeness, which influence *ST*.

Further, we noticed *ST* influences many factors: *BI*, *PE*, *EE*, and trust. As argued above, the factor of trust can be subdivided into *TB* and *TA*. Here, it is assumed that a highly transparent decision-making process results in an increasing *TB* (Cramer et al. 2008), while also increasing transparency results in a better *TA* of the user (Cody-Allen and Kishore 2006). *BI* is defined as the degree to how a user's intention changes through the level of *ST* (Peters et al. 2020). Lastly, an increase in *ST* results in a clearer assessment by the user, and thus the user's mental model assumes a higher performance of the system leading to increased *PE*. Likewise, a transparent system can reduce a user's efforts to understand the systems' inner working mechanisms (Wang and Benbasat 2016).

4.2.4.3 Attitude Towards Technology Extensions in UTAUT

Consistent with the theory of planned behavior, an individual's *attitude towards technology* (ATT) has been found to act as a mediating construct (Dwivedi et al. 2019; Kim et al. 2009; Yang and Yoo 2004). People are said to be more likely to accept technology when they can form a positive attitude towards it. It is important to note that the construct *ATT* is usually placed between the endogenous variables in the UTAUT context (e.g., *PE* and *EE*) and intention to use (e.g., *BI*). Furthermore, we believe that *ATT* is influenced the individual's pre-formed opinion about a popular technology. The prevailing opinion that forms into attitude is not changed easily and depends on an individual's prior exposure to the technology (Ambady and Rosenthal 1992). Factors accumulated in *ATT* can be religious beliefs, job security, attitude carried over from popular culture, as well as knowledge and familiarity and privacy, and relational closeness (Persson et al. 2021). Thus, it acts as a place to collect emotional attitude towards a technology, which in the case of AI is reinforced by its anthropomorphic and intransparent nature. While some studies show that not all of these factors are present in an individual's mind, general states of mind like fear towards the technology can influence and form the person's attitude (Dos Santos et al. 2019; Kim 2019). Thus, we argue to include *ATT* and hypothesize that the mediation strength and thus indirect connections to *ATT* are increasingly present for intelligent systems.

4.2.4.4 Model and Hypotheses

As a result of the above construct derivation, we present our UTAUT model for intelligent systems along with the hypotheses and their respective direction (- or +) in Figure 35. The measurement model can be divided into three major parts: i) UTAUT core (*PE*, *EE*, and *BI*), ii) UTAUT AI (*TA*, *TB*, *ST*, and *ATT*), and iii) moderators (gender, age, experience).

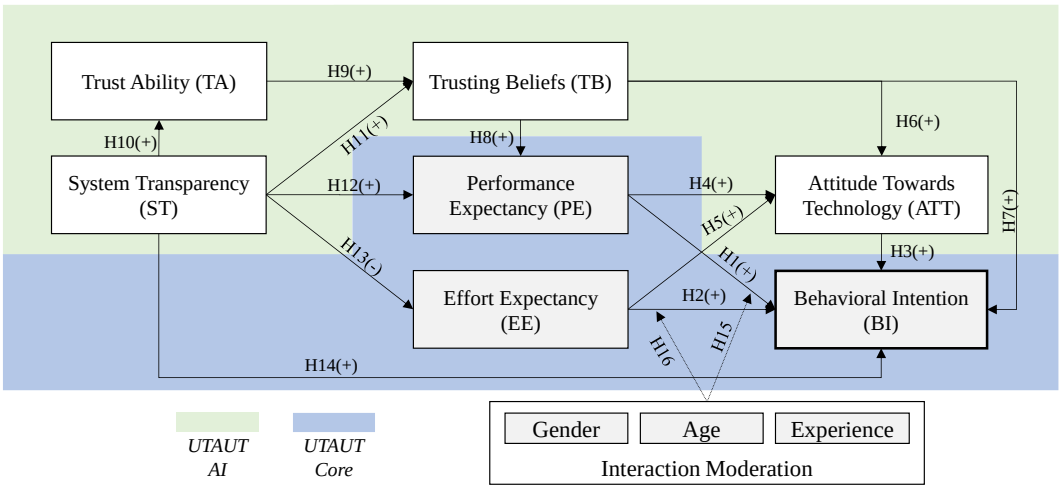


Figure 35. Derived Acceptance Model for Intelligent Systems

The derivation of the hypotheses from i) UTAUT core research is primarily based on general research on UTAUT (e.g., Dwivedi et al. 2019; Venkatesh et al. 2003). Nevertheless, these construct interrelations can also be found in UTAUT studies on trust or system transparency (e.g., Lee and Song 2013; Wang and Benbasat 2016).

The construct *BI* represents our target variable. It measures the strength of a user's intention to perform a specific behavior (Fishbein and Ajzen 1977). Here, it is about the willingness of a user to adopt an intelligent system. The construct is influenced endogenously by the two basic UTAUT constructs of *PE* and *EE*. *PE* measures the degree to which an individual believes that using the system will help to attain gains in job performance. This includes factors such as perceived usefulness, job-fit, relative advantage, extrinsic motivation, and outcome expectation (Venkatesh et al. 2003). *EE* measures the degree of ease associated with the use of the system, including factors such as perceived ease of use and complexity (Venkatesh et al. 2003). For both constructs, we assume that they have a positive influence on *BI*. This correlation can be seen in UTAUT (e.g., Dwivedi et al. 2019; Venkatesh et al. 2003) as well as in UTAUT model studies on trust and on *ST* (Cheng et al. 2008; Cody-Allen and Kishore 2006; Lee and Song 2013; Wang and Benbasat 2016). Thus, we state:

H1: *Performance Expectancy positively affects Behavioral Intention.*

H2: *Effort Expectancy positively affects Behavioral Intention.*

The hypotheses of ii) UTAUT AI, and thus, for *ATT*, *TA*, *TB*, and *ST* are primarily based on the references from Table 27 and Table 28 as well as Venkatesh et al. (2003)'s considerations.

ATT is defined as an user's overall affective reaction to using a technology or system (Venkatesh et al. 2003). While the authors did not include *ATT* in his final model, it is regularly used in the context of

decision support systems. UTAUT research, as well as TAM research on trust, indicate that *ATT* has a positive effect on *BI* (e.g., Chen 2013; Hwang et al. 2016; Mansouri et al. 2010). That is, people form intentions to engage in behaviors to which they have a positive attitude (Dwivedi et al. 2019). Inversely, it is assumed that both *PE* and *EE* have a positive influence on a user's *ATT*. Suleman et al. (2019) derive this significantly positive influence from the TAM research (Hsu et al. 2013; Indarsin and Ali 2017) and later confirm it in their own research. Dwivedi et al. (2019) and Thomas et al. (2013) confirm the connection. We summarize these findings by our next hypotheses:

H3: *Attitude Towards Technology positively affects Behavioral Intention.*

H4: *Performance Expectancy positively affects Attitude Towards Technology.*

H5: *Effort Expectancy positively affects Attitude Towards Technology.*

Trust is regarded as a necessary prerequisite to forming an effective intelligent system (e.g., Dam et al. 2018) and, thus, it is a crucial construct to building our model. In Section 4.2.4.1, we have explained that two subtypes of trust are particularly important in our context: *TA* and *TB*. *TA* measures the assumed technical competencies of the system to solve a task (Schoorman et al. 2007). *TB* is about the user's confidence in the system to fulfill a task as expected (Mayer et al. 1995). For *TB*, we expect a positive effect on *ATT* and on *BI*, as preliminary trust-based UTAUT extensions indicate (e.g., Ha and Stoel 2009; Indarsin and Ali 2017). For Suleman et al. (2019), *TB* was the most influential and significant factor affecting a participant's *ATT*. The positive influence of *TB* on *BI* is well proven by several UTAUT studies (Choi and Ji 2015; Lee and Song 2013). We summarize this with the next hypotheses:

H6: *Trusting Beliefs positively affects Attitude Towards Technology.*

H7: *Trusting Beliefs positively affects Behavioral Intention.*

In turn, we assume that *TA* has a positive influence on a user's *TB*, which in turn has a positive influence on *PE*. However, the direction of the latter construct linkage is disputed in prior research. While Oliveira et al. (2014), Nilashi et al. (2016), and Wang and Benbasat (2016) assume that *PE* has a positive influence on *TB*, Cody-Allen and Kishore (2006), Lee and Song (2013), and Choi and Ji (2015) think that *TB* affects *PE*. Yin et al. (2019) show that people's confidence in a third party's decision-making increases when the observed performance of that third party, here the intelligent system, is higher than their own expected decision rating for it. Therefore, we assume a positive influence of *TB* on *PE*. The influence of *TA* on *TB* derived from the general trust perception theory by Mayer et al. (1995) is not disputed. Cramer et al. (2008) or Choi and Ji (2015) show examples of a positive effect. Accordingly, we formulate our hypotheses:

H8: *Trusting Beliefs positively affects Performance Expectancy.*

H9: *Trust Ability positively affects Trusting Beliefs.*

Trust – as a multifaced term – is assumed to have a strong correlation with *ST* (e.g., Dam et al. 2018). *ST* measures the user's understanding of how the decision logic of a system works (Hebrado et al. 2011). In other words, it represents the why of an intelligent system's decision considering its inner decision logic as well as the characteristics that determine a certain result. As the user of such an intelligent system decides whether or not to adopt the system recommendation, *ST* might influence his/her decision-making process. We expect a positive effect of *ST* on *TA* and *TB* based on the findings of Pu and Chen

(2007) and Wang and Benbasat (2016). The former found that users assign a recommender system a higher level of competence if the decision-making process is explained, which is traceable. The latter is supported by the preliminary UTAUT research of Brunk et al. (2019), Hebrado et al. (2013), Nilashi et al. (2016), Peters et al. (2020), and Chen and Sundar (2018). For example, Peters et al. (2020) found that *ST* significantly positively influenced trust in the intelligent system in the context of testing the consumer's willingness to pay for transparency of such black-box systems. We conclude with the hypotheses:

H10: *System Transparency positively affects Trust Ability.*

H11: *System Transparency positively affects Trusting Beliefs.*

Technology acceptance research supposes that *ST* also influences the residual UTAUT constructs of *PE*, *EE*, and *BI*. We derive the assumed positive effect of *ST* on *PE* from Zhao et al. (2019), who revealed that a higher level of a DSS supports the user's perception of the performance of that system. We assume a negative effect for the influence of *ST* on *EE*. If users understand how a system works and how calculations are performed, they will perceive that the use of the system requires more effort (Gretzel and Fesenmaier 2006). We expect a positive influence of *ST* for *BI*. Making the reasoning behind a recommendation transparent allows for an understanding of the recommendation process, which significantly increases acceptance (Bilgic and Mooney 2005). This significant and strong influence is also reflected in further studies by Venkatesh et al. (2016) and Hebrado et al. (2011). From this, we derive the following hypotheses.

H12: *System Transparency positively affects Performance Expectancy.*

H13: *System Transparency negatively affects Effort Expectancy.*

H14: *System Transparency positively affects Behavioral Intention.*

The hypothesis for the iii) moderators are also part of the original UTAUT model according to Venkatesh et al. (2003).

We assume that *gender*, *age*, and *experience* have a moderating effect on the constructs of *PE*, *EE*, and *BI*. We derive this assumption from the initial UTAUT model (Venkatesh et al. 2003). It has been confirmed in several other UTAUT studies (e.g., Alharbi 2014; Esfandiari and Sokhanvar 2016; Wang and Benbasat 2016). We address this through two more hypotheses:

H15: *Gender, Age, and Experience moderate the effects of PE on BI.*

H16: *Gender, Age, and Experience moderate the effects of EE on BI.*

4.2.5 Research Evaluation

4.2.5.1 Study Use Case

In the following, we offer an exploration of the theoretical constructs put forward. For this purpose, we defined a real-life use case and transferred it to the UTAUT model in a step-by-step procedure. In this way, we validate the applicability of our proposed model. Moreover, we gain first insights into the user's willingness to accept intelligent systems at their workplace.

We consider industrial machine maintenance to be a suitable scenario. Its focus is to maintain and restore the operational readiness of machinery to keep opportunity costs as low as possible. In contrast to reactive strategies, anomalous machine behavior can be identified and graded early using statistical techniques to avoid unnecessary work. Given the technological possibilities to collect large and multifaceted data assets in a simplified manner, intelligent systems based on machine learning are a promising alternative for maintenance decision support (Carvalho et al. 2019b).

In this context, rolling bearings are used in many production scenarios of different manufacturers. For example, they are often installed in conveyor belts for transport or within different engines and show signs of wear and tear over time that requires maintenance (Pawellek 2016).

For our evaluation, we decided to use an automated production process to manufacture window and door handles, as these are common everyday items every respondent can relate to. In our scenario, there shall be several production sections connected by high-speed conveyor belts. Inside these conveyor belts, several bearings are installed. These are monitored by sensors to monitor change (e.g., noise sensor, vibration, and temperature). A newly introduced intelligent system evaluates this data automatically. In case of anomalous data patterns, a dashboard displays warnings and errors with concrete recommendations for action (cf. Appendix III).

The respondents of the survey(s) shall be confronted with a decision situation that tests whether or not the user adopts the system recommendation in his or her own decision-making process. That is, they need to decide for or against an active intervention in the production process as recommended by the system. In an extreme case, the optical condition of the conveyor belt bearings is perceived as good. However, the system recommends that the conveyor belt must be switched off immediately. This error does not occur regularly, and the message contradicts the previous experience of the service employee (here, the respondent) with this production section. As additional information, we provide the reliability of the system recommendations and hint at the high follow-up costs in case of a wrong decision.

4.2.5.2 Study Design

Our design and conduct of the survey are based on Šumak et al. (2010), which we modified to our objective. We used five steps to obtain our study results: i) collection of established measurement items; ii) pre-selection by author team; iii) reduction by experts; iv) evaluation and refinement through pre-study; and v) execution of the main study.

See Appendix III for the results of each step as well as primary and secondary source(s) for all measurement items. A more detailed result table of the validity and reliability measures of the pre-study and main study is available in Appendix III.

Step i). First, we collected those measurement items that already exist for the respective constructs of interest and are, thus, empirically proven.

As we adopted *PE*, *EE*, and *BI* from Venkatesh et al. (2003), we built on their findings. Venkatesh et al. (2003) chose the measurement items for UTAUT by conducting a study and testing the measurement items for consistency and reliability. For the additional constructs *ATT*, *ST*, *TA*, and *TB*, we examined the source construct measurement items as well as examples of secondary literature and derived constructs. Initially, we used three items to form the construct of ATT – one was adopted from Davis et al.

(1992) and two from Higgins and his co-authors (Compeau et al. 1999; Thompson et al. 1991). As we derived *ST* from perceived understandability as well as perceived transparency, we initially included five items from Madsen and Gregor (2000) in addition to two items from Cramer et al. (2008). The measurement items for *TA* and *TB* were derived from McKnight et al. (2002) (trust benevolence) and Lee and Turban (2001) (trust propensity).

Step ii). Next, we discussed the appropriateness of each of the collected measurement items within the team of authors.

The team members merge knowledge in the respective domains of industrial maintenance, technology acceptance, and (X)AI research. Special attention was paid to the duplication of potential item questions and their feasibility for the use case. We reduced the total number of measurement items for the model's constructs from 71 to 24.

Step iii). Subsequently, we conducted an expert survey with practitioners from industrial maintenance regarding our intended main study.

The survey with ten experts had two goals: reduction of the remaining measurement items and gaining an understanding of the explainability of intelligent system dashboards. For the former, we explained each of the model measurement constructs briefly to the experts. Subsequently, the experts had to select the most appropriate remaining measurement items for the use case per measurement construct. They were given at least one vote and at most votes for half the items. Then, we selected the final measurement items based on a majority vote. For the latter, we presented the experts with four different maintenance dashboards of intelligent systems as snapshots adapted from typical software in the respective field (e.g., Aboulian et al. 2018; Moyne et al. 2013). Here, the experts rated their perceived level of explanation goodness on a seven-point Likert scale and chose their favorite dashboard. This ensured that the dashboard for the quantitative survey has inherent explainability and thus provides enhanced system transparency (cf. Appendix III).

Step iv). Then, we conducted a quantitative pilot study to examine our questionnaire and research design critically (Brown et al. 2010). The testing includes checks for internal consistency, convergent reliability, indicator reliability, and discriminant validity.

The study contained 60 valid responses. Here, we ensured representative respondents, that is, maintenance professionals holding a position to use an intelligent system for their job-related tasks (e.g., experience in maintenance). We provided the participants with a description of the exemplary use case and screenshots of the prototype. We asked them to respond to their perceptions of each of the measurement items on a five-point Likert scale. See Table 29 for the assessment of measurement items and Appendix III for a summary of our decisions on individual items.

Table 29. Validation and Reliability Testing of Pre-Study

Constr.	Assessment Measurement Items					
	CA	**AVE**	**CR**	**FL Criterion**	**Cross-Loadings**	**Item Loadings**
PE	0.86	0.64	0.90	-	-	-
EE	0.74	0.57	0.84	-	-	EE1
ST	**0.67**	0.75	0.86	-	-	-
TB	**0.23**	0.56	**0.67**	-	TB4 (*BI*)	TB3, 4
TA	0.74	0.66	0.85	-	-	-
ATT	**0.67**	0.59	0.81	-	-	ATT2
BI	0.83	0.74	0.89	-	-	-
Internal consistency: Cronbach's alpha (CA) > 0.7; composite reliability (CR) > 0.7 (Gefen et al. 2000; Hair et al. 2011) *Convergence reliability*: average variance extracted (AVE) > 0.5 (Hair et al. 2011) *Indicator reliability*: item loadings 0.7<x<1 (Hair et al. 2011) *Discriminant validity*: cross-loadings; Fornell-Larcker (FL) criterion (Fornell and Larcker 1981; Hair et al. 2011)						

Step v). We conducted our main quantitative study in January 2021. Table 30 comprises the final set of measurement items. We, again, checked for internal consistency, convergent reliability, indicator reliability, and discriminant validity. Further, we included control questions (CQ) following Meade and Craig (2012) and Oppenheimer et al. (2009) to increase result validity.

Table 30. Final Set of Measurement Items for Main Study

Cons.		Measurement Item	Reference(s)
PE	PE1	Using this system in my job would enable me to accomplish tasks more quickly.	Davis (1989)
	PE2	Using this system would improve my job performance.	
	PE3	Using this system would make it easier to do my job.	
	PE4	I would find this system useful in my job.	
	PE5	Using this system would increase my productivity.	Moore and Benbasat (1991)
EE	EE1	Learning to operate this system would be easy for me.	Davis (1989)
	EE2	I would find it easy to get this system to do what I want it to do.	
	EE3	My interactions with this system would be clear and understandable.	
	EE4	I would find this system easy to use.	
ATT	ATT1	The actual process of using this system would be pleasant.	Davis et al. (1992)
	ATT2	This system would make work more interesting.	Thompson et al. (1991)
	ATT3	I would like to work with this system.	Compeau et al. (1999)
	ATT4	Using the system would be a bad/good idea.	Peters et al. (2020); Taylor and Todd (1995)
	ATT5	Using the system would be foolish/wise move.	
BI	BI1	If this system was available to me, I would intend to use this system in the future.	Venkatesh et al. (2003)
	BI2	If this system was available to me, I predict I would use this system in the future.	
	BI3	If this system was available to me, I would plan to use this system in the future.	
ST	ST1	I would understand how this system will assist me with decisions I have to make.	Madsen and Gregor (2000)
	ST2	I would understand why this system provided the decision it did.	Cramer et al. (2008)

	ST3	I would understand what this system bases its provided decision on.	
TA	TA1	This system would be competent in providing maintenance decision support.	Cheng et al. (2008); McKnight et al. (2002)
	TA2	This system would perform maintenance decision support very well.	
	TA3	In general, this system would be proficient in providing maintenance decision support.	
TB	TB1	It would be easy for me to trust this system.	Cheng et al. (2008); Lee and Turban (2001); Wang and Benbasat (2007)
	TB2	My tendency to trust this system would be high.	
	TB3	I would tend to trust this system, even though I have little or no knowledge of it.	
CQ	CQ1	I would not find this system easy to use.	-
	CQ2	Although I may would not know exactly how this system works, I would know how to use it to make decision regarding the quality of its output. Please do not rate this statement and please choose scale point one instead to ensure the data quality of this survey. This only applies to this question.	Meade and Craig (2012)
	CQ3	I have read all questions carefully and answered truthfully.	
	CQ4	Thank you for taking the time to participate in this survey. We end the survey by capturing data about the demographics of the participants. As such, data about gender, age, and experience in the topic of the survey is being collected. In addition, we want to make sure the collected data is reliable. Please select the option "No answer" for the next question that asks about the length of the survey and simply write "I've read the instructions" in the box labeled "Additional remarks".	Oppenheimer et al. (2009)

We acquired a total of 240 participants who completed the questionnaire via the academic survey platform *prolific.com*. Out of this sample, 240 respondents answered CQ1 correctly. Twenty-three respondents failed CQ2. For CQ3 and CQ4, we decided to add a tolerance of ±1 point. The scale for CQ3 was inverted, and answers compared to PE4, while answers for CQ4 were compared to TB1. The final dataset consists of 160 samples. The average participant was male and 35.8 years old with 2.6 years of experience in industrial maintenance as well as with AI.

All constructs achieved reliability and validity across all measurements. Values for Cronbach's alpha, average variance extracted, and composite reliability are well above their respective thresholds. Item ATT2 was below this limit for item loadings ($0.59 < 0.7$) and was thus excluded from the measurement model, resulting an overall good reliability of ATT. We did not observe any cross-loadings, and none of the constructs failed the Fornell-Larcker criterion (cf. Table 31). See Appendix III for null validation and reliability testing results.

Table 31. Validation and Reliability Testing of Main Study

Constr.	Assessment Measurement Items					
	CA	AVE	CR	FL Criterion	Cross-Loadings	Item Loadings
PE	0.91	0.74	0.93	-	-	-
EE	0.85	0.70	0.90	-	-	-
ST	0.87	0.80	0.92	-	-	-
TB	0.85	0.77	0.91	-	-	-
TA	0.89	0.82	0.93	-	-	-
ATT	0.86	0.71	0.91	-	-	-
BI	0.95	0.90	0.97	-	-	-

Internal consistency: Cronbach's alpha (CA) > 0.7; composite reliability (CR) > 0.7 (Gefen et al. 2000; Hair et al. 2011)

Convergence reliability: average variance extracted (AVE) > 0.5 (Hair et al. 2011)

Indicator reliability: item loadings 0.7<x<1 (Hair et al. 2011)

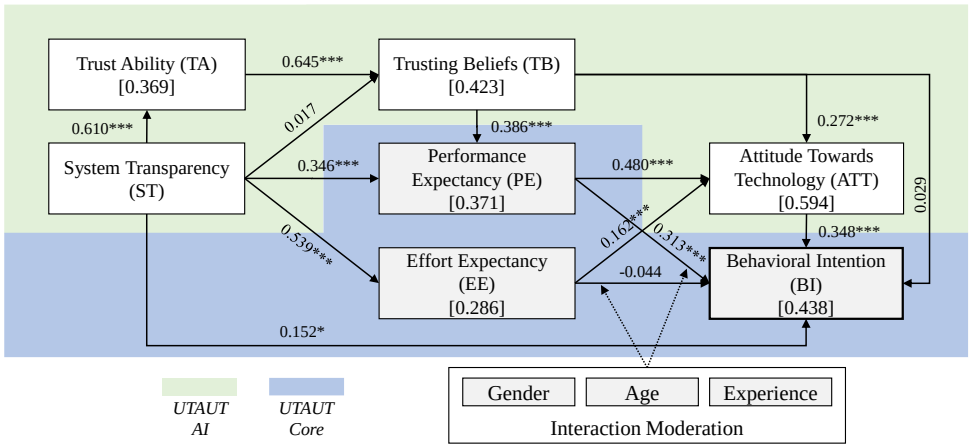
Discriminant validity: cross-loadings; Fornell-Larcker (FL) criterion (Fornell and Larcker 1981; Hair et al. 2011)

4.2.5.3 Study Results

In the following, we present the results from the main study. The estimated model with *direct effect* estimates is depicted in the upper part of Table 32, while the lower part contains the observed *indirect effects*.

Table 32. Results of Main Study

UTAT Results



Indirect Effects

Construct	Indirectly Effecting	Strength	p-Value
EE	BI	0.056	0.059
PE	BI	0.167	0.003
ST	ATT	0.441	0.000
ST	BI	0.278	0.000
ST	PE	0.159	0.000
ST	TB	0.394	0.000
TA	ATT	0.295	0.000
TA	BI	0.198	0.000
TA	PE	0.249	0.000
TB	ATT	0.185	0.000
TB	BI	0.268	0.000

4.2.5.3.1 The Role of UTAUT Core Constructs

First, we examine the role of the initial exogenous UTAUT constructs *PE* and *EE*. In accordance with Venkatesh et al. (2016) and Dwivedi et al. (2019), *PE* is connected significantly to *BI*. While we observe this effect of *PE* with magnitude 0.313, we cannot confirm a significant effect of *EE* on *BI*. Thus, we can confirm H1 but reject H2. However, we can confirm a significant effect from *ATT* to *BI* in its exogenous role with an effect strength of 0.348. With the established confirmation of H3, we can observe a significant effect of magnitude 0.162 from *EE* to the construct *ATT* in its endogenous role, resulting in an indirect relationship to *BI*. Likewise, with a comparably more substantial effect than its direct connection (0.480), *PE* affects *ATT* significantly. We can therefore confirm H4 and H5, respectively. Comparing the bias-corrected confidence intervals of *EE* to *BI* (width 0.338, from -0.218 to 0.120) and *EE* to *ATT* (width 0.25, from 0.027 to 0.278) further strengthen the notion that *EE* affects *BI* rather indirectly through *ATT* in our context of intelligent systems, confirming results by Dwivedi et al. (2019) and Thomas et al. (2013).

4.2.5.3.2 The Role of User's Attitude Towards Intelligent Systems

Since *ATT* is defined as an affective reaction, we conclude that this construct has increased presence in the case of intelligent systems, resulting in its role as a transitory connection of *EE* and *PE* to *BI*. It is reasonable to assume that a user is less affectionate about AI technology when it seems to be complicated to use. However, since intelligent systems are attributed with black-box properties, the ease of use can be difficult to determine beforehand. Hence, a direct connection between *EE* and *BI* seems less likely in the case of intelligent systems. The strong indirect relationship of *PE* to *BI* via *ATT* can be strengthened further by the notion of algorithm appreciation. Logg et al. (2019) found that an algorithmic system that is perceived as complex is expected to have high performance, preferable to that of humans. Thus, the increased *PE* will positively influence their *ATT* before an intention to use is formed. Contrary, the notion of algorithm aversion, as expressed by Castelo et al. (2019) can cause the *PE* to drop if it is observed or expected that the system errs, resulting in a transitory decrease of positive attitude towards the system and making it less likely for the intelligent system to be used. This can be explained by the feeling of missing control over the (partially) autonomous intelligent system (Dietvorst et al. 2015).

4.2.5.3.3 The Role of Trust Towards Intelligent Systems

Further, we examine the role of the trust-related exogenous constructs. We observe a significant effect from *TB* on *ATT* with a strength of 0.272. Again, we assume an indirect relation to *BI* through *ATT*, since the direct effect of *TB* on *BI* is not significant. This confirms that, especially in the context of intelligent systems, trust influences the affection towards technology and, in a transitory fashion, the intention to use said technology. In addition, both *TB* and *ATT* are highly affection-based constructs, and thus a connection between them seems highly appropriate. We can therefore confirm H6 and reject H7. We also found that *TB* has an effect on *PE* with a magnitude of 0.345. The confidence interval (width 0.269, from 0.239 to 0.508) confirms a strong effect along with hypothesis H8. The observations are in accordance with the findings of Cody-Allen and Kishore (2006), Lee and Song (2013), Choi and Ji (2015) and thus confirm H8. Drawing from the findings of Logg et al. (2019), we can explain the

increase in trust through algorithm appreciation that occurs with increasing performance of the algorithm. Thus, if a user experiences a well-performing intelligent system, the user is more likely to increase trust in the system subsequently. To no surprise, also the user's pre-existing level of trust in the algorithm's ability to perform well, *TA*, has a very strong effect on *TB* with a magnitude of 0.645, confirming H9.

4.2.5.3.4 The Role of Transparency of Intelligent Systems

Finally, we investigate the role of system transparency. Regarding the trust constructs *TA* and *TB*, we can confirm H10 since we observe a very strong effect of *ST* on *TA* with a magnitude of 0.610. However, we cannot confirm a significant direct connection from *ST* to *TB* and, thus, reject H11. This is not surprising since we expect the user to form trusting beliefs based on the pre-existing trust in the system's ability that can be better assessed when the user has access to an explanation of the system or the underlying algorithms.

Regarding the initial UTAUT indicators, we find that an understanding of the system does also affect the expected performance, as we observe a strong effect of 0.346 of *ST* on *PE*, confirming H12. The effect can be explained by the influences of explanations on perceived performance and decision towards an intelligent system as described by Wanner et al. (2020a) through the means of local and global explanations. Through a global explanation of the intelligent system, the user is made aware of its complexity, which can lead to increased performance expectancy using the fact that intelligent systems based on deep learning models are expected to outperform other systems. Likewise, local explanations that explain a single prediction enable a consensus between the mental model of the user and the system resulting in increased *PE*. An even more potent effect of *ST* was observed regarding *EE* with magnitude 0.539 and confirming H13. Revealing the complexity of the system through global explanations also enables the user to realize the effort required to implement an intelligent system, thus increasing *EE*. Besides, we observe a direct effect of *ST* on *BI*, confirming H14 at the .10 significance level with a magnitude of 0.152. These results are in line with Wanner et al. (2020a), who indicate that explainability plays a key role when deciding on an intelligent system. The direct effect is rather low compared with the indirect effect via *PE*, which is also in accordance with their findings, where explainability was not as strong a decision factor as performance. In summary, we find that *ST* poses a strong influential factor concerning the attitude and intention to use an intelligent system either indirectly through previously introduced constructs or as a minor direct effect.

4.2.5.3.5 The Role of User Characteristics

Lastly, we look at the moderating effects of *age*, *gender*, and *experience* on *PE* and *EE*. We found no significant moderating effects of either variable or construct, contradicting the findings of Alharbi (2014) and Esfandiari and Sokhanvar (2016). We assume that this is because our pre-screening sets boundary conditions that do not allow for a great deal of variance within the participants. Thus, we observed mostly minor experience and age gaps. In addition, due to the application domain, the sample was skewed towards men (68.75 %), barely allowing for reliable variation.

4.2.6 Discussion

4.2.6.1 Theoretical Implications

4.2.6.1.1 Performance is King (When Looking at Direct Effects)

We extended the modified UTAUT model by Dwivedi et al. (2019), which itself is based on the UTAUT model of Venkatesh et al. (2003), and derived additional constructs and connections in the context of intelligent systems acceptance and use. The direct and indirect effects of *PE* play a major role and are comparable to the findings of Dwivedi et al. (2019). The findings of Wanner et al. (2020a) confirm the dominating role of the expected performance. Contrary, we found that the expected effort is not of major concern when looking at the direct effects since it only delivers impact via indirect connections. We consider this as a first indication of the increased difficulty to build a direct intention to use in the case of intelligent systems, since the intention relies on the affection towards the system more heavily as expressed by the extended UTAUT model of Dwivedi et al. (2019). Thus, while performance is king, it is insufficient to focus only on direct effects when evaluating intelligent systems acceptance and use.

4.2.6.1.2 Human Attitude and Trust Steer Acceptance as Latent Indirect Factors

As mentioned previously, the strength of indirect effects delivered through the more affectionate construct of *ATT* is substantial and shows the necessity for recognizing the deviation from a purely performance- and effort-centered model. Following that thought of increased affection constructs, we found that initial *TB* plays an essential role in determining the *PE* regarding the system. Thus, we revealed a significant indirect influence of PE so that we assume it is more likely that a user thinks the system will perform well when he or she trusts the system.

This transitory connection reveals the importance of trust in the context of intelligent system acceptance. The strong effect of *TA* also reveals that a prior belief in the system's problem-solving capability is fundamental. Especially when looking at the discussion of algorithm appreciation vs. algorithm aversion, this particular construct plays a central role in building up *TB* towards the system. We theorize that the observation of algorithm appreciation or aversion is connected to *TA* and *TB* since they determine what to expect from a system. Trusting a system and expecting super-human performance in the case of algorithm appreciation can turn into mistrust when an aversion is built up due to individuality of a single task or erratic system behavior (Dietvorst et al. 2015; Logg et al. 2019). However, as argued in XAI literature, an explanation of some sort can help to increase trust in the system (Adadi and Berrada 2018; Páez 2019).

4.2.6.1.3 System Transparency Enables Trust Building and Contributes to Performance Expectancy in Both Ways

Including *ST*, we found that revealing the system's internal decision structure (global explanation) and explaining how it decides in individual cases (local explanation) has positive effects on almost all constructs. First, we can confirm that an understanding of or at least visibility into the decision process of the system has a powerful effect on the user's (initial) trust in the system, confirming the often-

postulated connection that motivates much XAI research (Ribeiro et al. 2016b). Second, we find that *ST* also has substantial effects on *PE* and in terms of usability (i.e., *EE*). We expected the strong connection of *ST* to *EE* as a global system explanation is usually required to determine the effort it takes to efficiently train and subsequently use an intelligent system (Wanner et al. 2020a). It is reasonable to assume that the presence of an explanation in a psychological sense reduces uncertainty and thus technological anxiety towards the system (Miller 2019). Therefore, we theorize that the presence of local and global explanations lets the user shift to a more rational behavior since he or she can make more informed decisions rather than relying on their gut when dealing with black-box intelligent systems.

When comparing the observed effects with related literature such as Wanner et al. (2020a), which deals with determining the decision factors for adopting intelligent systems, we find that the relationship between explanation performance and using a system is a more complex one. While we cannot draw conclusions regarding a trade-off as stated in Wanner et al. (2020a), we found that the presence of an explanation indirectly influences the expected performance of a system, which is often the dominant influence factor. Therefore, we argue that while performance remains an essential factor for the actual intention to use, *ST* should be attributed a more critical role than current findings suggest since it can significantly increase the *PE* (or lower it depending on the revealed information through the explanation).

Additionally, taking temporal factors into account, we argue that initial trust factors and subsequently expected performance and attitude towards the system are formed by the information that is revealed before the system is used. That is, the availability of *ST* can steer those factors in one direction or another before the user sets his or her *PE*. Thus, we argue that it is less of a situational trade-off and more of a decision process that is repeated with each use and thereby manifesting in the user's attitude toward the system and AI technology in general.

4.2.6.2 Practical Implications

4.2.6.2.1 Use Expectation Management to Form Attitude Towards the System

In order to avoid disappointment and algorithmic aversion, managing the expectations towards performance can increase subsequent intention to use, even if the problem field for application is limited in the process since hesitation is build up through the system's self-signaling of suboptimal performance. In line with Dietvorst et al. (2016), it is important to manage expectation and show the user control opportunities of the system. This can be done with a pre-deployment introductory course and involving users in the configuration state while using their knowledge in the training of the algorithms at the base of the intelligent system (Nadj et al. 2020).

Besides providing support for managing expectations and learning to use the system (Dwivedi et al. 2019), overcoming initial hesitation has a high priority in the case of intelligent systems.

4.2.6.2.2 Control the Level of System Transparency Based on the Target Audience's Capabilities and Requirements

Global explanations depict the inner functioning and complexity of an intelligent system. They are suitable to manage the expected effort when procuring an intelligent system, specifically through either outsourcing or in-house development. In addition, global explanations can provide a problem/system-fit perspective in that the user can observe whether the complexity of the model is suitable for the task. For example, using a complex deep learning model for an intelligent system to detect simple geometric shapes such as cracks might even decrease performance.

Local explanations can assist with explaining single predictions of intelligent systems, helping the user to compare the decision process by i) visualizing the steps towards the decision (e.g., by creating images of the intermediate layers of the artificial neural network) and by ii) attributing the input data importance regarding the output decision (e.g., by creating a heatmap of input pixels that caused the intelligent system's decision).

Explanations can also prove useful as a communication bridge between developers of the intelligent system who are not domain experts and the domain experts who are AI-novices. This helps to diagnose the model and create a common understanding of the decision process from a human point of view enabling all stakeholders to jointly avoid false system behavior that can lead to algorithm aversion, such as learning a wrong input-output relation.

However, disclosing too much information about the principal logic of the intelligent system can lead to the opposite effect (Hosanagar and Jair 2018; Kizilcec 2016). Especially for the stakeholder group of domain experts that are the users of the system, as opposed to developers who are required a global explanation to diagnose system failure.

4.2.6.2.3 Implement Trust Management Independent of Transparency Efforts

Our results also show that trust, while being influenced by transparency, is not solely explained by it. In accordance with Madsen and Gregor (2000), the pre-existing propensity to trust that is reflected by *TB* requires extra treatment that goes beyond simply providing explanations. Thus, trust issues need to be addressed head-on by implementing guidelines for trustworthy AI (Thiebes et al. 2020). Furthermore, companies should think about introducing trust management. For similar reasons, the standard and idea of risk management were introduced decades ago: identify uncertainty roots and trust concerns and create trust policies (Müller et al. 2021).

The uncertainty regarding *PE* and *EE* could be reduced proactively by offering training to the users to experience the intelligent system to form a feeling of beneficence (Thiebes et al. 2020). Using the system in a training session in a non-critical context can support the acceptance of the system and provide a solution to the initial uncertainty about the performance. According to Miller (2019), this could provide partial transparency, in this case, as an indicator of ability and performance.

4.2.6.3 Limitations

Within our study, we presented a use case based on a medium-stake scenario. Here, wrong decisions have consequences such as machine breakdown or downtimes within the production plant. This can result in high monetary loss. Nevertheless, wrong decisions do not endanger human lives. We used this scenario for two reasons. First, for the sake of generalization, and second, we tried to replicate a typical industrial mid-stake maintenance use case. However, following Rudin (2019), we need to keep in mind that user behavior may differ in high-stake use cases due to the potential consequences of wrong decisions. This also applies to low-stake use cases.

Further, we focused on user perception. Consequently, we cannot verify if the user's perception corresponds to the actual user behavior. This is especially related to the following: *PE* on whether the system can increase the user's productivity; *EE* on whether the user finds the system easy to use; and *ST* on whether the user understands why the system made the decision it did. The latter is closely related to findings from Herm et al. (2021b), who state a gap between the perceived explainability of intelligent system explanations and user task solving performance in a hybrid intelligence situation.

Lastly, within our use case, we provided a textual and graphical explanation for intelligent system predictions. While many different XAI augmentation techniques have been developed in XAI research, further evaluation of these techniques seems necessary. Similarly, the results may differ when different XAI augmentation techniques are applied. Hereby, inappropriate explanations can cause an overload of the user's cognitive capacity (Grice 2019). Furthermore, a personalized explanation can increase the behavior intention (Schneider and Handali 2019).

4.2.6.4 Conclusion and Outlook

By extending the UTAUT model with factors of attitude, trust, and system transparency, we were able to explain better the factors that influence the willingness to accept intelligent systems in the workplace.

Our extension centers on affection constructs such as *ATT*, *TB*, and *TA* while simultaneously integrating *ST* as an opportunity to steer both to address the information asymmetry between black-boxed, anthropomorphic agents and their human principal.

On the one hand, our model enables researchers to understand the influence of this human factor for intelligent systems and in more general for analytical AI models. On the other hand, our findings can help to create measures to reduce adoption barriers in practice and thus better leverage AI capabilities. Since our research is based on the UTAUT model and established extensions, we assume that our results are of general nature and transferable to other domains.

Since our research results clearly indicate how behavioral intention is influenced by this human factor, we aspire to develop design principles for intelligent systems that contribute to the user's willingness to accept and use these systems in their daily work.

4.3 Effects of XAI Framework on Model Explanation

Abstract. Digital products and services make it possible to use data profitably. Particularly in highly complex applications, e.g., as those found in modern industry, such digital services in the form of intelligent decision support systems (DSS) can be a great support for human decision-making. On the other hand, these systems are subject to criticism because the underlying calculations are often not transparent and contain a residual error. This may be reflected in user rejection of the system's advice. To better understand the impact of such systems, the paper addresses the problem with an empirical investigation towards user confidence and performance. An industrial quality inspection scenario is used as an applied application case. The results highlight that intelligent DSSs affect and even improve user confidence and corresponding to their related performance. However, a significant difference in the influence of different transparency levels between black-box-, grey-box-, and white-box-based DSS tool support was rejected.[15]

4.3.1 Introduction

Digital products and services are increasingly being used, both within society and in business contexts. This is also evident in the modern manufacturing environment, where production processes are becoming progressively more complex due to modern machines, data processing, and fast cycle-times (e.g., Muchiri et al. 2011). To enable humans to cope with the immense amount of information, digital services in the form of intelligent decision support systems (DSS) should help them. These artificial intelligence (AI) systems process incoming data fully automatically to minimize the complexity of the real world. Despite the immense advances in the capabilities of such AI systems, their effectiveness depends critically on the willingness of users to integrate their advice into the decision-making process (Dam et al. 2018).

In addition to organizational and technical challenges, there are, thus, psychological barriers to adoption. Here, especially system transparency seems critical (Dam et al. 2018). This contradicts today's research efforts on AI algorithms focusing on performance (La Cava et al. 2021). A trade-off arises as the trend intensifies the problem of a lack of human comprehension of the underneath AI model computational logic as progress is achieved in particular through more complex modeling approaches. This trade-off is the research subject in the field of explainable AI (XAI). XAI research seeks to develop models and

[15] This paper is published within the 27th Americas Conference on Information Systems (AMCIS) as 'Do You Really Want to Know Why? Effects of AI-based DSS Advice on Human Decisions' (Wanner 2021). The paper was selected as 'Top 25% Paper AMCIS' and nominated for the Best Paper Award. The conference paper was invited for a special issue of the AIS journal Transactions on Human-Computer Interaction (THCI).

A substantial preliminary work for this paper is the paper published within the 41st International Conference on Information Systems (ICIS) as 'White, Grey, Black: Effects of XAI Augmentation on the Confidence in AI-based Decision Support Systems' (Wanner et al. 2020).

methods that explain these powerful 'black-box models' in a user-friendly way (Gunning and Aha 2019).

Despite the yet still young XAI research domain, two ways show particular promise: the use of a per-se explainable AI model that is iteratively optimized in its performance (Rudin 2019) and the use of ex-post XAI augmentations for black-box models ('white-box'). This is to make its inherent computational logic (Rudin 2019) and/ or a particular system's advice tractable ('grey-box') (Ribeiro et al. 2016b). However, it remains unclear to what extent the explanations affect human decision-making.

Due to a lack of empirical evidence on explanatory approaches and designs, many XAI researchers are calling for socio-technical research efforts (e.g., Miller 2019; Ribeiro et al. 2016b). This paper, therefore, adopts a socio-technical perspective and is related to the Information Systems (IS) subfield of Behavioral Science. Through its empirical form, it aims to better understand the extent to which advice from (X)AI-based DSS affects the human decision-making process. For this purpose, an empirical study simulating a realistic decision-making task adapted from the domain of industrial quality control is used. The main objects of investigation are the user's perceived subjective confidence in his decision and the associated objective decision performance. The intention is summarized in the research question (RQ):

RQ: *How does advice from (X)AI-based DSS influence human decision-making in terms of subjective confidence and objective performance?*

The elaboration of the research question implies three major contributions. On the one hand, a theoretical transfer of the human decision-making process to (X)AI research is made, which can serve as a starting point for further research intentions. On the other hand, it is possible to better understand the extent to which such DSSs affect their users in a data-driven practice context, such as the one chosen in this study for the upcoming Industry 4.0 era. Furthermore, the results allow conclusions to be drawn about the design of such intelligent digital services in terms of user expectations of the associated system explainability.

To this end, the paper is structured as follows. First, in the section 'Foundations and Related Work' the theoretical foundations of AI-based DSS and the human decision-making process as well as relevant prior work are presented. Section 'Methodology and Hypotheses' includes the methodological basis. Likewise, the hypotheses to be tested are elaborated here. The section of 'Empirical XAI Study' provides information on the design and implementation of the study. Next, 'Results and Interpretation' comprises the statistical analysis and a critical interpretation of the results. Finally, in 'Conclusion, Limitations, and Outlook', a summary, limitations, and an outlook on future research opportunities are given.

4.3.2 Foundations and Related Work

Human Reasoning. Human decision-making is a logical sequence of mental activities to make the best choice possible regarding a predefined aim. The following explanation is a consolidation of the elaboration and insights given by Simon (1977), Schwenk (1984), Hilton (1996), and Miller (2019). The sequence is divided into five sections: 1) goal/ problem; 2) information; 3) mental model; 4) choice; and 5) review.

First, the decision objective or problem must be identified and defined. This implies both the recognition and diagnosis of the underlying problem and its possible causes. Consequently, the decision-maker

attempts to obtain appropriate information. This serves as input for generating his mental model to weigh-up possible alternatives. In this process, a simplified model of reality is generated based on the problem descriptions and the given knowledge. Here, on the one hand, causal discounting takes place. It describes the process, in which the assumed probability of an option decreases due to the attribution of a causal relationship of the information with respect to a (better) alternative option. In causal backgrounding, on the other hand, irrelevant causes are discarded. This corresponds to a selection process. Ultimately, alternatives are ranked based on the problem description to select the most relevant or best solution. After the decision is made, a critical evaluation of one's choice takes place. The choice experiences and insights in turn feed back into one's mental model and can impact future decision-making.

Intelligent (explainable) DSS. Decision support systems exist for several decades. While initially rule-based approaches were used, today's (intelligent) DSS often include AI models to calculate outcomes. AI is to be understood as a subfield of machine learning, in which mathematical models and algorithms are used to automatically recognize patterns in data series that are of particular interest for the respective application (Alpaydin 2020). Nowadays, it is foremost about improving the performance of such models (La Cava et al. 2021). This is enabled foremost by approaches from the field of artificial neural networks (ANN). On the counterpart, these models have computational logic that is difficult for humans to comprehend. So, they are considered to be poorly explainable and are referred to as 'black-box models' (Adadi and Berrada 2018).

Information asymmetry between black-box models and their users might lead to an increased skepticism about the system, regardless of its performance. The reason is seen in a lack of confidence that might even avoid the user to consider the system's advices given in one's decision-making process (Dam et al. 2018). Confidence is the degree of belief that an action is correct. It is related to the human ability to estimate the probability that a decision is 'right' (Grimaldi et al. 2015). Therefore, XAI research seeks to best solve the perceived trade-off between AI model's performance and model's explainability (Gunning and Aha 2019). Model performance is described as the accuracy of the system to solve a task (Gilpin et al. 2018). Model explainability is the degree to which the system is understandable to its user (Dam et al. 2018).

In general, there are two XAI approaches to counter the problem related to the missing explainability of black-box models: (1) The pure avoidance of black-box models. That is, using a white-box model that is per-se considered explainable, which is then iteratively improved (Rudin 2019). The most common example of this is decision trees. And (2) the transformation of a black-box model into a grey-box model. This ex-post model extension is used to make the internal computational logic (Rudin 2019) or its reasoning for a particular advice transparent to the user (Dam et al. 2018). For this purpose, some XAI augmentation frameworks already exist that support this (e.g., Ribeiro et al. 2016b).

Related Studies. Research on the generic topic of explanation perception revealed first insights into how different types of explanation (styles) affect human decision-making. Studies for example showed that the provision of human-meaningful explanations (e.g., Koo et al. 2015), supports the mental model building (e.g., Kulesza et al. 2013), moderates trust (e.g., Kizilcec 2016), and also influences the decision-making abilities of the user (e.g., Nourani et al. 2019). Providing too much information, however, leads to an opposing effect as it exceeds the mental processing abilities and decreases the overall decision performance (Schaffer et al. 2019). Thus, in line with Dellermann et al. (2019), it is important to

counterbalance the information provided and take advantage of both, humans and machines in a hybrid intelligent form.

In accordance with the research question, prior studies already deal with the complex interplay between human perception, confidence, performance, and decision-making. Closest to the own RQ is the work of Zhang et al. (2020). The authors conducted two experiments to evaluate the effect of confidence scores and local explanations on the prediction accuracy and user's trust. While showing confidence scores increased trust calibration and people's confidence it did not improve the decision outcome. The provision of local explanations had no effect on trust and performance in their work. Likewise, the studies of Westbrook et al. (2005), Zhou et al. (2015a), and Heath and Gonzalez (1995) showed that displaying additional information does not improve the performance itself, but the decision confidence. Lai and Tan (2019) investigated how different gradual types of explanations in an AI-assisted decision system affect trust, confidence, and performance of the participants. The performance was slightly improved when explanations of the machine learning model were given and greatly improved when predicted labels were shown. Furthermore, Sieck and Yates (1997) examined how framing impacts choice and related confidence. They found that exposition effects raised the participants' confidence noticeably. The subjective confidence of the user can be seen as an indicator for the information-seeking behavior and performance (Desender et al. 2018).

4.3.3 Methodology and Hypotheses

The intention of this publication is to empirically test the effects of intelligent DSS and different kinds of explanation levels on human decision-making for a given set of possible choices (cf. Figure 36).

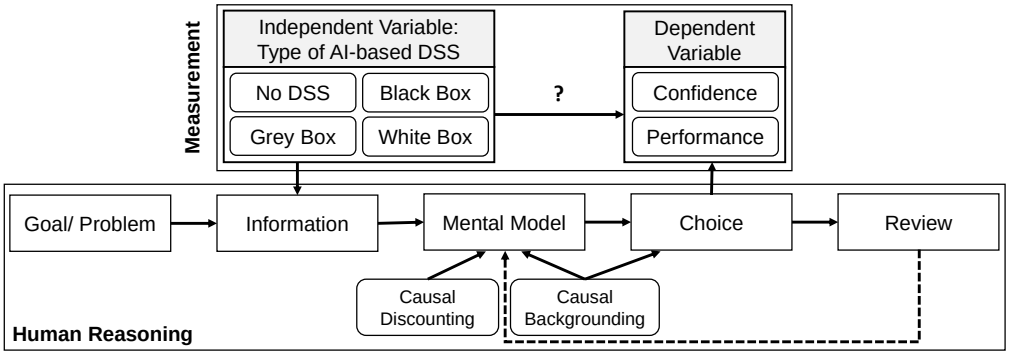


Figure 36: Research Design and Methodology

Research Method. The research design is adapted in accordance with Wanner et al. (2020b). The authors propose the empirical investigation of support provided to the human decision maker by different types of AI-based DSS as an independent group variable. In this context, the support can originate from a black-box, grey-box, or white-box AI-based DSS. This design is extended by the human decision-making process, as a synonym for human reasoning. Consequently, the independent variable 'intelligent DSS' or its advice provides its user with a special source of information in his information acquisition task. This could lead to a changed decision in his or her choice of the best alternative. The chosen alternative is strongly influenced by the confidence in the respective options for action (Peterson and Pitz 1988). Confidence is here measured as the user's ex-post perceived subjective feeling that they have made the best possible decision (Mohseni et al. 2021). Subjective confidence is in turn closely related

to objective accuracy, the choice resulting decision quality (e.g., Boldt and Yeung 2015). Therefore, performance is used as a second dependent variable to better understand how DSS effects affect decision quality (Zhang et al. 2020).

Hypothesis. The hypothesis development follows the division into the two target variables of subjective confidence and objective performance as well as the stimuli by the design of the respective DSS assistance.

In the human reasoning process, the complexity of reality is reduced by knowledge and experience. This implies a critical weighing of the meaningfulness of any given information (Lombrozo 2006). The more information is available, the more likely it is that a human can in-depth reason what is most valuable for their own decision (Bosnić and Kononenko 2009). In the context of AI-based DSS, explanations of the advice given can therefore be expected to help to improve trust and, consequently, to reduce perceived risk (Miller 2019). In their hypothesis development, Wanner et al. (2020b) argue that this occurs in particular through the given support in justifying outcomes. However, they also point out the potential impact of misuse effects that arise from overconfidence in the AI system due to the easy availability of relevant information (Bussone et al. 2015). A baseline value of 'No DSS' should make the theoretical contradiction experimentally testable (Wanner et al. 2020b; Zhang et al. 2020). Thus, the following hypothesis is adopted:

H1a: The use of an AI-based DSS will result in improved confidence in one's own decision than using no DSS (Wanner et al. 2020b).

System advice information differs between black-box, white-box, and grey-box model support. Due to their nested non-linear structure, black-box models are not interpretable by a human user (Adadi and Berrada 2018). Regarding the design of white-box models, it is assumed that they are already explainable for the human user and inherent an internal explanation (Rudin 2019). Thus, the user can critically weight the advice and check for meaningfulness of given information (Lombrozo 2006). The same applies to ex-post explanations of grey-box models. However, the forms of representation and presented advice information differ. As a consequence, negative aspects such as those of overconfidence can also have different effects on the human reasoning (Bussone et al. 2015). This is considered in the next hypothesis:

H1b: The influence of black-box, grey-box, and white-box augmentations on the confidence in the AI-based DSS will be significantly different compared to each other (Wanner et al. 2020b).

Explanations can provide humans with information to validate prognoses and hypotheses and detect causal connections (Bibal and Frénay 2016; Williams and Lombrozo 2013). Displaying suited explanatory content helps the user to interpret and predict the system's operations and confirm the mental models (Mueller et al. 2019). If users mistakenly trust some advice, it can have fatal consequences for the decision output and the performance. A correct mental model is therefore thought to be of great importance in building trust and enhancing human-AI task performance (Bansal et al. 2019; Zhang et al. 2020). Prior work highlights that explanations in AI-based DSS such as confidence scores affect the user's mental model and shape the performance as well as the user's trust and reliance (Lai and Tan 2019; Mueller et al. 2019; Zhang et al. 2020). Thus, it is hypothesized that AI-based systems are well-suited to support the human reasoning and improve the performance compared to a 'No DSS' baseline, leading to:

H2a: The use of an AI-based DSS will result in improved performance of one's own decision quality than using no DSS.

Prior studies in human-machine interface such as that of Dellermann et al. (2019) indicate that an effective form of hybrid intelligence between humans and machines perform best. Thus, a way has to be found in which the human as validator recognizes the errors of the machine. As explained in *H1b*, the information given by the system differs between black-box, white-box, and grey-box approaches. It can be assumed that white-box and grey-box models are superior to black-box AI systems. However, Rudin (2019) criticizes any ex-post explanation of something that is per se not self-explanatory and might lead to wrong conclusion. So, the effects on human reasoning between the three types of models should differ, formulated by:

H2b: The influence of black-box, grey-box, and white-box augmentations on the overall performance will be significantly different compared to each other.

Studies of perceptual decision tasks showed that human decision-making is strongly related to a sense of confidence (Kepecs and Mainen 2012). Also, subjective confidence has an impact on the objective decision performance indicated by the correlation between accuracy and confidence (Boldt and Yeung 2015; Yeung and Summerfield 2012). Performance and confidence will both be high when there is strong evidence for one decision option. In turn, when there is no preferred choice, the accuracy and the confidence decrease both (Desender et al. 2018). This assumption is adopted and serves as the third hypothesis:

H3: There is a significant positive correlation between the ex-post subjective confidence of the decision and the decision quality.

4.3.4 Empirical XAI Study

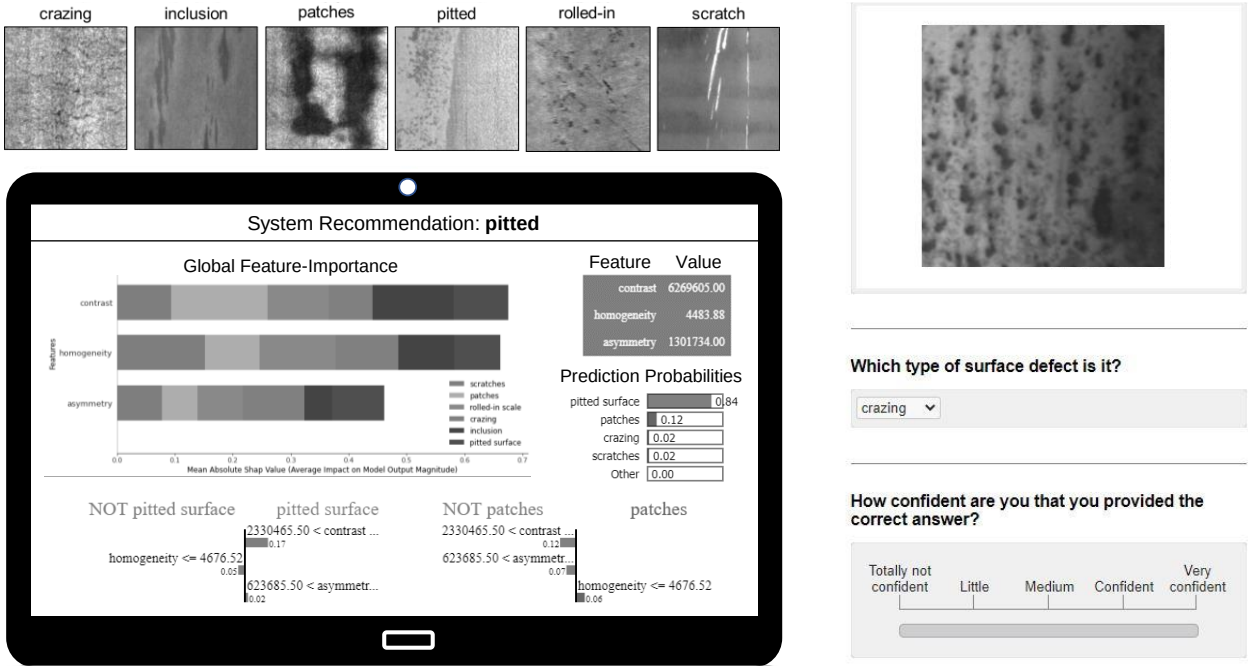


Figure 37: Example from the Empirical Study with Grey-box AI DSS

4.3.4.1 Use Case

A practical application scenario from industrial quality control is used for the empirical study. It represents a task that does not require specific knowledge and is easy to understand. Thus, it allows for a quantitative investigation. The dataset and scenario are provided by the Semeion' institute (cf. Zhao et al. 2017). Their declared objective is to implement a suitable machine learning model for automatic pattern recognition.

The dataset chosen contains 1800 grayscale surface images of hot-rolled steel plates. Each of these is related to one of the six different types of defects with some specific characteristics (cf. Figure 37, top left). For each defect class, a total of 300 samples exists. Likewise, for each image, in addition to the information of the defect class itself, pre-calculated image values based on a Grey-Level-Co-Occurrence-Matrix (GLCM) are given. These contain the five attributes contrast, homogeneity, dissimilarity, energy, and asymmetry. Due to the grayscale differences, a suitable form of hybrid intelligence in particular seems to be target-oriented.

4.3.4.2 Technical Realization

Due to the nature of a classification problem, some common methods were tested including *DecisionTree* (DT), *BaggingClassifier*, *RandomForestClassifier*, *ExtraTreesClassifier*, and *GradientBoostingClassifier*. DTs are considered to be per-se explainable to human users, and thus, were chosen as the white-box DSS solution. The random forest (RF) serves as the backbone for the black-box DSS solution. By applying hyper-tuning, an accuracy of about 90% was achieved for the RF. The DT gained an accuracy of about 85%. These results ensure good comparability between the two approaches. For the grey-box DSS solution, two XAI augmentation frameworks were applied on top of the RF. For global explainability, the feature-importance by the *SHapley Additive exPlanations* (SHAP) is used. For local explainability, the model's confidence is presented by using *Local Interpretable Model-agnostic Explanations* (LIME). This includes the probability per class and the reasoning behind the best two options (cf. Figure 37, dashboard on the corner-left).

4.3.4.3 Study Design

In the study, the participants take on the role of a quality inspector. The task is to correctly classify presorted defects for an effective rework (cf. Figure 37, top right). As a light-constrain, this should be done within a maximum of 15 seconds to avoid an interruption of production. Despite the high performance of the respective DSSs, all three machine learning models correctly classified only 10 out of 14 (≈70%) cases selected in the empirical study. The correctly classified cases differ partially.

The study design is a combination of within-subject and between-subject design. The former corresponds to the fact that the study was divided into two rounds (Zhang et al. 2020). In both, the same 14 cases (images) are randomized shown, with one extra case being a control question. Both times, the participant is asked to assign the case shown to one of the defect classes. Further, he or she should ex-post rate his or her confidence in the decision made on a five-point Likert scale (cf. Figure 37, corner right). The design of the questions is based on Huysmans et al. (2011). In the first round, the participant does not receive any support. This subconsciously anchors his or her case decisions (see Figure 36).

This sensibilization is re-used in the second round. Here, participants are assigned to one of the three treatment groups (black-box; grey-box; white-box) and receive a corresponding DSS assistance for their second time of case decision-making.

4.3.5 Results and Interpretation

4.3.5.1 Demographics

The empirical study included a total of 262 participants (black-box: 87; grey-box: 86; white-box: 89). Two exclusion criteria served to ensure data quality. On the one hand, filtering was based on a control question. It tested the correct assignment of a defect case from the omnipresent decision aid to verify the participant's concentration. The second exclusion criterion was the participant's performance measurement. This was considered in relation to the time required (probability of guessing: 2.3 per round; average study duration: approx. 10min). So, five participants were excluded from the statistical analysis (black-box: 1; grey-box: 2; white-box: 2).

The study was conducted via the academic survey platform *prolific.co*. In consequence, it is subject to a monetary motivation ($10/hrs.). Likewise, the best participants by performance received a further bonus ($5) as an incentive to perform particularly well. As pre-selection of the study, only participants with an industrial background were admitted ensuring a high initial affinity to the industrial use case. Of the 257 participants, 185 were male and 72 were female. The majority of participants (≈80%) were from Europe, followed by America (≈8%) and Asia (≈6%). The average age is 35.8 years, with a median of 34 years. Expanding on this, participants were asked about their willingness to take risks and their willingness to accept AI at the workplace. Both questions were mostly answered with 'high' ('very low' to 'very high').

4.3.5.2 Results

The selection of appropriate statistical methods for the data analysis is oriented on Huysmans et al. (2011) and Zhang et al. (2020). Both teams conducted comparable experiments with comparable measurements. Inferential statistical methods are used.

The following descriptions are structured according to the hypothesis formed (cf. Section 4.3.3). All results depicted refer to Figure 38 and Table 33. The target variable subjective confidence was examined using a five-point Likert scale, representing ordinal values. For H1a and H1b, thus, non-parametric statistics are to be applied. The target variable objective performance is measured numerical by the answers given. Here, the correct answer in each case is known by the author, so parametric statistics are applicable for H2a and H2b.

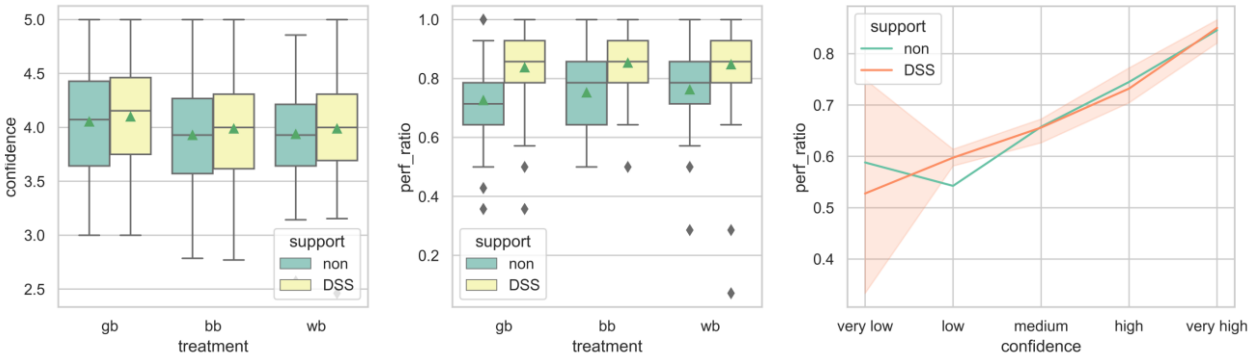


Figure 38: Comparison of before and after treatment of the test series

Table 33: Results of the test-statistics per hypothesis

#	TEST	COMPARISON	p-VALUE	RES.
H1a	Signed Wilcoxon	Non vs. DSS	0.000	yes
H1b	Kruskal-Wallis	BB vs. GB vs. WB	0.207	no
H2a	Paired T-Test	Non vs. DSS	0.000	yes
H2b	One-way ANOVA	BB vs. GB vs. WB	0.716	no

To test for a difference in perceived confidence between the repeated measurements, a *signed Wilcoxon test* was performed. The test confirmed that the difference is significantly positive between the two groups. Thus, the hypothesis is confirmed (**H1a**). To further test for a difference in perceived subjective confidence between the three groups, a *Kruskal-Wallis test* was performed. The test showed that there was no significant difference between the three treatments. This rejects the hypothesis (**H1b**).

In step two, the difference in decision performance between the repeated measurements was tested by a *paired T-test*. The test confirmed a significant positive correlation between the two groups. Therefore, the hypothesis could be confirmed (**H2a**). Additionally, to test for a difference in decision performance between the three groups, a *one-way ANOVA* was performed. The results revealed that there is no significant difference. Consequently, no post-hoc test was performed, and the hypothesis rejected (**H2b**).

To test for a positive correlation between the perceived confidence in the decision and its performance, a visual presentation was selected (cf. Figure 38). The results show that with increasing confidence in one's own decision, the decision performance also increases. The hypothesis is, thus, confirmed (**H3**). As a remark, the plotted standard deviation corresponds to the variation between the three treatment groups.

4.3.5.3 Discussion

The empirical study reveals that there is a significant improvement in the subjective confidence in a decision with the aid of an intelligent DSS. This in turn is closely related to the objective performance, so that a positive form of hybrid intelligence is shown for the respective industrial use case.

The results are foremost in line with findings from previous works. In particular, the improved confidence in one's own decision by expanding the available information about the system's advice has been confirmed several times (e.g., Heath and Gonzalez 1995; Sieck and Yates 1997). However, evidence of a direct positive relationship to objective performance seems unclear. For example, the results of Zhang et al. (2020) show an improvement in confidence due to enhanced AI system advice information, but without an improvement in decision outcome. This is in line with Westbrook et al. (2005), Heath and Gonzalez (1995), and Zhou et al. (2015a). In contrast, the findings of Lai and Tan (2019) highlight that enhanced explainability improves both: subjective confidence and objective performance. Zhang et al. (2020) argue that this result is due to the strong difference between their study's human performance and AI performance. The empirical study at hand refutes this assumption. As shown in Figure 3, there is initially comparable objective performance between humans (≈75%) and machines (≈70%). After treatment by an intelligent DSS, it is improved. This finding of hybrid intelligence as the best performer is consistent with the one by Dellermann et al. (2019). A possible explanation for the different results would be a modified form of the argumentation by Gilpin et al. (2018). They argue that the perceived explainability of models is highly dependent on the characteristics, knowledge, and experience of the individual. Another explanatory approach is a strong dependence on the particular use case and the prior knowledge required for it. Only if an explanation is both, perceived as explainable and the user understands its meaning, it will have an impact on performance (Miller 2019).

For the second part of the empirical investigation, the results show no significant difference. Thus, a treatment with different transparency levels to support the human decision-maker (black-box DSS; grey-box DSS; and white-box DSS) does not seem to have a significant impact on confidence and performance.

The result predominantly contradicts existing findings. It should be noted, however, that little empirically generated knowledge exists in this specific context yet. As argued above, enhanced insight into system computation leads to improved confidence (Heath and Gonzalez 1995; Westbrook et al. 2005; Zhou et al. 2015a). Both prior works in the AI-based DSS context by Lai and Tan (2019) and Zhang et al. (2020) also support this statement. Thus, there should be a differential effect between the lack of explainability of a black-box AI-based DSS vs. a given explainability by white-box or grey-box DSS. This effect has even been experimentally demonstrated by Lai and Tan (2019). By gradually increasing the system explainability, starting from a black-box model, they showed an improvement in confidence and performance.

There are possible explanations for the divergent results of the conducted empirical study. On the one hand, existing evidence from the field of explanation perception shows that human-meaningful explanations are necessary for beneficial advice information from intelligent systems (Koo et al. 2015). Therefore, it is possible that the advice information shown was not human-meaningful enough for the respective use case. On the other hand, there might be an overwhelming of too much information. Thus, the positive effects of the higher transparency levels of white-box or grey-box DSS treatment have a partially negative impact as well (Schaffer et al. 2019). Further, misuse effects may have affected an over-reliance on the provided DSS regardless of its design, due to the ease of availability of appropriate information (Bussone et al. 2015). However, the improved performance measured as a hybrid intelligence argues against this, so it is rather unlikely here. Similarly, the result may be due to an ex-ante lack of user understanding of the inherent logic of the AI-based DSS. The user did not receive any validation

of the results in the empirical study, so he could not know when the algorithm was right and when it was wrong. In other words, the user could not be sure that the explanation was correct, even in the case of a white-box and a grey-box AI DSS (Dietvorst et al. 2015). Therefore, there is much to suggest that the nature of the explanation could not have had an impact.

4.3.6 Conclusion, Limitations, and Outlook

In this paper, the question of how (X)AI-based DSS affect human decision-making was investigated. A case from industrial quality assurance was used as the basis for an empirical study. Through a before vs. after treatment comparison and a group subdivision (black-box; grey-box; white-box), effects of AI DSS advice on human decision-making could be revealed. On the one hand, the confidence in the participants own decision increased, on the other hand, the correlated quality of performance improved. However, a difference between the three system designs, and thus the explanation levels, could not be confirmed.

Possible reasons could be related to the existing limitations of this paper. On the one hand, subjective influences are conceivable due to the empirical survey. Likewise, it remains unclear whether an increased explicability of the system leads in parallel to an overwhelming of the decision-maker. Positive influences due to created transparency could have an opposite effect after a certain level of advice information. In addition, a lack of difference between the types of explanations (black-box; grey-box; white-box) could also have been the simplicity of the use case. Participants may therefore not have needed further explanation. Moreover, the chosen example was without serious consequences for wrong decisions and, thus, only of low-stake. Lastly, the participants could have inferior biases. This could be, in particular, overconfidence in the quality of one's own decisions. Likewise, the automation bias as overly rely on algorithm and its opposite manifestation of automation aversion are possible (Westbrook et al. 2005; Zhang et al. 2020).

This is where future research could come in and address these limitations. On the one hand, it should be better understood what positive but also negative influences different forms of explainability have regarding the human decision-making process. On the other hand, it would be exciting to investigate whether the transferable study design yields different results for other criticalities. An example would be the extension to a low-stake use case (e.g., IRIS) and a high-stake use case (e.g., from cancer tomography).

5 Discussion of the Results

In this chapter, the results from the three main parts of the thesis – systematization, perception, and adoption – are critically reflected upon. This is separated into two sections: the connections between the thesis research efforts (cf. Chapter 5.1) and their connections to the related work (cf. Chapter 5.2).

5.1 Connections Between Research Efforts

The following descriptions include a brief review of the contents and results of the respective publications divided by section (systematization, user perception, adoption). This is followed by an elaboration on the interrelationships between the subsequent publications and the research efforts. Figure 31 serves to illustrate this scheme and highlights the most important topics, results, and connections for each publication.

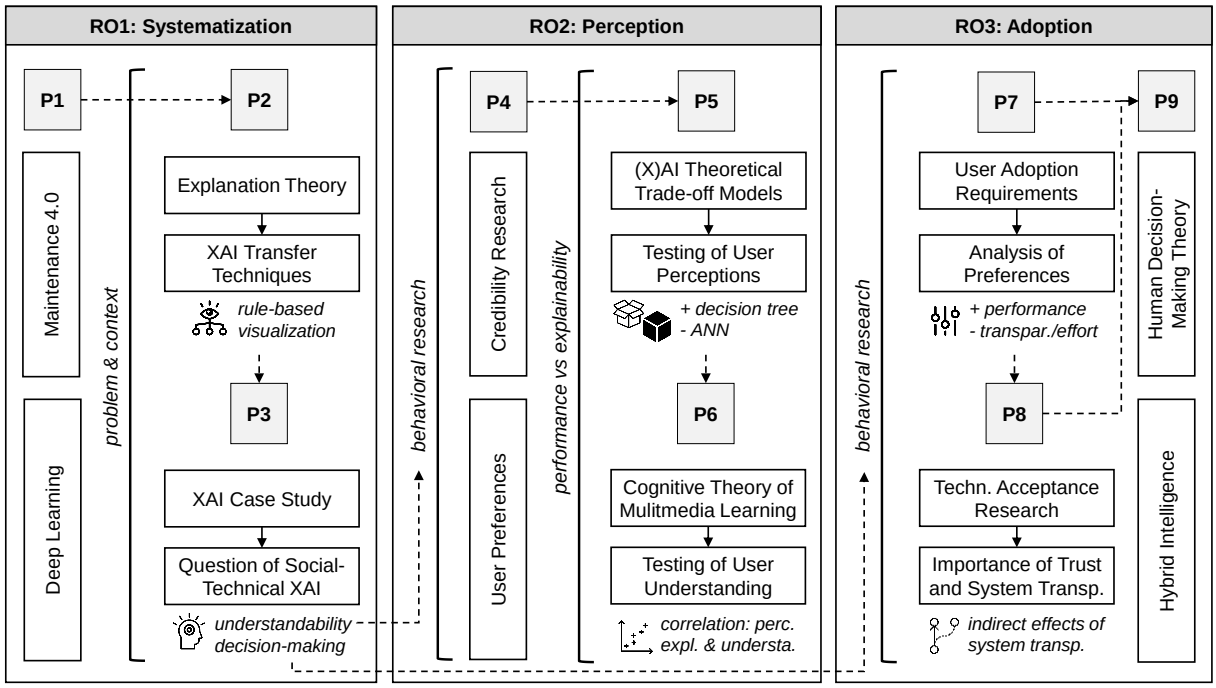


Figure 39: Connections Between Research Efforts

The section **'Systematization of the Field'** (C2) was about understanding the existing situation in the I4.0 environment of research and practice. This was connected with a systematization of XAI transfer techniques and a proof of the necessity of socio-technical XAI studies (cf. Figure 39, left).

P1. The development and results of P1 have shown that numerous data-driven analysis methods and applications are being researched for the extensive changes connected to the I4.0 paradigm. The methodical systematization revealed that industrial maintenance and production are the focus of current research efforts. Both areas are closely linked to one another in modern manufacturing, in accordance with the paradigm of 'smart manufacturing'. In particular, approaches for condition analysis, defect analysis, and monitoring are being strongly researched in an effort that can be termed 'Maintenance 4.0'. For this purpose, existing data is primarily evaluated using advanced business analytics methods

foremost by predictive maturity and technically realized by ML approaches. Over the last three years (since 2018), methods from the field of deep learning, in particular, have found increasing use.

These findings provided the research context for further studies. On the one hand, this is reflected in the choice of application areas for the respective investigations. For example, P3 combined monitoring and condition analysis with modern predictive maintenance analysis techniques. The studies from P5, P6, and P7 focus on ML/ DL methods from the field of condition analysis in industrial maintenance scenarios. P11 takes industrial defect analysis as an application domain. On the other hand, the results from the temporal trend analysis in P1 are used as a starting point to clarify whether the trend towards DL techniques can lead to the ineffectiveness of AI-based DSSs due to their inherent black-box model characteristic. This leads to the research area of XAI, with a call for transparent AI models.

P2. The prior XAI finding and associated desire for transparent AI models formed the backbone of the investigation in P2. First, the theoretical socio-technical backgrounds with the connected explanatory theory were presented to better understand what is already known from the social side. Likewise, a reappraisal of the existing XAI transfer techniques is given, which covers the technical side. The results reveal that there are already a considerable number of possibilities to convert different types of AI black-box models into white-box models to make them explainable. This served to foster understanding about the initial models and final representation. The majority of XAI transfer techniques use a conversion to visualizations and rules. In addition to existing capabilities, it became apparent that such transfers are often criticized. For example, Rudin (2019) criticizes explaining something that is per se not explicable to humans by introducing the associated complexity of a second (white-box) model. Similarly, some researchers point out that there is a loss of model accuracy during transfers (e.g., Kraus and Feuerriegel 2019; Vásquez-Morales et al. 2019).

The findings from P2 formed the basis for some additional research efforts. On the one hand, P2 allows us to recognize that visualizations and rule-based explanatory techniques are particularly promising. This in turn implies the inclusion of ex-post explanatory approaches via grey-box models in XAI socio-technical research efforts as a potential remedy to the assumed ineffectiveness (due to opacity) of black-box AI approaches. Here, XAI research already offers augmentation frameworks such as SHAP and LIME. The two frameworks mentioned were used in the publications of P6 and P9. Likewise, this knowledge was utilized to design the dashboard variations for an explainable and technically feasible AI-based DSS in P8.

P3. P3 takes the aforementioned criticisms of P2 as a starting point to better understand whether there is a lack of explainability of such converted white-box models. In line with the results of the derivation of the existing transfer techniques, a rule-based engine with a visual component should be used. Additionally, the goal was to understand whether there is a loss of model accuracy during transfers. The publication P3 originates from a use case with its own developed procedure in the context of a practical research project for industrial maintenance. The elaboration of the results showed that a transfer of inherent processes of a trained black-box model in a white-box model – here a rule-based system – is feasible. In the thesis relevant industrial maintenance use case, no performance loss was observed as a result of the transfer. The transparency created by the readable set of rules met with great interest from researcher and practitioners. Nevertheless, it remains unclear to what extent the user can actually read and understand the rules. In more complicated monitoring sections, the model's inherent logic was

difficult to understand. The derived rules became quite long and non-intuitive, which contradicts the conclusions derived from P2.

With the new findings of P3, it further became clear that there has been too little knowledge in the field of socio-technical XAI research to understand how the opacity of modern AI modeling approaches affects the user in specific scenarios. In other words, it remains uncertain how such approaches to making black-box models transparent change human decision-making in practice. The positive feedback from practitioners in response to the developed technical approach contradicts the recognized problem regarding difficult understandability. On the one hand, this requires an awareness of the user's perception of explainability and his or her associated comprehension of such AI-based recommendations. This motivated the research efforts in the section on '(X)AI DSS User Perception' (C3). On the other hand, the adoption readiness of those users to incorporate the AI-based DSS into their decision-making process is not yet clear. More precisely, it is not known which attributes – such as the perceived explainability of the system or the objective system performance – are of great importance for users, knowledge that is necessary in order to derive effective actions to overcome adoption barriers. This motivated the research efforts in the section on '(X)AI DSS Adoption' (C4).

The section **'(X)AI DSS User Perception'** (C3) was about achieving a better understanding of the perception of the explainability of ML/ DL models from a user perspective. This encompassed user preferences of the main dimensions of model performance and model explainability, as well as actual understanding (cf. Figure 39, middle).

P4. In publication P4, the effect of data analysis on the user's perception of the objective truth of given information was investigated. The target variable was determined by a structural equation model with several derived constructs. Four constructs were represented by the four properties of Big Data – naming velocity, volume, variety, and veracity. Additionally, three further constructs of the data quality were used: timeliness, completeness, and accuracy. The results of a subsequent quantitative survey highlight that the completeness and the associated accuracy of the information presented have a particularly strong influence on the perception of objective truth. In contrast, the timeliness of the data seems less crucial.

Transferring these results to the context of XAI, it illustrates the necessity of the two dimensions of model explainability and model performance. The dimension of 'timeliness' – i.e., the real-time capability of the systems – seems inessential. This confirmation served as evidence that further investigation of the two theoretical XAI dimensions was merited. In particular, it remained unclear how the user's perception of the two dimensions varies regarding different kinds of ML/ DL models (P5) or even ex-post explanations by XAI augmentation frameworks (P6). In addition, it is not known how perceived explainability is correlated with user understanding (P6). These research efforts will extend the findings from P2, where it was already recognized that visualizations and rule-based white-box models seem promising. Likewise, it should be determined whether these two XAI dimensions are in a contrary relationship to each other or could be optimized independently.

P5. P5 was concerned with a better understanding of the trade-off between model performance and model explainability. The subject of the investigation was different types of ML/DL. These have only been theoretically compared against each other so far. Thus, the objective was to conduct such an investigation under realistic practical conditions. In accordance, representative AI models for linear regression, decision trees, support vector machines, ensembles, and deep learning were technical implemented.

This was realized in four different scenarios. The scenarios were intended to show whether there are differences between low-stakes and high-stakes use cases, as well as classification and regression use cases. To measure perceived explainability, the implementation was empirically assessed using a survey. It was shown that there are some differences between the scenarios and stakes. Nevertheless, important generalizable findings could be derived. It became clear that the DL model showed the best performance with the worst explanatory power. In contrast, it was confirmed that rule-based approaches like the decision tree are perceived as highly explainable by humans.

The results in P5 highlight two approaches that seem promising for the socio-technical optimization of AI support in most use cases: 1) never using a black-box model and instead using a rule-based approach such as a decision tree, or 2) using a back-box model if it offers the highest initial performance and make it explainable in an appropriate way. However, both approaches raise further questions. On the one hand, it remains unclear whether rule-based approaches, such as a decision tree, are also associated with a high degree of comprehensibility of the presented results by the user. On the other hand, it is unclear to what extent the use of XAI augmentation frameworks for ex-post explanation of black-boxes can keep up with the perceived explainability of rule-based white-boxes (cf. P6).

P6. In publication P6, the relationship between perceived explainability and real comprehensibility from a user perspective was examined in more detail. The aim was to better understand how well the user understands the recommendations given by the important types of ML/DL models. The investigation was carried out using the comprehensibility levels according to the 'Cognitive Theory of Multimedia Learning' by Mayer (2005). In addition to the common ML methods and a pure DL black-box model, an explained DL black-box variant was included. The ex-post explanation was done using the XAI augmentation framework SHAP. Again, different criticality was considered by different application scenarios. The underlying ML problems were of regression type only. Besides some differences in terms of the stakes, generalizable findings could be derived. The results made clear that there is a correlation between the two dimensions of perceived explainability and objective understandability. Here, again, the decision tree showed a particularly good fit. Nevertheless, the ex-post explained DL black-box model outperformed it with respect to both dimensions – model explainability and model performance.

The results of P6 highlight the importance of explaining DL approaches. Initial evidence was provided that XAI augmentation frameworks can add value to human-machine interaction. This was demonstrated by their high model performance and perceived model explainability. Such augmentation also offers users a comprehensible presentation of the information. Nevertheless, the implications of the research output of P6, along with its preceding publications P4 and P5, from the field of '(X)AI DSS User Perception' remain limited. In particular, it is not clear to what extent human users would actually consider such intelligent decision support systems in their everyday work. Thus, it remains an open question as to which factors are crucial for system adoption. Related to this is the need to understand how important individual factors are for the user and to what extent these factors influence each other. Only in this way can appropriate measures be derived to enable effective human-machine interaction and remove existing barriers to adoption.

The section **'(X)AI DSS Adoption'** (C4) was about better understanding the most important adoption factors for a human user deciding whether to incorporate the AI-based DSS into his or her task-solving. This encompassed an understanding of the balancing of adoption factors, the direct and indirect effects

of individual factors, and the actual effects of AI-based DSS advice on human decision-making (cf. Figure 39, right).

P7. P7 addressed the question of which factors are important to the user in selecting an appropriate AI-based DSS system. For this purpose, a decision-making process was simulated by implementing three AI-based best-practice decision support systems for a high-stakes decision-making scenario in industrial maintenance. Through the use of an expert survey, decision and attitude factors were evaluated using the Analytical Hierarchy Process (AHP) method. It was found that systems using similarity-based matching or direct modeling for remaining useful life estimation performed best. On the factor level, the results show that system performance is of particular importance to users. The two other dimensions – implementation effort and system transparency – were not that important and were rated about the same.

These results somewhat contradict the assumptions made in previous research efforts. In particular, the results in P5 and P6 suggested that explainability is as important to users as performance. This was particularly evident in the demonstrated link between perceived explainability and user understanding. In the absence of explainability, the user does not understand the results of the algorithm and must trust it blindly. This would mean that users would rather follow the advice of the algorithm when it exhibits higher performance as opposed to having the ability to critically question and thus validate the advice of the system. This contradicts the commonly accepted understanding of an effective human-machine interaction (e.g., Dellermann et al. 2019). Therefore, it seems as though not all influence factors and possible biases have been considered. To address this, a further investigation of additional factors and effect relationships was undertaken in P8.

P8. The intention behind the research effort in P8 was to clarify the question of why AI-based DSSs have been used only hesitantly in industrial maintenance. The aim was to identify possible barriers responsible for this lack of acceptance. For this purpose, the Unified Theory of Acceptance and Use of Technology (UTAUT) was used and modified accordingly to the context of intelligent DSS. The designed modification of the UTAUT model expanded the UTAUT core, particularly with regard to the constructs of trust and system transparency. Via expert panels and quantitative studies, it was ultimately shown that system transparency has a positive indirect impact on a user's willingness to adopt an AI-based DSS. That is, increased system transparency causes the user to perceive other factors as more important than they would be rated without this indirect influence, such as that of system performance.

These new findings in P8 confirm the preceding results from P7. The study again proves that the perceived performance of an AI-based DSS has a high impact on the user's willingness to adopt such systems. The extended investigation further allows for a better understanding of the effects of system transparency. From the results of the new study, it can be deduced that although system transparency itself is not perceived as highly significant by the user there is a strong indirect impact, which therefore implies a certain unconscious bias. Nevertheless, despite the research achievements, it remains unclear to what extent such a system will affect human decision-making in practice. In addition to the readiness for adoption itself, it can be assumed that positive experiences in the sense of increased performance from man and machine will promote sustainable and effective system use to boost overall adoption rates. This open issue is addressed in P9.

P9. The aim of the research in P9 was to better understand how intelligent DSSs affect human decision-making. In addition, the goal was to investigate whether there are differences between the assistance

provided by such a system in the form of a black-box, grey-box, or white-box model. The measurement variables were the ex-post confidence in the decision made and the associated decision quality. By means of different significance tests, it was proven that both the subjective confidence and the objective performance are improved through the support of an AI-based DSS. It was also found that there is a positive correlation between the two target variables. A significant difference in the influence of different 'system explanations' – here black-box, grey-box, and white-box-based tool support – was rejected.

These results prove that the use of AI-based DSS can yield great benefits in terms of daily-work performance. Similarly, the results from P9 show that human decision makers have a good understanding of their own decision quality. This is particularly consistent with the findings from P6. A perceived high explainability of the algorithm leads to a better understanding. The user's assessment of perceived explainability therefore seems good (P5, P6). Though, the two studies contradict each other, as in P9 no change in objective decision quality was found between black-box, grey-box, and white-box AI-based explanations. However, study P9 explicitly points out that this might be related to the study design and the simplicity of the use case. The participant had no possibility to check the results of the algorithm at any time despite its own assumptions. Also, it was no high-stakes scenario, so that errors did not have serious consequences. That the criticality of the scenario is important for users is supported by the two studies from P7 and P8. While an exclusive consideration of P7 suggests performance is the most important factor for a user, P8 showed that this leads to false conclusions, since system transparency (and thus system explainability) has an indirect effect on adoption readiness. In conclusion, it seems important to conduct further studies that confirm this basic assumption derived by the research efforts.

5.2 Connections Between Contributions and Related Work

The following descriptions include a brief review of the research orientation for the various research objectives (RO1-RO3). This is followed by a short discussion of the related topics of interest (RO1a-RO3c), comparing them to the existing knowledge of related work.

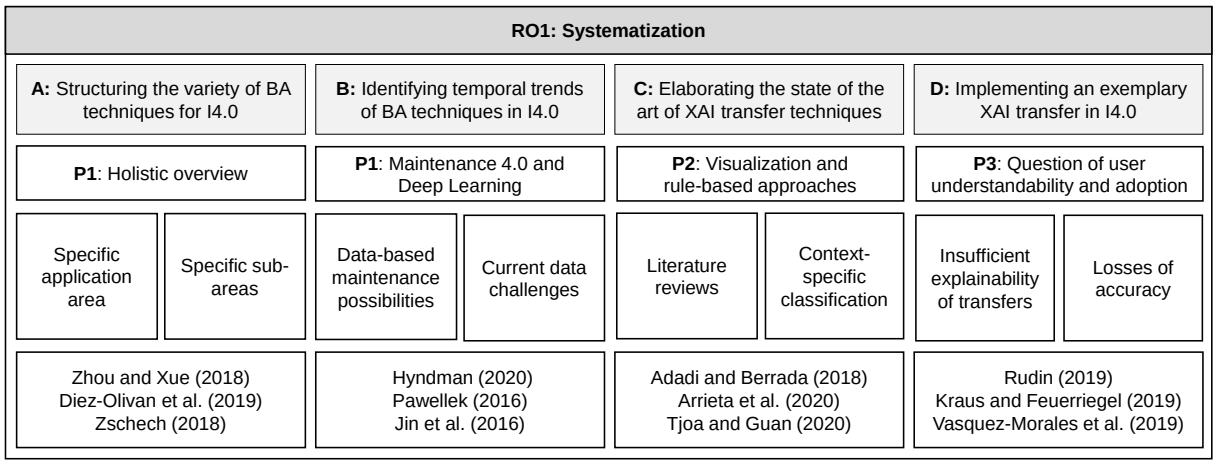


Figure 40: Thesis Contributions vs. Related Work on RO1 – Systematization

RO1: 'Systematization of (X)AI techniques for Industry 4.0'. RO1 was about the systematization of the research field. In line with most studies conducted in this area, a DSR approach was chosen. In particular, there are numerous case studies that present and evaluate a new approach from the field of

machine learning for an I4.0 application. The argumentation line per topic of interest that follows is supported by a short overview in Figure 40, highlighting the contribution, the existing research focus and the most important preliminary publications.

Existing research pertaining '*a) Structuring the variety of BA techniques for I4.0*' has concentrated on different forms of complexity reduction. The focus has mostly been on structuring specific application areas such as ML (e.g., Diez-Olivan et al. 2019; Sharp et al. 2018; Wuest et al. 2016). Similarly, there are contributions in specific sub-areas such as process monitoring (e.g., Sutharssan et al. 2015; Zhou and Xue 2018) and production planning (e.g., Reis and Gins 2017; Sutharssan et al. 2015). A holistic overview was lacking. Thus, the elaboration of P1 represents a valuable addition for practitioners and researchers. This entails both, strengths and weaknesses compared to existing works. It provides the reader with a better overview of the overall context and interrelationships. This prevents 'silo mentality'. In contrast, there is a lack of detail in specific dimensions and characteristics, so that important information may have been lost. Positioning the developed taxonomy, it allows for a general understanding and sensibilization from which further information should be considered. An example is the taxonomy of Zschech (2018), which offers a detailed elaboration on and assistance for the design of maintenance analytics.

In conjunction with this was '*b) Identifying temporal trends of BA techniques in I4.0*'. This can be critical as it allows for the strategic planning of 'smart factories' that prior work did only to a limited extent. It also ensures that there is an awareness of necessary side-topics and problems. For example, maintenance applications seem to be increasingly supported by deep learning approaches (Wanner et al. 2020a). In order for these approaches to become effective, it advocates solving related issues such as the need for large amounts of data or removing possible psychological adoption barriers due to the lack of comprehensibility of the inherent computational logic for human users. Such a holistic temporal analysis for the specific area of I4.0 has not existed until now. Therefore, there are no direct comparative works. However, a number of current data challenges show that algorithms from the field of deep learning outperform common ML types (e.g., Hyndman 2020). Likewise, Pawellek (2016) and Jin et al. (2016), among others, show that the area of maintenance can benefit greatly from data-based approaches such as those found in the I4.0 paradigm.

'*c) Elaborating the state of the art of XAI transfer techniques*' was done in P2. The need derives from the fact that existing XAI research contributions deal with a literary reappraisal of contexts and classifications. Here, the works of Adadi and Berrada (2018) and Arrieta et al. (2020) seem particularly important. Similarly, further contributions for specific fields, such as medicine, can be found (Tjoa and Guan 2020). Although a variety of XAI transfer techniques existed prior to the study in P2, there had been no research effort to structure them. However, such a review validates the direction of the research and allows for the identification of research gaps. The review in P2 of existing techniques (e.g., Kraus and Feuerriegel 2019; Liu et al. 2004; Vásquez-Morales et al. 2019) confirmed that rule-based and visual explanatory approaches are especially heavily researched. This is also in line with existing XAI assumptions: Decision trees are considered particularly suitable (e.g.,Rudin 2019) and visual representations are often used for the ex-post explanation of black-box models by XAI augmentation frameworks such as SHAP (Lundberg and Lee 2017). Likewise, the review structure enables one to either address a research gap or implement an adequate XAI-transfer.

As shown in P2, there are already some case studies dealing with approaches and related evaluations of XAI transfer techniques. Within the XAI research community, however, such transfers seem to be viewed critically. In particular, Rudin (2019) makes her point by saying that black-box AI models should not be made explainable by white-box AI models. Extending this, the results of Kraus and Feuerriegel (2019) and Vásquez-Morales et al. (2019) show that performance losses are to be expected with such transitions. By '*d) Implementing an exemplary XAI transfer in I4.0*' it turned out that such criticism is justified (P3). Although a loss of model performance was avoided in the presented use case, the explainability of the derived rules seem too complex for a human user to understand properly. Thus, it is questionable to what extent rule-based explanations are actually suitable for making internal computational logics and the advice of an AI model transparent. The study represents a starting point for further research but does not itself clarify the questions that have arisen; neither does existing research.

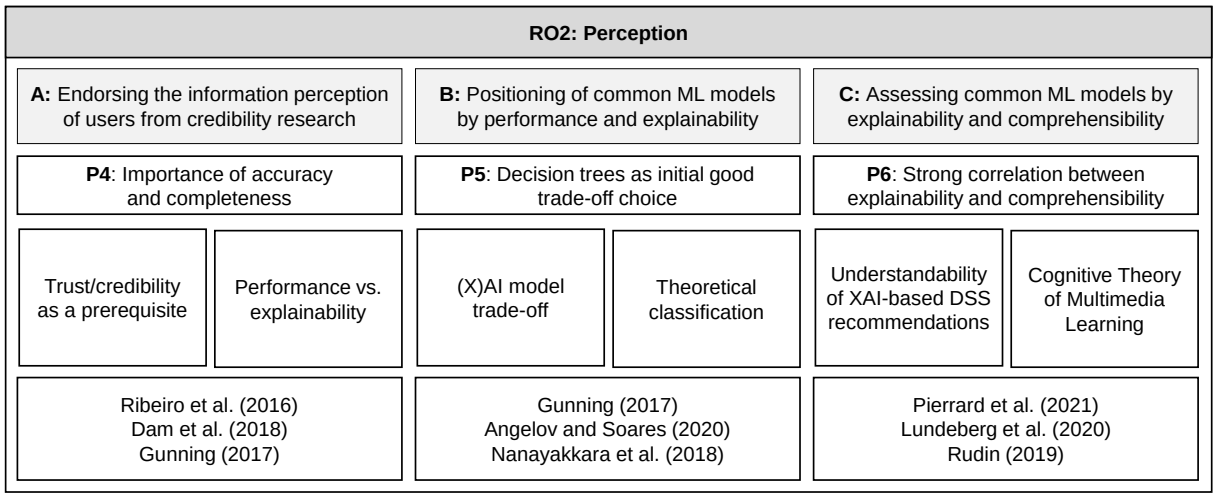


Figure 41: Thesis Contributions vs. Related Work on RO2 – Perception

RO2: 'Perception of (X)AI explanations from a user perspective'. RO2 was aimed at achieving a better understanding of how users perceive (X)AI model results. The research orientation of the BR was chosen here. This is also in line with most of the existing socio-technical studies conducted in this area. In particular, there have been several empirical investigations to better understand factors like understanding, trust, and fairness. A focus on model performance vs. model explainability vs. model comprehensibility is rare. Figure 41 is used to support the line of argumentation per topic of interest that follows.

The first research contribution of C3 of this thesis was about '*a) Endorsing the information perception of users from credibility research*'. Credibility research is concerned with understanding whether given information is true and, likewise, what is necessary to perceive information as being true. For some XAI researchers, credibility is the necessary prerequisite for an AI system to become effective in a real-world application in the first place (e.g., Dam et al. 2018; Ribeiro et al. 2016b). Here, it should be mentioned that this is restricted to applications in which humans have to perform the physical execution and/or make the final decision. By combining data quality criteria with perceived objective truth, P4 proved important foundational knowledge for XAI research. The results highlight that accuracy and completeness are particularly important in order to perceive given information as the objective truth. This confirms the validity of the focus of XAI research, i.e., model performance vs. model explainability (Gunning and Aha 2019). It indicates also that findings from credibility research can be applied to a data

analytics context, which is, e.g., reflected in the importance of credibility for human decision-making (Wanner 2021).

XAI research assumes a trade-off between model explainability and model performance, which must be resolved in the best possible way (Gunning and Aha 2019). In theory, there are initial differences between different types of ML/ DL models, although this has not been practically demonstrated (Angelov and Soares 2020; Morocho-Cayamcela et al. 2019; Nanayakkara et al. 2018). The investigation of '*b) Positioning of common ML models by performance and explainability*' in P5 thus addressed a research gap. The results validated that the theoretical classification is mostly true. However, there is no linear ordering of the different model types regarding the trade-off mentioned. Likewise, the statements about the dependence of the respective users seem to be correct (Cui et al. 2019). Furthermore, the results confirm Rudin's argument that rule-based approaches, such as a decision tree, are particularly appropriate for human decision-makers (Rudin 2019). In line with existing AI research, it had been previously recognized that DL approaches are mostly superior to ML approaches (e.g., Hyndman 2020). Nevertheless, the results suggested that these models have a poor perceived explainability.

In addition to the perceived explainability of an (X)AI-based DSS on the part of the user, the extent to which the user understands the explanations presented is particularly important with regard to the final decision quality. Only in this way can he evaluate the recommendations of the system and effectively contribute to a hybrid intelligence. While previous socio-technical XAI studies have already partially investigated the understandability of (X)AI-based DSS (e.g., Hu et al. 2021; Pierrard et al. 2021; van der Waa et al. 2021), there had been no investigation into a potential connection between model explainability and model understandability. Therefore, P6 addressed the question '*c) Assessing common ML models by explainability and comprehensibility*'. Overall, it was found that there is a positive correlation between the two dimensions. The results again show that rule-based explanatory approaches, such as a decision tree, provide good user comprehensibility (see also P2 and P5). Likewise, it was confirmed that ex-post explanations of XAI augmentation frameworks (i.e., SHAP) are well suited to meet the explanation expectations of users of such intelligent systems. This is in line with previous work such as that of Lundberg et al. (2020). The criticism that such grey-box models are only an approximation and thus inherently inaccurate (Rudin 2019) cannot be confirmed. In conclusion, the results illustrate that current XAI research is moving in the right direction by developing new methods for ex-post explanations such as LIME (Ribeiro et al. 2016b) and SHAP (Lundberg and Lee 2017).

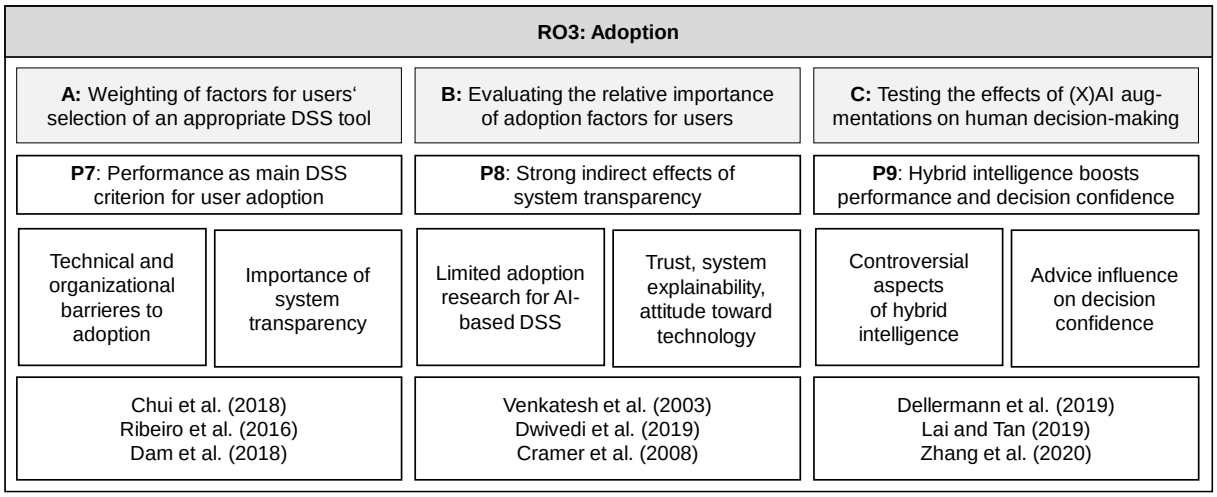


Figure 42: Thesis Contributions vs. Related Work on RO3 – Adoption

RO3: 'Adoption factors of (X)AI-based DSS for Industry 4.0'. RO3 was about gaining a better understanding of the factors that are most important for (X)AI DSS adoption from a user perspective. The research orientation of the BR was chosen here. Despite the fact that only a few socio-technical XAI studies have been done on this topic, there are many interdisciplinary BR studies from related fields. These include, for example, social sciences, psychology, and human-machine interaction research. It therefore seemed important to apply the findings to the research field of XAI. To support the line of argumentation in the following, Figure 42 illustrates the most important information by topic of interest.

Evidence already exists regarding technical and organizational barriers to the adoption of AI-based DSS (Chui et al. 2018; Duscheck 2017; Milojevic and Nassah 2018). Similarly, psychological barriers have been shown to be a result of the lack of system transparency (Mokyr et al. 2015; Reder et al. 2019). Therefore, prior knowledge should be used to better understand the '*(a) Weighting of factors for users' selection of an appropriate DSS tool*'. To this end, the study in P7 used, for the first time in the XAI context to the best of the author's knowledge, an AHP-based analysis in conjunction with prototypical implementations of (X)AI-based DSS. The comparison of the three measurement constructs – effort, explainability, and performance – highlighted that performance is critical to users. Users seem to care less about explainability and effort than having high system performance. This is consistent with the prior findings from RO1, the findings from P4, and the basic intention of XAI research to use high-performing black-box models as a baseline (among others, Gunning and Aha 2019). It is also consistent with the automation bias according to which users rely too much on delegation to algorithms (Cummings 2004). The result of a low significance of explainability for the user is, however, in contrast to the intention to achieve the highest possible system transparency. Likewise, this contradicts the basic assumption that users reject AI-based DSS advice in the absence of system transparency, which is assumed to be linked to user trust (Dam et al. 2018; Ribeiro et al. 2016b). Therefore, it remains questionable whether the results of the study were biased and/or explain too little about the overall relationships.

Within IS research there are numerous adoption studies. In the AI context, however, only a few studies exist so far (e.g., Fan et al. 2018; Hein et al. 2018; Portela et al. 2013). In particular, adoption research (Venkatesh et al. 2003) has scarcely been used in the (X)AI research community. Socio-technical studies mostly focused on selected measurement variables such as trust, system explainability, and attitude toward technology (among others, Cody-Allen and Kishore 2006; Cramer et al. 2008; Dwivedi et al.

2019). The publication P8 therefore deals with the question '*b) Evaluating the relative importance of adoption factors for users'*. Through the study in P9, it was able to achieve a more holistic perspective to understand interaction effects. On the one hand, the results confirmed the great importance of the perceived performance of the AI-based DSS from section RO2 and P7. On the other hand, it became clear that perceived system transparency, and thus system explainability, has a significant effect through other constructs such as perceived performance. Therefore, the study results extend state of the art research in that it proves that the focus of XAI research on model explainability and model performance is justified. Likewise, it becomes clear that indirect effects exist, which need to be considered in subsequent studies.

In many potential application areas of (X)AI-based approaches, there is a need for human-machine interaction. Here, the algorithm itself cannot act autonomously due to, e.g., necessary physical interventions or legal requirements. Therefore, the investigation in P9 dealt with the question of '*c) Testing the effects of (X)AI augmentations on human decision-making*'. The results confirm the positive effects of a hybrid intelligence. This is in line with the results from previous works by Dellermann et al. (2019) and Lai and Tan (2019). Similarly, a positive correlation between subjective confidence and objective decision quality was demonstrated, which confirms prior work such as that of Lai and Tan (2019). Nevertheless, some researchers seem to obtain different results here. While there is a consensus that subjective confidence can be improved by intelligent system support, the results of Zhang et al. (2020) and Westbrook et al. (2005), for example, do not show any improvement in decision quality by the addition of further information. This is consistent with the findings from P9 that white-box and grey-box models do not represent a significant improvement over black-box models. However, the assumption is made that biases are present due to the results of the preceding chapters of this work as well as the associated study limitations from P9. In particular, the lack of evaluation of the algorithm by the user (Dietvorst et al. 2015) and the problem of information overload (Poursabzi-Sangdeh et al. 2018; Schaffer et al. 2019) seem to be important here. The partial finding of the same impact for white-box, grey-box, and black-box AI-based DSS therefore seems questionable.

6 Concluding Remarks and Future Research

In the following, a short version of my own elaboration of each section is given first. This is followed by a summary of limitations. Finally, suggestions for future research are presented.

Research Summary. The first part of this thesis was about the systematization of the field of (X)AI research in I4.0. First, a structuring of the variety of BA techniques for I4.0 was investigated. It became apparent that the field of industrial maintenance is being heavily researched (P1). This suggests that there are profitable improvements to be made here through expanded measurement infrastructures, interconnection, and modern data analysis methods. This should address the subjectivity of task performance and the lack of expert staff (Wanner et al. 2019a). Through the connected identification of temporal trends of BA techniques in I4.0, it was evident that advanced BA approaches of predictive and prescriptive maturity are emerging. The related technical realization is predominantly based on techniques from the field of deep learning (P1). In turn, there is a need for XAI methods. DL models are not comprehensible for the human decision-maker and can be met with rejection regardless of high-performance capability. Therefore, a review of the state-of-the-art of XAI transfer techniques was undertaken. This highlighted the technical XAI transfer methods developed to convert black-box AI models into per se explainable white-box AI models, such as decision trees. It was shown that transfer techniques for visualization and derived rulesets are especially heavily researched (P2). The theoretical elaboration was practically evaluated with the help of an I4.0 use case, applying the approach of a derived ruleset. The limitation insights show that further research is needed to obtain a better understanding of the trade-off between model performance and model explainability in order to form an effective hybrid intelligence (P3).

The second part of this thesis was about the perception of (X)AI explanations from a user perspective. First, a connection was made to credibility research. This was done in the context of Big Data in order to better understand the effects of analyzed data on the perceived objective truth of the presented information by users. The scientific theory utilized was first presented in Habermas et al. (1984) 'Theory of Communicative Action'. It was shown that the accuracy of the presented information and the variety/ completeness have a significant impact on the target variable (P4). With this in mind, the next goal was to better understand the trade-off between model performance and model explainability. For this purpose, common ML algorithms were implemented in different use cases. A user study revealed the perceived explainability for each. The results showed that rule-based approaches, such as a decision tree, offer a particularly high level of perceived explainability. From a technical point of view, however, the ANN model yielded the best result, which, on the other hand, scored worst in terms of perceived explainability (P5). In conclusion, it can be stated that effective explainability in modern approaches from the field of DL is particularly desirable. If neither XAI augmentation nor XAI transfer is undertaken, decision trees should be used. This was also shown in the assessment of common ML models in terms of explainability and comprehensibility. Here, an attempt was made to better understand the extent to which the human decision-maker actually understands the outcome presented by an AI-based DSS. Again, different ML models were used. In addition, an XAI augmentation was applied to the ANN algorithm via the SHAP framework. This yielded the best results, while the decision tree was second (P6).

The third part of this thesis was about the adoption of (X)AI DSS. Here, again, the research context was I4.0. First, there was an investigation into which factors are most important to the intended user when selecting a proper system as an AI-based DSS. The three areas of effort, performance, and explainability – derived from central IS theories – were investigated and substituted by different measures like, e.g., the inference time. By means of an AHP according to Saaty (2004) the users' preferences could be derived. Here it was shown that users particularly care about the performance of the systems. Explainability and effort, on the other hand, were about equal but less important (P7). This illustrates that the development of XAI augmentation frameworks focused on making DL and ensemble ML approaches explainable, which have an initial high-performance capability but low per-se explainability, is reasonable and important. From a higher-level perspective, the next goal was to better understand the factors on the decision to adopt an AI-based DSS system. For this purpose, a proprietary adoption model was derived using the UTAUT reference model of Venkatesh et al. (2003). Through multiple studies and statistical analyses, it was revealed that system transparency, and thus model explainability, plays a much more important role than first assumed. Highly significant indirect effects on other constructs such as trust or perceived performance were proven (P8). This highlights the importance of XAI research investigations. In conclusion, an attempt was made to better understand through these findings how performance and system explainability affect human decision-making. To this end, a test design was developed to compare the impact of different types of (X)AI models (no support, black-box, white-box, grey-box) on users' choice confidence and the related quality of the outcome. For this purpose, a use case to test this design was performed (P9). The result showed that (X)AI DSS support has a positive effect on perceived confidence in one's decision. Furthermore, a correlation between confidence and decision quality was demonstrated. In other words, an effective hybrid intelligence of human and machine achieved a better result either entity on its own. With respect to a distinction between the degrees of explanation of black-box, white-box, and grey-box, however, no significant differences could be detected (P9). It can be assumed that this is due to the low criticality and connected simplicity of the selected use case as this result contrasts with preliminary findings (among others, Lai and Tan 2019).

Research Limitations. The numerous developments and associated contributions within the research field of socio-technical XAI are partly subject to limitations or else require further evaluation. In particular, it is pointed out that the strong empirical research orientation is associated with common limitations of surveys per se. In particular, this implies certain shortcomings of the study design and the subjectivity of participants. Depending on the context of application and design, different biases can thus become apparent and distort the results. Even if an attempt was made to keep these biases to a minimum and to ensure a high degree of generalizability through appropriately large samples, this must be accounted for. It should also be mentioned that monetary incentives were used in some of the studies. Likewise, the use of publicly accessible data sets to ensure the traceability of the research itself is associated with a corresponding restriction in terms of practical reality.

This is associated with a critical weighing of the research artifacts created. In other words, the results can always be questioned in an expanding manner. The associated problem is often that individual publications are subject to limitations in the treatment of topics and formal requirements. Empirical surveys that have been carried out could therefore have been further evaluated and substantiated in some cases. Further statements made remain limited to the respective investigations. Here, a generalization of the

results would have to take place through future work, in order to be able to derive theories and recommendations for action, if necessary.

Future research. Future research could start at different points and extend the studies presented here. In the section 'Systematization of the Field', a taxonomy for socio-technical XAI studies is conceivable. On the one hand, such a reappraisal could represent the current state of research in a compact way and could be a complement to the frequently cited contribution of Adadi and Berrada (2018). On the other hand, such a reappraisal would provide future XAI researchers with guidelines to design their own study investigations. Furthermore, it is becoming easier to discuss study results and incorporate these into the research context. Likewise, more research can be done on the technical side of XAI transfers. Specifically, there is a lack of concrete use cases in real-world practice environments, such as those presented by Wanner et al. (2019a). Other use cases, such as within the domain of medicine (Holzinger et al. 2019) or regarding the application of further existing XAI transfer techniques (Wanner et al. 2020c), are conceivable.

In the section dealing with '(X)AI DSS User Perception', future research efforts could push the investigation into the differences among various XAI augmentation frameworks. Examples of the use of frameworks such as SHAP, LIME, and Anchor show that calculations and representations can differ. Therefore, on the one hand, it would be interesting to better understand how human decision-makers perceive ex-post explanations. On the other hand, as in the preceding research by Wanner et al. (2021a) or Herm et al. (2021b), performance must also be considered. This implies a review of, e.g., the accuracy of the frameworks' substitution of the calculation. Another conceivable approach would be to conduct a study with scientific reference to diminishing returns. Preliminary work, such as that of Zhang et al. (2020), indicates that above a certain performance level by the AI algorithm behind a decision support system, there is no significant improvement in the user's confidence in the calculation correctness. It would therefore be interesting to better understand the relationship between explainability and performance under an economic substitution. In other words, it would be valuable to understand how much a human decision-maker is willing to sacrifice performance to achieve better explainability and vice versa.

In the section addressing '(X)AI DSS Adoption', for example, it would be interesting to better understand the extent to which different stakeholders weight certain features of an intelligent DSS in their selection preference. This can be done by extending the AHP study design (cf. Wanner et al. 2020a) to an ANP. Furthermore, it would be equally intriguing to see to what extent this reveals differences in various domains and at different criticalities. Decision-makers from different domains have varying personal characteristics and experience or knowledge relevant to their respective use case. This could also change with different levels of criticality. Another promising area for future research is the effectiveness of hybrid intelligence. Both Dellermann et al. (2019) and Wanner (2021) show that this is the ideal to strive for, as it offers the best overall performance. However, since there are also many contrary findings here (e.g., Lai and Tan 2019; Zhang et al. 2020), it would be important to better understand whether this is conditioned by the use case with its criticality, individual characteristics of the respondents, study setups, or other influences. In particular, there seems to be a lack of use cases in real environments, with real problems and the corresponding employees who perform with such AI-based system support in their daily work.

Appendix

Appendix I: Overall List of Publications

(* element of this thesis | ** preliminary work of this thesis)

Table 34: List of Author's Publications

Year	Title	Outlet	Status	VHB J.
2021	Entscheidungsunterstützung mit KI: Eine Analyse technischer und sozialer Faktoren für die industrielle Instandhaltung in Deutschland	INDUSTRIE 4.0 Management	published	-
2021	Design Principles for Shared Maintenance Analytics in Fleet Management	International Conference on Design Science Research in Information Systems and Technology (DESRIST)	published	C
2021	Critical Success Factors for Process Modeling Projects – Analysis of Empirical Evidence	Pacific Asia Conference on Information Systems (PACIS)	published	C
2021	A Taxonomy and Archetypes of Business Analytics in Smart Manufacturing	The Data Base for Advances in Information Systems (SIGMIS)	accepted for publication*	B
2021	I'm Telling You! Effects of AI-based DSS Advices on Human Decision-Making	American Conference on Information Systems (AMCIS)	published*	D
2021	Digitalisierungspotenziale der Instandhaltung 4.0: Von der Aufbereitung binärer Daten zum Einsatz transparenter künstlicher Intelligenz	HMD Edition, IoT – Best Practices	published	-
2021	A Theoretical Acceptance Model for Intelligent Systems	Journal of Information Systems Research (ISR)	under review*	A+
2021	Stop Ordering Machine Learning Algorithms by their Explainability! An Empirical Investigation of the Tradeoff between Performance and Explainability	IFIP Conference e-Business, e-Services, and e-Society (I3E)	published*	C
2021	In AI we trust? A trust-extended acceptance model for AI-based maintenance systems	European Conference of Information Systems (ECIS)	published**	B
2021	I don't get it, but it seems valid! The connection between explainability and comprehensibility in (X)AI research	European Conference of Information Systems (ECIS)	published*	B
2021	Process selection for RPA projects – A holistic approach	De Gruyter: Robotic Process Automation	published	-
2021	A Social Evaluation of the Perceived Goodness of Explainability in Machine Learning	Journal of Business Analytics (JBA)	published	-
2020	The Development of a Consensual Mechanism for Autonomous Drive: Enabling of a Law-compliant Programming Basis in Dilemma Situations.	Internationale Tagung Wirtschaftsinformatik (WI)	published	C
2020	Best Practice: Vom Forschungsprojekt zum Mehrwert in der industriellen Praxis.	Konferenz Angewandte Automatisierungstechnik in Lehre und Entwicklung (AALE)	published	-
2020	Bridging the Architectural Gap in Smart Homes between User Control and Digital Automation.	International Conference on Design Science Research in Information Systems and Technology (DESRIST)	published	C

2020	Machine Learning and Complex Event Processing: A Review of Real-time Data Analytics for the Industrial Internet of Things	Enterprise Modelling and Information Systems Architectures - International Journal of Conceptual Modeling (EMISAJ)	published	C
2020	How Much Is the Black Box? The Value of Explainability in Machine Learning Models	European Conference on Information Systems (ECIS)	published*	B
2020	How Much AI Do You Require? Decision Factors for Adopting AI Technology	International Conference on Information Systems (ICIS)	published*	A
2020	White, Gray, Black: Effects of XAI Augmentation on the Confidence in AI-based Decision Support Systems	International Conference on Information Systems (ICIS)	published**	A
2019	Big Data Analytics in Sustainability Reports: An Analysis based on the Perceived Credibility of Corporate Published Information	Business Research Journal	published*	B
2019	Machine Learning und Complex Event Processing: Effiziente Echtzeitauswertung am Beispiel Smart Factory	Internationale Tagung Wirtschaftsinformatik (WI)	published	C
2019	Countering the Fear of Black-boxed AI in Maintenance: Towards a Smart Colleague	Pre-ICIS Symposium Prototype Track (SIGDSA)	published	-
2019	Process Selection in RPA Projects: Towards a Quantifiable Method of Decision Making	International Conference on Information Systems (ICIS)	published	A
2019	Verwendung binärer Datenwerte für eine KI-gestützte Instandhaltung 4.0	Praxis der Wirtschaftsinformatik (HMD)	published*	D
2019	Two-Sided Digital Markets: Disruptive Chance Meets Chicken or Egg Causality Dilemma	IEEE Conference on Business Informatics (CBI)	published	-
2018	Akzeptanz und Erwartungshaltung zu Gamification an deutschen Bildungseinrichtungen: Eine qualitative Studie für Baden-Württemberg	Multikonferenz Wirtschaftsinformatik (MKWI)	published	D

Remark: Most of the publications listed have at least one co-author.

Appendix II: Overview of Publications of this Thesis

Table 35: Overview Publication P1

Title	A Taxonomy and Archetypes of Business Analytics in Smart Manufacturing
Author(s)	Wanner, Jonas; Wissuchek, Christopher; Welsch, Giacomo; Janiesch, Christian
Location	ACM SIGMIS Database
VHB-Ranking	B
Status	accepted for publication (2021)
Abstract	Fueled by increasing data availability and the rise of technological advances for data processing and communication, business analytics is a key driver for smart manufacturing. However, due to the multitude of different local advances as well as its multidisciplinary complexity, researchers as well as practitioners struggle to keep track of the progress and to acquire new knowledge, as there is a lack of a holistic conceptualization. To address this issue, we performed an extensive structured literature review yielding 904 relevant hits to develop a quadripartite taxonomy as well as to derive archetypes of business analytics in smart manufacturing. The taxonomy comprises the meta-characteristics application domain, orientation as the objective of the analysis, data origins, as well as analysis techniques. They comprise 8 dimensions with a total of 52 distinct characteristics. Using a cluster analysis, we found six archetypes that represent a synthesis of existing knowledge on planning, maintenance (reactive, offline and online predictive), monitoring, and quality management. A temporal analysis highlights the push beyond predictive approaches and confirms that deep learning already dominates novel applications. Our results provide a starting point to enter the field, but they can also be a work of reference as well as a guide to assess the adequacy of own instruments.

Table 36: Overview Publication P2

Title	How much is the black box? The value of explainability in machine learning models
Author(s)	Wanner, Jonas; Herm, Lukas-Valentin; Janiesch, Christian
Location	European Conference on Information Systems (ECIS)
VHB-Ranking	B
Status	published (2020)
Abstract	Machine learning enables computers to learn from data and fuels artificial intelligence systems with capabilities to make even super-human decisions. Yet, despite already outperforming pre-existing methods and even humans for specific tasks in gaming or healthcare, machine learning faces several challenges related to the uncertainty of the analysis result's trustworthiness beyond training and validation data. This is because many well-performing algorithms are black boxes to the user who – consequently – cannot trace and understand the reasoning behind a model's prediction when taking or executing a decision. In response, explainable AI has emerged as a field of study to glass box the former black box models. However, current explainable AI research often neglects the human factor. Against this backdrop, we study from a user perspective the trade-off between completeness, as the accuracy of a model's prediction, and interpretability, as the way of model prediction understanding. In particular, we evaluate how existing explainable AI model transfers can be used with a focus on the human recipient and derive recommendations for improvements. As a first step, we have identified eleven types of glass box models and defined the fundamentals of a well-founded survey design to understand better the factors that support interpretability and weighing them against improved yet black-boxed completeness.

Table 37: Overview Publication P3

Title	Verwendung binärer Datenwerte für eine KI-gestützte Instandhaltung 4.0
Author(s)	Wanner, Jonas; Herm, Lukas-Valentin; Hartel, Dennis; Janiesch, Christian
Location	HMD Praxis der Wirtschaftsinformatik
VHB-Ranking	D
Status	published (2019)
Abstract	The fourth industrial revolution is quickening the digital transformation of shop floors, enabling immense potential for optimization. Maintenance is an important area that can profit decisively from making digital information serviceable. It serves to guarantee a smooth production process. Currently, unexpected problems still lead to high opportunity costs. Effectively addressing them is hampered by a lack of transparency, which makes it difficult for service staff to detect, localize, and identify faults. Innovative data analysis methods, which allow to intelligently evaluate and use machine condition data, promise a remedy. In the future, these will support maintenance issues and optimize the overall process. However, the condition of current shop floors in German medium-sized manufacturing companies appears inadequate. As a survey conducted by us revealed, machinery data still comes mainly from light sensors, motor voltages, and positioning scanners. Such binary data values complicate data analysis of modern evaluation methods. The paper at hand addresses this problem without a need for shop floor extensions. Together with partners from industry, a step-by-step development approach was developed to show how comprehensive maintenance support is possible despite restrictions on binary data values. The implementation is based on techniques from the areas of process mining and machine learning. A demonstrator evaluates the practical suitability.

Table 38: Overview Publication P4

Title	Big data analytics in sustainability reports: an analysis based on the perceived credibility of corporate published information
Author(s)	Wanner, Jonas; Janiesch, Christian
Location	Business and Research
VHB-Ranking	B
Status	published (2019)
Abstract	The credibility of sustainability reports has been the subject of scientific research for several years. The problem is often referred to as the so-called credibility gap, which is based on information asymmetries. The situation is further complicated by the limited rationality of human action as improvements to reports do not necessarily translate into credibility gains. Research has proposed and extracted several methods to overcome the issue. Hitherto, most approaches to solve the problem focused on marketing-oriented approaches. This work takes a new approach and explores the extent to which information technology can increase credibility using the potential of big data analytics. We base our research on the relationship of the quality of information and on the perception of objective truth as postulated in the Habermas Theory of Communicative Action. We use the forecast-oriented Partial Least Squares Methodology for the review of hypotheses extracted from literature and expert surveys. The result confirms potential of the criteria of volume and veracity while velocity and variety do not yield comparable potential concerning sustainability reporting.

Table 39: Overview Publication P5

Title	Stop Ordering Machine Learning Algorithms by their Explainability! An Empirical Investigation of the Tradeoff between Performance vs. Explainability
Author(s)	Wanner, Jonas; Herm, Lukas-Valentin; Heinrich, Kai; Janiesch, Christian
Location	Conference on e-Business, e-Services and e-Society (I3E)
VHB-Ranking	C
Status	published (2021)
Abstract	Numerous machine learning algorithms have been developed and applied in the field. Their application indicates that there seems to be a tradeoff between their model performance and explainability. That is, machine learning models with higher performance are often based on more complex algorithms and therefore lack interpretability or explainability and vice versa. The true extent of this tradeoff remains unclear while some theoretical assumptions exist. With our research, we aim to explore this gap empirically with a user study. Using four distinct datasets, we measured the tradeoff for five common machine learning algorithms. Our two-factor factorial design considers low-stake and high-stake applications as well as classification and regression problems. Our results differ from the widespread linear assumption and indicate that the tradeoff between model performance and model explainability is much less gradual when considering end user perception. Further, we found it to be situational. Hence, theory-based recommendations cannot be generalized across applications.

Table 40: Overview Publication P6

Title	I don’t get it, but it seems valid! The connection between explainability and comprehensibility in (X)AI research
Author(s)	Herm, Lukas-Valentin; Wanner, Jonas; Seubert, Franz; Janiesch, Christian
Location	European Conference on Information Systems (ECIS)
VHB-Ranking	B
Status	published (2021)
Abstract	In explainable artificial intelligence (XAI) researchers try to alleviate the intransparency of high-performing but incomprehensible machine learning models. This should improve their adoption in practice. While many XAI techniques have been developed, the impact of their possibilities on the user is rarely being investigated. It is neither apparent whether an XAI-based model is perceived to be more explainable than existing alternative machine learning models nor is it known whether the explanations actually increase the user comprehension of the problem, and thus, their problem-solving performance ability. In an empirical study, we asked 165 participants about the perceived explainability of different machine learning models and an XAI augmentation. We further tasked them to answer retention, transfer, and recall questions in three use cases with different stake. The results reveal high comprehensibility and problem-solving performance of XAI augmentation compared to the tested machine learning models.

Table 41: Overview Publication P7

Title	How Much AI Do You Require? Decision Factors for Adopting AI Technology
Author(s)	Wanner, Jonas; Heinrich, Kai; Janiesch, Christian; Zschech, Patrick
Location	International Conference on Information Systems (ICIS)
VHB-Ranking	A | Additional: Best student paper in track award and nomination for best student paper of conference award
Status	published (2020)
Abstract	Artificial intelligence (AI) based on machine learning technology disrupts how knowledge is gained. Nevertheless, ML's improved accuracy of prediction comes at the cost of low traceability due to its black-box nature. The field of explainable AI tries to counter this. However, for practical use in IT projects, these two research streams offer only partial advice for AI adoption as the trade-off between accuracy and explainability has not been adequately discussed yet. Thus, we simulate a decision process by implementing three best practice AI-based decision support systems for a high-stake maintenance decision scenario and evaluate the decision and attitude factors using the Analytical Hierarchy Process (AHP) through an expert survey. The combined results indicate that system performance is still the most important factor and that implementation effort and explainability are relatively even factors. Further, we found that systems using similarity-based matching or direct modeling for remaining useful life estimation performed best.

Table 42: Overview Publication P8

Title	A Theoretical Acceptance Model for Intelligent Systems
Author(s)	Wanner, Jonas; Popp, Laurell; Heinrich, Kai; Herm, Lukas-Valentin; Janiesch, Christian
Location	Journal of Information Systems Research
VHB-Ranking	A+
Status	under review (2021)
Abstract	Contemporary decision support systems are increasingly relying on artificial intelligence technology to form intelligent systems. These systems have human-like decision capacity for selected applications based on advances in machine learning. In industrial maintenance, among other industries, they already enhance maintenance tasks such as diagnosis and prognosis. However, adoption by end-users remains rather hesitant. At the same time, there is a lack of (guidance for) independent, rigorous studies that investigate this phenomenon. In response, our research is concerned with the application and extension of the established Unified Theory of Acceptance and Use of Technology (UTAUT) to provide a theoretical model that better explains the interaction of end-users with intelligent systems. In particular, we consider the extension by the constructs of trust and transparency, which we consider as major technology acceptance factors due to the black-box nature of many machine learning algorithms. As a result, we derive an extended theoretical model based on a review of previous extensions for UTAUT. Our model answers several new hypotheses, and our proposed study design includes measurement items for the constructs trust ability, trusting beliefs, and system transparency. It provides the foundation for a better understanding of the human factor in intelligent system acceptance and use.

Table 43: Overview Publication P9

Title	Do You Really Want to Know Why? Effects of AI-based DSS Advice on Human Decisions
Author(s)	Wanner, Jonas
Location	American Conference on Information Systems (AMCIS)
VHB-Ranking	D | Additional: Nomination for best paper of conference award
Status	published (2021)
Abstract	Digital products and services make it possible to use data profitably. Particularly in highly complex applications, e.g., as those found in modern industry, such digital services in the form of intelligent decision support systems (DSS) can be a great support for human decision-making. On the other hand, these systems are subject to criticism because the underlying calculations are often not transparent and contain a residual error. This may be reflected in user rejection of the system's advice. To better understand the impact of such systems, the paper addresses the problem with an empirical investigation towards user confidence and performance. An industrial quality inspection scenario is used as an applied application case. The results highlight that intelligent DSSs affect and even improve user confidence and corresponding to their related performance. However, a significant difference in the influence of different transparency levels between black-box-, grey-box-, and white-box-based DSS tool support was rejected.

Appendix III: Appendix of Publications of this Thesis

Publication P1:

For a list of all publications per search iteration and their respective references, please see Appendix A at https://arxiv.org/ftp/arxiv/papers/2110/2110.06124.pdf.

Iteration I. For our first iteration, we identified preliminary publications (cf. Section 2.1.2.5), which aim at a holistic view, but primarily for specific questions or areas (e.g., business potentials or ML) (Bang et al. 2019; Bordeleau et al. 2018; Cheng et al. 2018; Diez-Olivan et al. 2019; Fay and Kazantsev 2018; Gölzer et al. 2015; Gölzer and Fritzsche 2017; O'Donovan et al. 2015a; Sharp et al. 2018; Xu and Hua 2017). We used this knowledge to employ categorization schemes to derive an initial set of dimensions and characteristics.

Iteration II. In the second iteration, we focused on domain-specific preliminary publications (cf. again Section 2.1.2.5). The prerequisite for the analysis is that the respective authors prepared their data in a taxonomic or categorical fashion. We identified 16 relevant contributions (Baum et al. 2018; Bousdekis et al. 2015; Çaliş and Bulkan 2015; Cardin et al. 2017; Cerrada et al. 2018; Khan and Yairi 2018; Kim et al. 2018; Lee et al. 2018; Lee et al. 2014b; Priore et al. 2014; Reis and Gins 2017; Xu et al. 2017; Zarandi et al. 2018; Zhao et al. 2016; Zhou and Xue 2018; Zschech 2018). We extracted our categorization from each related work and compared it with the taxonomy from the first iteration. Based on this, we added, divided, or merged dimensions and characteristics.

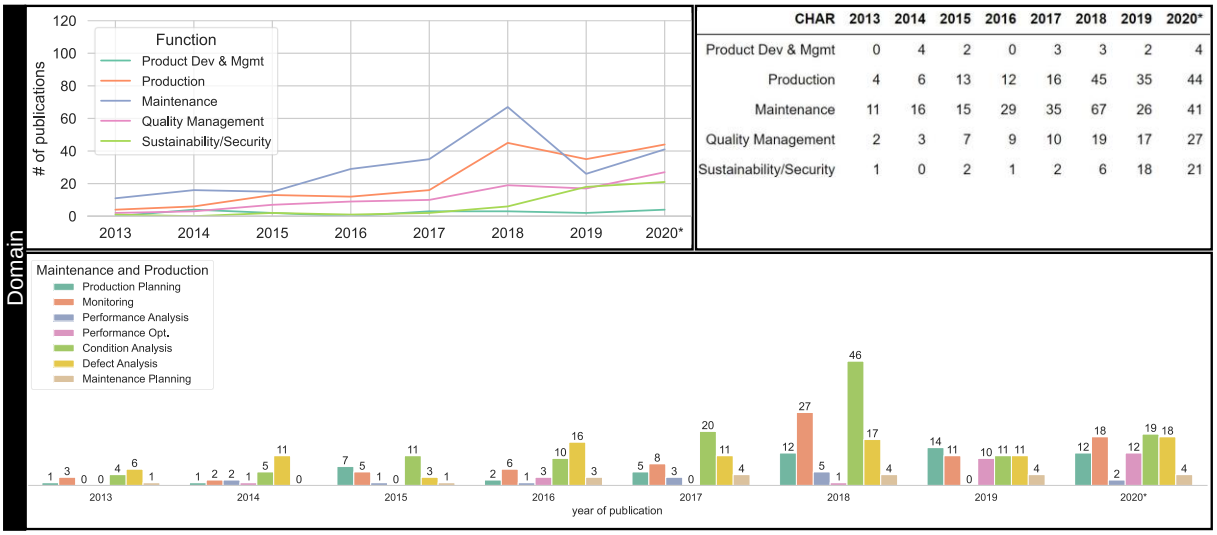
Iteration III. Due to the extensive structuring of the provisional taxonomy, in this iteration we decided to switch to an empirical-to-conceptual approach. We identified a total of 633 articles, which consider the use of BA within a specific smart manufacturing application case (cf. Section 2.1.4.1). We ensured possible modifications of the taxonomy and a possible post-validation by splitting the data. With a random share of 30 % (n=189) of the search results for each group, we were confirmed or even supplemented dimensions and characteristics.

Iteration IV. In the fourth iteration, we again selected a random share of 30 % (n=189) of the search results from the remaining 446 objects. Again, the objective was the validation or extension of dimensions and characteristics using the empirical-to-conceptual approach. However, the result revealed that no further modification was necessary. All closing conditions were satisfied, and we considered the development of the initial taxonomy complete.

Iteration V. To reconfirm our taxonomy's general structure with new research identified in our second literature survey, we decided to perform another conceptual-to-empirical approach. We identified seven further survey papers that prepared their results in a taxonomic or categorical fashion. None take a holistic approach (see Iteration I), they are all domain-specific (see Iteration II). Taking this into account, the articles did not discuss a domain, which was not yet included in our initial taxonomy. Most authors address industrial maintenance, mostly focusing on surveying analytics techniques (Zhang et al. 2019) others additionally take integration, data (Dalzochio et al. 2020) or specific maintenance functions into account (Zonta et al. 2020). Ding et al. (2020) employ artificial intelligence algorithms as a starting

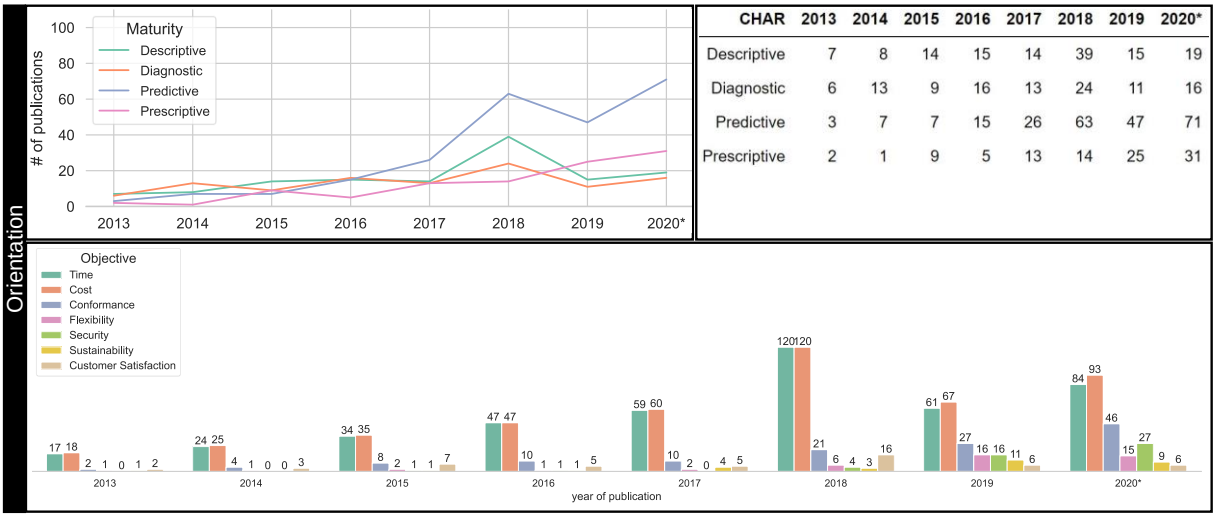
point and map these to specific use cases in maintenance and quality control. Finally, Cadavid et al. (2020) focus on production planning, but also include functions such as maintenance and product design. As the research is domain-specific, it partly addresses dimensions and characteristics on a lower granularity level. Our current taxonomy addresses these on a higher level with regard to the ending conditions (EC2.1) concise and (EC2.3) comprehensive, we did not alter the initial taxonomy.

Iteration VI. As we identified more objects on our second survey, ending condition (EC1.1) was not met anymore. Hence, we switched to an empirical-to-conceptual approach, following our procedure in the third and fourth iteration. We analyzed the 232 objects, by mapping them according to our current taxonomy. The results revealed that no further dimensions or characteristics were identifiable and all ending conditions were satisfied, as the research team was able to tag all objects successfully according to the existing dimensions and characteristics. In conclusion, the second literature search confirmed our initial taxonomy.



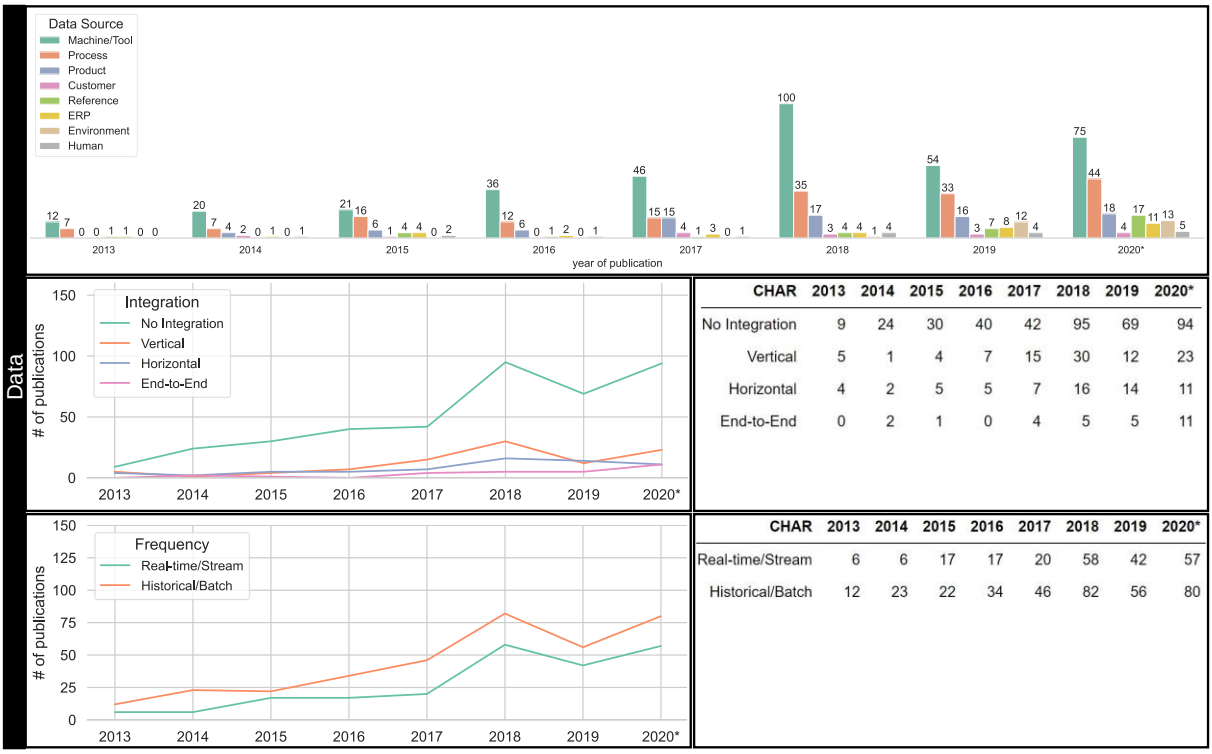
CHAR	2013	2014	2015	2016	2017	2018	2019	2020*
Product Dev & Mgmt	0	4	2	0	3	3	2	4
Production	4	6	13	12	16	45	35	44
Maintenance	11	16	15	29	35	67	26	41
Quality Management	2	3	7	9	10	19	17	27
Sustainability/Security	1	0	2	1	2	6	18	21

Figure 43: Temporal Variations of the Dimension *Domain*



CHAR	2013	2014	2015	2016	2017	2018	2019	2020*
Descriptive	7	8	14	15	14	39	15	19
Diagnostic	6	13	9	16	13	24	11	16
Predictive	3	7	7	15	26	63	47	71
Prescriptive	2	1	9	5	13	14	25	31

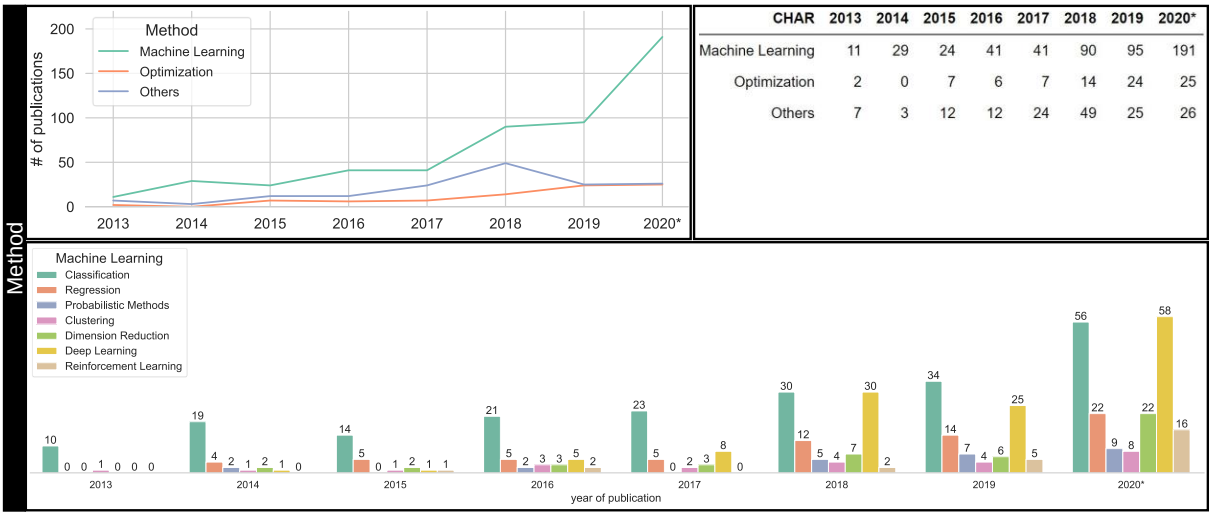
Figure 44: Temporal Variations of the Dimension *Orientation*



CHAR	2013	2014	2015	2016	2017	2018	2019	2020*
No Integration	9	24	30	40	42	95	69	94
Vertical	5	1	4	7	15	30	12	23
Horizontal	4	2	5	5	7	16	14	11
End-to-End	0	2	1	0	4	5	5	11

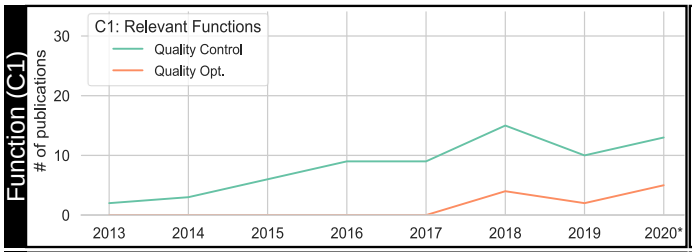
CHAR	2013	2014	2015	2016	2017	2018	2019	2020*
Real-time/Stream	6	6	17	17	20	58	42	57
Historical/Batch	12	23	22	34	46	82	56	80

Figure 45: Temporal Variations of the Dimension *Data*

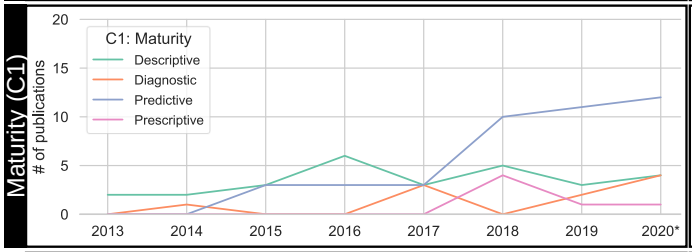


CHAR	2013	2014	2015	2016	2017	2018	2019	2020*
Machine Learning	11	29	24	41	41	90	95	191
Optimization	2	0	7	6	7	14	24	25
Others	7	3	12	12	24	49	25	26

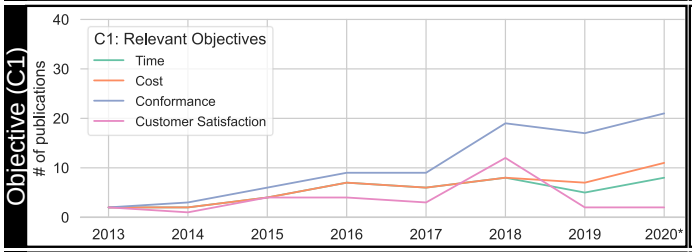
Figure 46: Temporal Variations of the Dimension *Method*



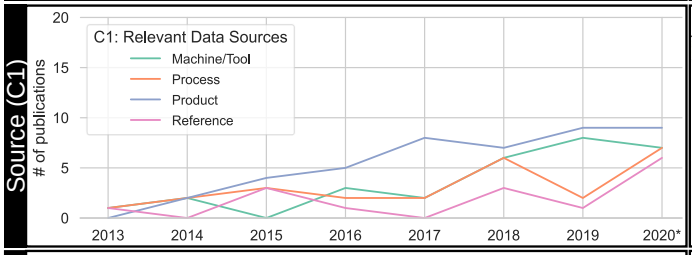
CHAR	2013	2014	2015	2016	2017	2018	2019	2020*
Quality Control	2	3	6	9	9	15	10	13
Quality Opt.	0	0	0	0	0	4	2	5



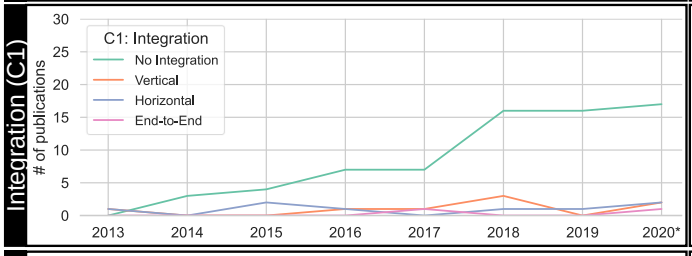
CHAR	2013	2014	2015	2016	2017	2018	2019	2020*
Descriptive	2	2	3	6	3	5	3	4
Diagnostic	0	1	0	0	3	0	2	4
Predictive	0	0	3	3	3	10	11	12
Prescriptive	0	0	0	0	0	4	1	1



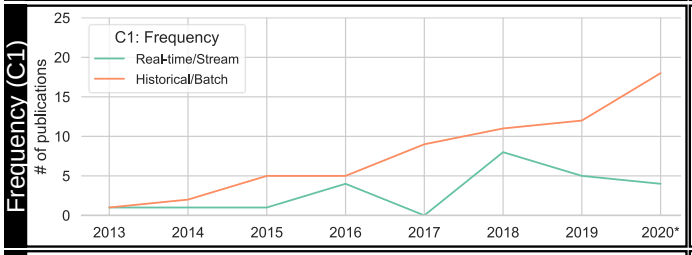
CHAR	2013	2014	2015	2016	2017	2018	2019	2020*
Time	2	2	4	7	6	8	5	8
Cost	2	2	4	7	6	8	7	11
Conformance	2	3	6	9	9	19	17	21
Customer Satisfaction	2	1	4	4	3	12	2	2



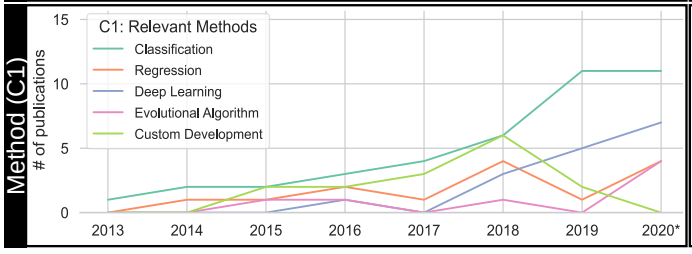
CHAR	2013	2014	2015	2016	2017	2018	2019	2020*
Machine/Tool	1	2	0	3	2	6	8	7
Process	1	2	3	2	2	6	2	7
Product	0	2	4	5	8	7	9	9
Reference	1	0	3	1	0	3	1	6



CHAR	2013	2014	2015	2016	2017	2018	2019	2020*
No Integration	0	3	4	7	7	16	16	17
Vertical	1	0	0	1	1	3	0	2
Horizontal	1	0	2	1	0	1	1	2
End-to-End	0	0	0	0	1	0	0	1

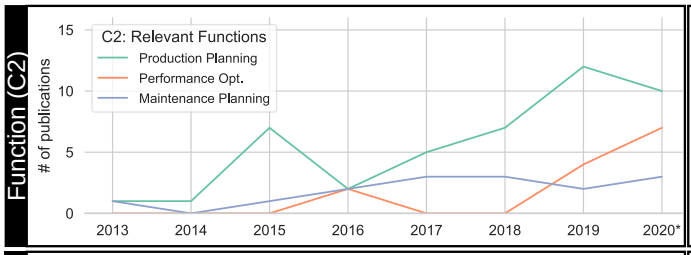


CHAR	2013	2014	2015	2016	2017	2018	2019	2020*
Real-time/Stream	1	1	1	4	0	8	5	4
Historical/Batch	1	2	5	5	9	11	12	18

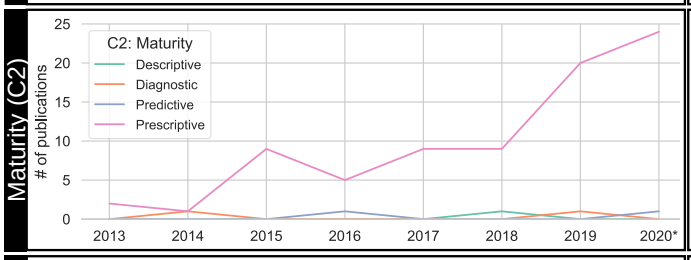


CHAR	2013	2014	2015	2016	2017	2018	2019	2020*
Classification	1	2	2	3	4	6	11	11
Regression	0	1	1	2	1	4	1	4
Deep Learning	0	0	0	1	0	3	5	7
Evolutional Algorithm	0	0	1	1	0	1	0	4
Custom Development	0	0	2	2	3	6	2	0

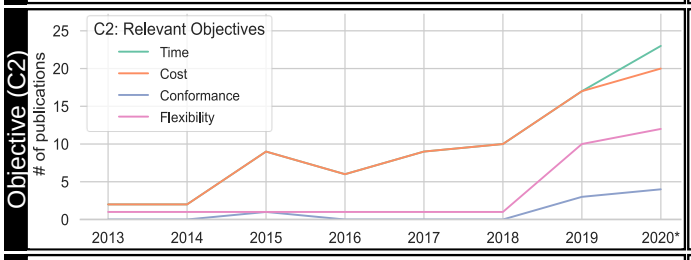
Figure 47: Temporal Variations of the Archetype *Quality Management* (C1)



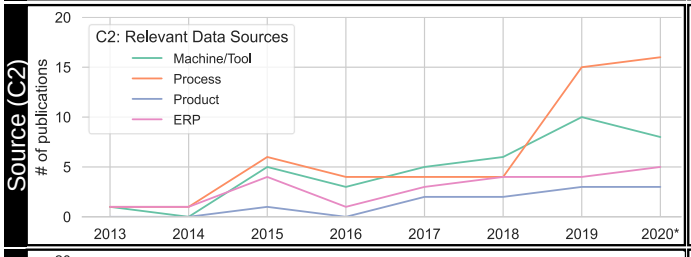
CHAR	2013	2014	2015	2016	2017	2018	2019	2020*
Production Planning	1	1	7	2	5	7	12	10
Performance Opt.	0	0	0	2	0	0	4	7
Maintenance Planning	1	0	1	2	3	3	2	3



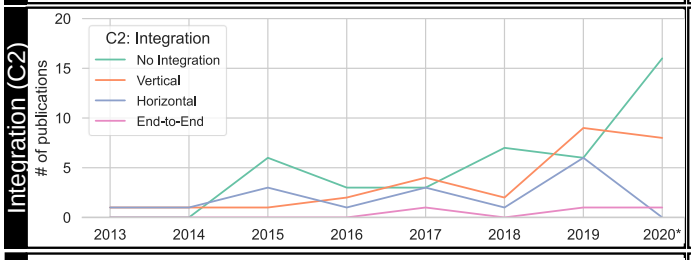
CHAR	2013	2014	2015	2016	2017	2018	2019	2020*
Descriptive	0	0	0	0	0	1	0	0
Diagnostic	0	1	0	0	0	0	1	0
Predictive	0	0	0	1	0	0	0	1
Prescriptive	2	1	9	5	9	9	20	24



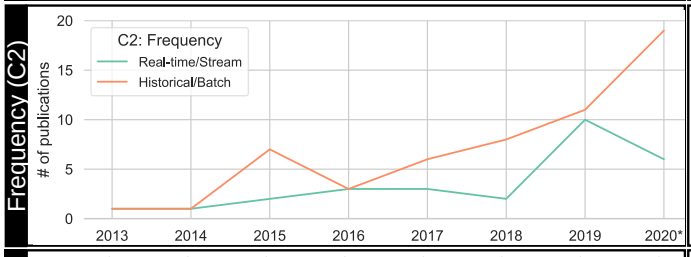
CHAR	2013	2014	2015	2016	2017	2018	2019	2020*
Time	2	2	9	6	9	10	17	23
Cost	2	2	9	6	9	10	17	20
Conformance	0	0	1	0	0	0	3	4
Flexibility	1	1	1	1	1	1	10	12



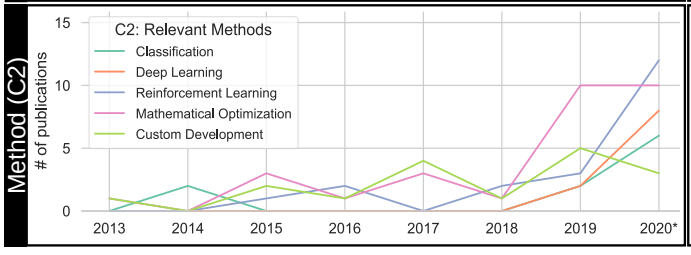
CHAR	2013	2014	2015	2016	2017	2018	2019	2020*
Machine/Tool	1	0	5	3	5	6	10	8
Process	1	1	6	4	4	4	15	16
Product	0	0	1	0	2	2	3	3
ERP	1	1	4	1	3	4	4	5



CHAR	2013	2014	2015	2016	2017	2018	2019	2020*
No Integration	0	0	6	3	3	7	6	16
Vertical	1	1	1	2	4	2	9	8
Horizontal	1	1	3	1	3	1	6	0
End-to-End	0	0	0	0	1	0	1	1

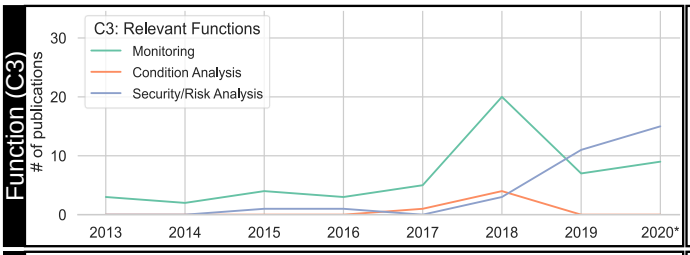


CHAR	2013	2014	2015	2016	2017	2018	2019	2020*
Real-time/Stream	1	1	2	3	3	2	10	6
Historical/Batch	1	1	7	3	6	8	11	19

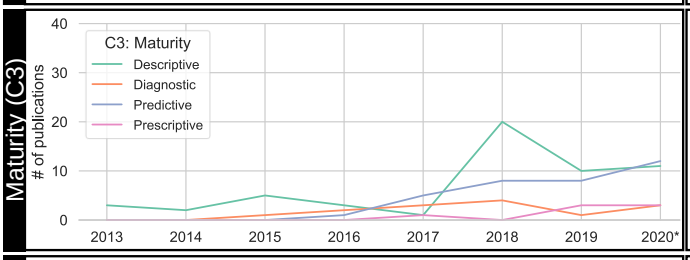


CHAR	2013	2014	2015	2016	2017	2018	2019	2020*
Classification	0	2	0	0	0	0	2	6
Deep Learning	0	0	0	0	0	0	2	8
Reinforcement Learning	0	0	1	2	0	2	3	12
Mathematical Optimization	1	0	3	1	3	1	10	10
Custom Development	1	0	2	1	4	1	5	3

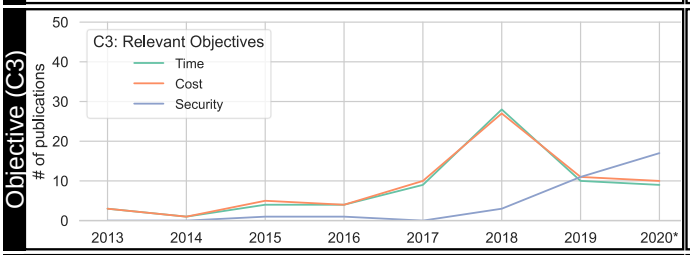
Figure 48: Temporal Variations of the Archetype *MRO Planning* (C2)



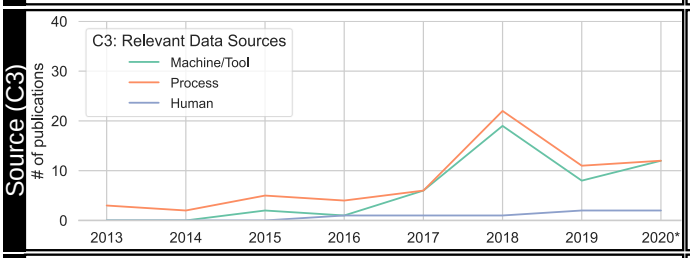
CHAR	2013	2014	2015	2016	2017	2018	2019	2020*
Monitoring	3	2	4	3	5	20	7	9
Condition Analysis	0	0	0	0	1	4	0	0
Security/Risk Analysis	0	0	1	1	0	3	11	15



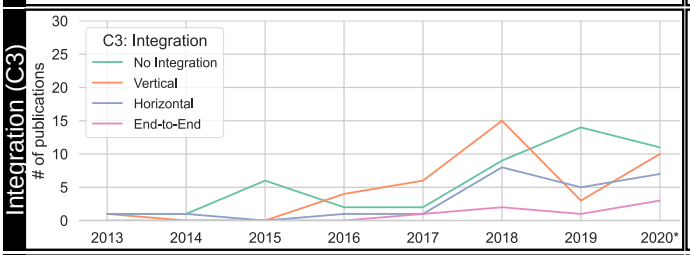
CHAR	2013	2014	2015	2016	2017	2018	2019	2020*
Descriptive	3	2	5	3	1	20	10	11
Diagnostic	0	0	1	2	3	4	1	3
Predictive	0	0	0	1	5	8	8	12
Prescriptive	0	0	0	0	1	0	3	3



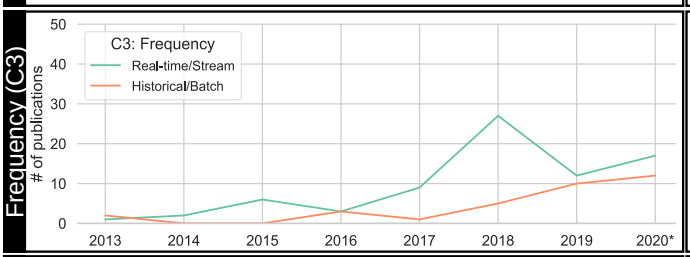
CHAR	2013	2014	2015	2016	2017	2018	2019	2020*
Descriptive	3	2	5	3	1	20	10	11
Diagnostic	0	0	1	2	3	4	1	3
Predictive	0	0	0	1	5	8	8	12
Prescriptive	0	0	0	0	1	0	3	3



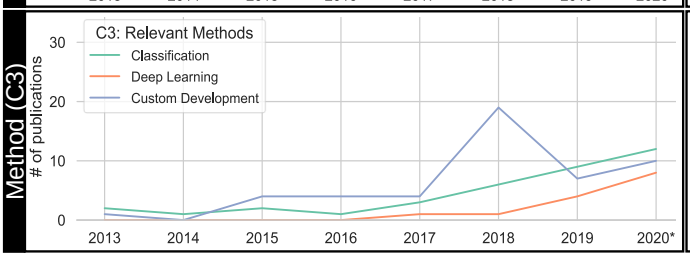
CHAR	2013	2014	2015	2016	2017	2018	2019	2020*
Machine/Tool	0	0	2	1	6	19	8	12
Process	3	2	5	4	6	22	11	12
Human	0	0	0	1	1	1	2	2



CHAR	2013	2014	2015	2016	2017	2018	2019	2020*
No Integration	1	1	6	2	2	9	14	11
Vertical	1	0	0	4	6	15	3	10
Horizontal	1	1	0	1	1	8	5	7
End-to-End	0	0	0	0	1	2	1	3

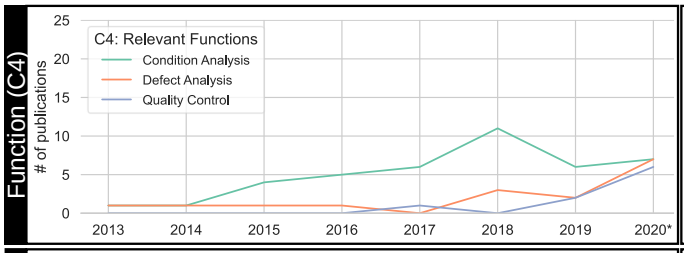


CHAR	2013	2014	2015	2016	2017	2018	2019	2020*
Real-time/Stream	1	2	6	3	9	27	12	17
Historical/Batch	2	0	0	3	1	5	10	12

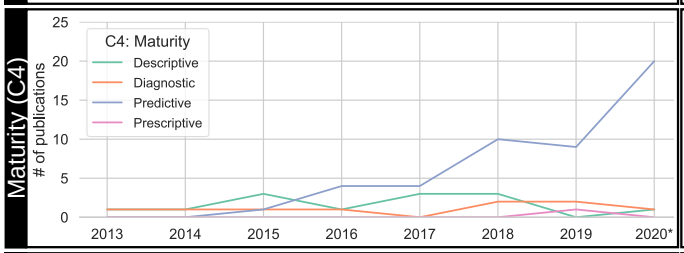


CHAR	2013	2014	2015	2016	2017	2018	2019	2020*
Classification	2	1	2	1	3	6	9	12
Deep Learning	0	0	0	0	1	1	4	8
Custom Development	1	0	4	4	4	19	7	10

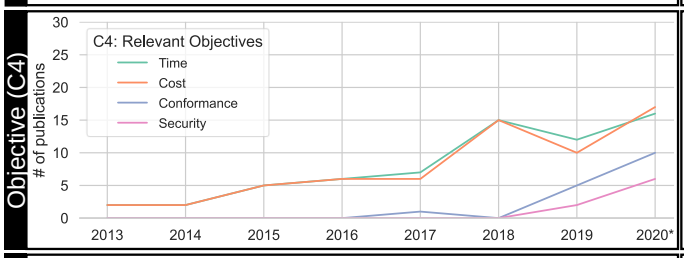
Figure 49: Temporal Variations of the Archetype *MRO Monitoring* (C3)



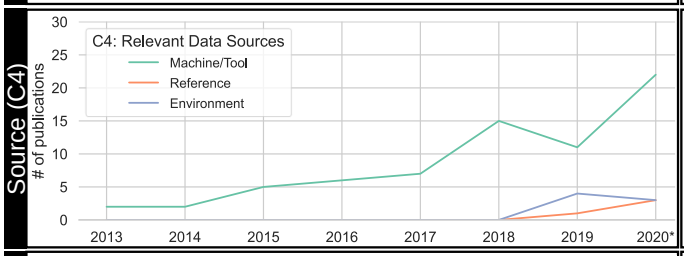
CHAR	2013	2014	2015	2016	2017	2018	2019	2020*
Condition Analysis	1	1	4	5	6	11	6	7
Defect Analysis	1	1	1	1	0	3	2	7
Quality Control	0	0	0	0	1	0	2	6



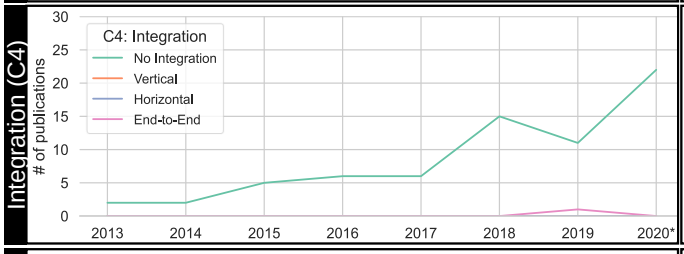
CHAR	2013	2014	2015	2016	2017	2018	2019	2020*
Descriptive	1	1	3	1	3	3	0	1
Diagnostic	1	1	1	1	0	2	2	1
Predictive	0	0	1	4	4	10	9	20
Prescriptive	0	0	0	0	0	0	1	0



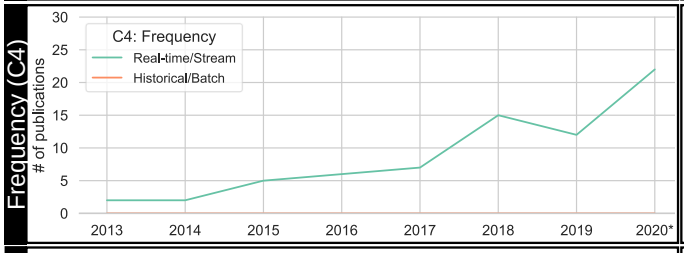
CHAR	2013	2014	2015	2016	2017	2018	2019	2020*
Time	2	2	5	6	7	15	12	16
Cost	2	2	5	6	6	15	10	17
Conformance	0	0	0	0	1	0	5	10
Security	0	0	0	0	0	0	2	6



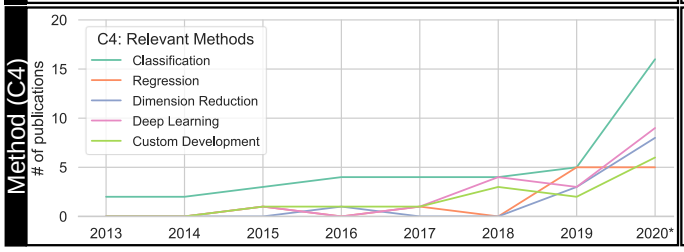
CHAR	2013	2014	2015	2016	2017	2018	2019	2020*
Machine/Tool	2	2	5	6	7	15	11	22
Reference	0	0	0	0	0	0	1	3
Environment	0	0	0	0	0	0	4	3



CHAR	2013	2014	2015	2016	2017	2018	2019	2020*
No Integration	2	2	5	6	6	15	11	22
Vertical	0	0	0	0	0	0	0	0
Horizontal	0	0	0	0	0	0	0	0
End-to-End	0	0	0	0	0	0	1	0

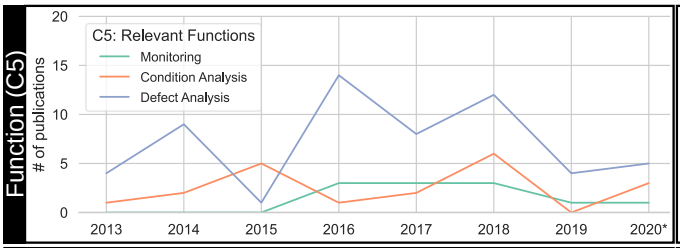


CHAR	2013	2014	2015	2016	2017	2018	2019	2020*
Real-time/Stream	2	2	5	6	7	15	12	22
Historical/Batch	0	0	0	0	0	0	0	0

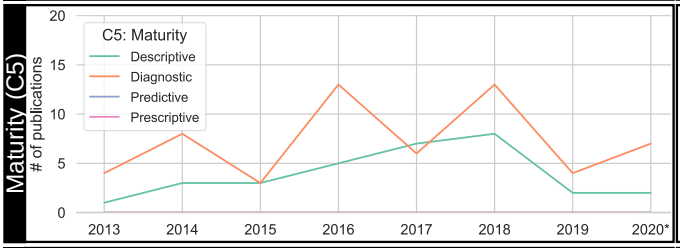


CHAR	2013	2014	2015	2016	2017	2018	2019	2020*
Classification	2	2	3	4	4	4	5	16
Regression	0	0	1	0	1	0	5	5
Dimension Reduction	0	0	0	1	0	0	3	8
Deep Learning	0	0	1	0	1	4	3	9
Custom Development	0	0	1	1	1	3	2	6

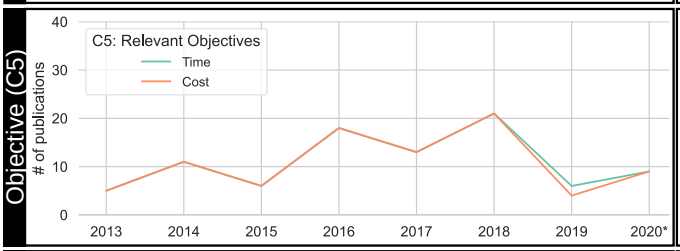
Figure 50: Temporal Variations of the Archetype *Online Predictive Maintenance* (C4)



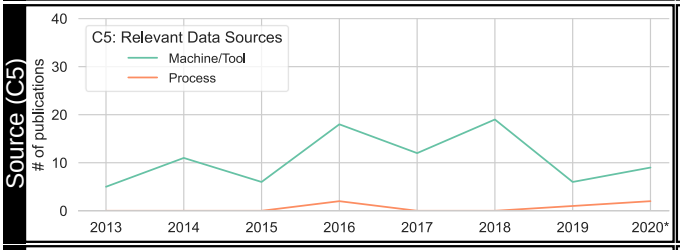
CHAR	2013	2014	2015	2016	2017	2018	2019	2020*
Monitoring	0	0	0	3	3	3	1	1
Condition Analysis	1	2	5	1	2	6	0	3
Defect Analysis	4	9	1	14	8	12	4	5



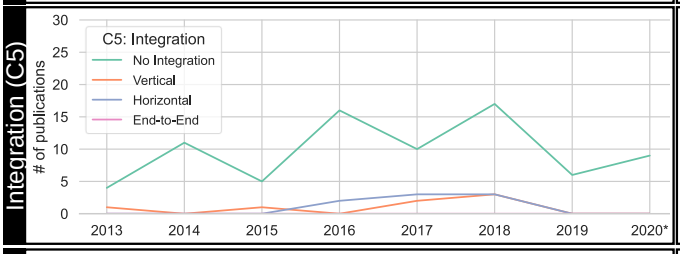
CHAR	2013	2014	2015	2016	2017	2018	2019	2020*
Descriptive	1	3	3	5	7	8	2	2
Diagnostic	4	8	3	13	6	13	4	7
Predictive	0	0	0	0	0	0	0	0
Prescriptive	0	0	0	0	0	0	0	0



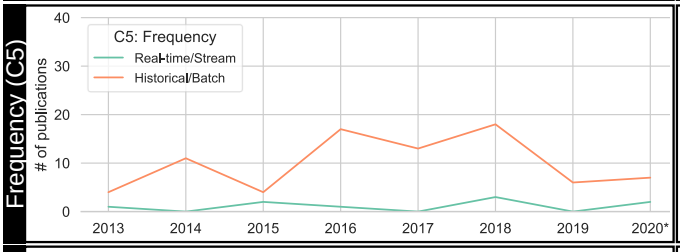
CHAR	2013	2014	2015	2016	2017	2018	2019	2020*
Time	5	11	6	18	13	21	6	9
Cost	5	11	6	18	13	21	4	9



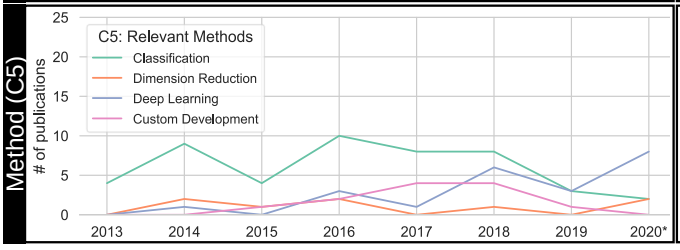
CHAR	2013	2014	2015	2016	2017	2018	2019	2020*
Machine/Tool	5	11	6	18	12	19	6	9
Process	0	0	0	2	0	0	1	2



CHAR	2013	2014	2015	2016	2017	2018	2019	2020*
No Integration	4	11	5	16	10	17	6	9
Vertical	1	0	1	0	2	3	0	0
Horizontal	0	0	0	2	3	3	0	0
End-to-End	0	0	0	0	0	0	0	0

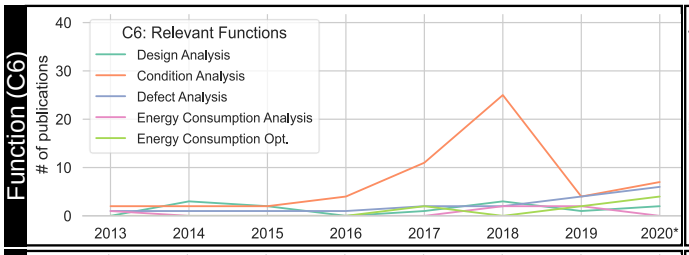


CHAR	2013	2014	2015	2016	2017	2018	2019	2020*
Real-time/Stream	1	0	2	1	0	3	0	2
Historical/Batch	4	11	4	17	13	18	6	7

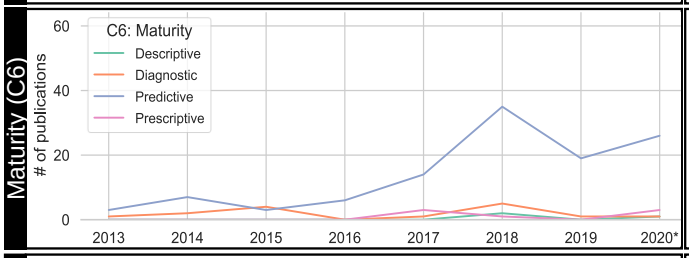


CHAR	2013	2014	2015	2016	2017	2018	2019	2020*
Classification	4	9	4	10	8	8	3	2
Dimension Reduction	0	2	1	2	0	1	0	2
Deep Learning	0	1	0	3	1	6	3	8
Custom Development	0	0	1	2	4	4	1	0

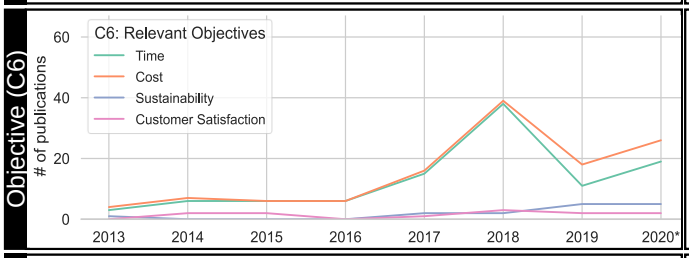
Figure 51: Temporal Variations of the Archetype *Reactive Maintenance* (C5)



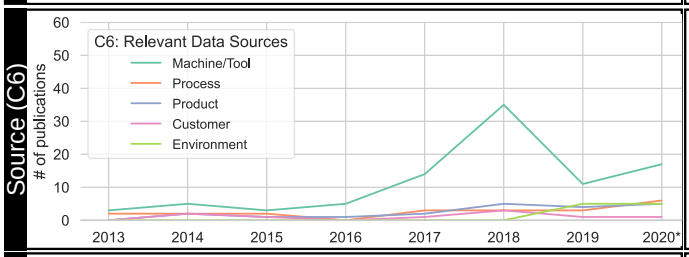
CHAR	2013	2014	2015	2016	2017	2018	2019	2020*
Design Analysis	0	3	2	0	1	3	1	2
Condition Analysis	2	2	2	4	11	25	4	7
Defect Analysis	1	1	1	1	2	2	4	6
Energy Consumption Analysis	1	0	0	0	0	2	2	0
Energy Consumption Opt.	0	0	0	0	2	0	2	4



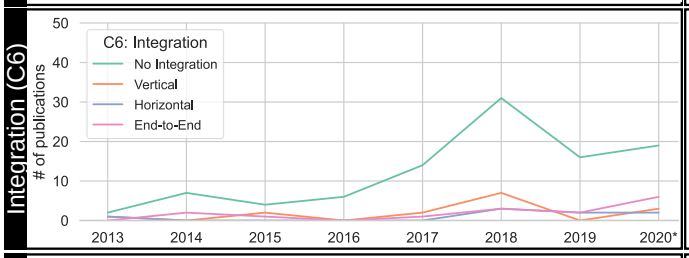
CHAR	2013	2014	2015	2016	2017	2018	2019	2020*
Descriptive	0	0	0	0	0	2	0	1
Diagnostic	1	2	4	0	1	5	1	1
Predictive	3	7	3	6	14	35	19	26
Prescriptive	0	0	0	0	3	1	0	3



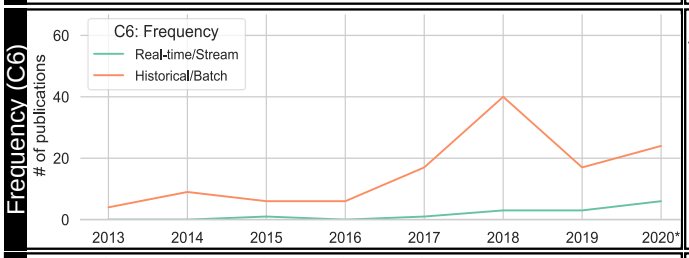
CHAR	2013	2014	2015	2016	2017	2018	2019	2020*
Time	3	6	6	6	15	38	11	19
Cost	4	7	6	6	16	39	18	26
Sustainability	1	0	0	0	2	2	5	5
Customer Satisfaction	0	2	2	0	1	3	2	2



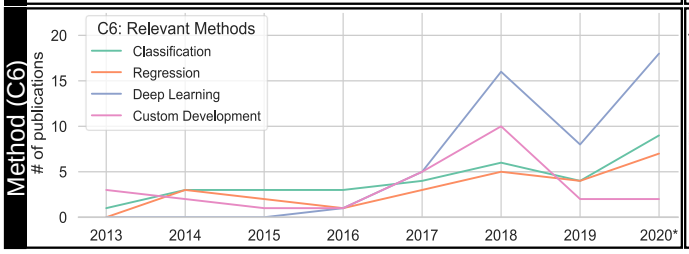
CHAR	2013	2014	2015	2016	2017	2018	2019	2020*
Machine/Tool	3	5	3	5	14	35	11	17
Process	2	2	2	0	3	3	3	6
Product	0	2	1	1	2	5	4	5
Customer	0	2	1	0	1	3	1	1
Environment	0	0	0	0	0	0	5	5



CHAR	2013	2014	2015	2016	2017	2018	2019	2020*
No Integration	2	7	4	6	14	31	16	19
Vertical	1	0	2	0	2	7	0	3
Horizontal	1	0	0	0	0	3	2	2
End-to-End	0	2	1	0	1	3	2	6



CHAR	2013	2014	2015	2016	2017	2018	2019	2020*
Real-time/Stream	0	0	1	0	1	3	3	6
Historical/Batch	4	9	6	6	17	40	17	24



CHAR	2013	2014	2015	2016	2017	2018	2019	2020*
Classification	1	3	3	3	4	6	4	9
Regression	0	3	2	1	3	5	4	7
Deep Learning	0	0	0	1	5	16	8	18
Custom Development	3	2	1	1	5	10	2	2

Figure 52: Temporal Variations of the Archetype *Offline Predictive Maintenance* (C6)

Publication P2:

Table 44: XAI Transfer Model Techniques Classified by ML Type

	Supervised Learning						*Unsupervised Learning*	
	(A)NN	**CNN**	**Long Short-term Memory**	**Random Forest**	**Gradient Boosting**	**SVM**	**Clustering Algorithms**	**Fuzzy System**
Decision Tree	(Evans et al. 2019; Liu et al. 2018a; Matetic 2019; Páez 2019)	(Liu et al. 2018a)	–	(Fauvel et al. 2019; Iwasaki et al. 2019; Tolomei et al. 2017)	(Fauvel et al. 2019; Luna et al. 2019; Tolomei et al.	(Baryannis et al. 2019; Fauvel et al. 2019; Iwasaki et al. 2019)	(El Bekri et al. 2019)	(Yong et al. 2009)
Ruleset	(Guidotti et al. 2018a; Hayashi 2018; Johansson et al. 2005; Páez 2019; Vásquez-Morales et al. 2019)	(Liu et al. 2004; Oviedo et al. 2019; Xi and Panoutsos 2018)	-	(Crielaard and Papapetrou 2018; Guidotti et al. 2018a)	–	(Guidotti et al. 2018a; Polato and Aiolli 2019; Singh et al. 2019)	(Yousefi et al. 2019)	(Castro and Camargo 2005; Juang and Chen 2012)
Natural Language Processing	(Carvalho et al. 2019a; Ehsan et al. 2019)	(Dong et al. 2017; Kang et al. 2019)	(Ehsan et al. 2018)	–	–	–	–	–
Visualization	(Elshawi et al. 2019; Karimi et al. 2019; Kovalerchuk and Neuhaus 2018; Mothilal et al. 2020; Oviedo et al. 2019; Panigutti et al. 2020; Weidele et al. 2020)	(Beniwal et al. 2019; Chen et al. 2020; Fawaz et al. 2019; Guo et al. 2018; Loyola-González 2019; McGovern et al. 2019; Monroe et al. 2019; Natekar et al. 2020; Shen et al. 2019;	(AlSaad et al. 2019; Sellam et al. 2019)	(Elshawi et al. 2019; Iwasaki et al. 2019; Li et al. 2019; Tan et al. 2016)	(Li et al. 2019; Tan et al. 2016; Thurier et al. 2019)	(Baryannis et al. 2019; Elshawi et al. 2019; Grazioli et al. 2019; Iwasaki et al. 2019)	(Elshawi et al. 2019; Lamy et al. 2019; Matetic 2019)	–
Feature & Metadata Analysis	(Koh and Liang 2017; Ornes and Sklansky 1997; Shimodaira 1996; Vásquez-Morales et al. 2019; Wang et al. 2010)	(Alzantot et al. 2019; Du et al. 2018; Koh and Liang 2017; Liu et al. 2018b)	(Koh and Liang 2017)	(Petkovic et al. 2018; Virgolin et al. 2020)	(Thurier et al. 2019; Virgolin et al. 2020)	(Turner 2016; Virgolin et al. 2020)	–	–
Bayesian inferences	(Chakraborty et al. 2017; Kraus and Feuerriegel 2019; Páez 2019)	-	(Guo et al. 2019a; Hara and Hayashi 2016; Kraus and Feuerriegel 2019)	–	–	(Iwasaki et al. 2019)	–	–
Guided Backpropagation	-	(Wickstrøm et al. 2018)	–	–	–	–	–	–
Linear Regression	-	-	–	(Luo et al. 2020)	–	–	(El Bekri et al. 2019)	–
Forecast w. Correction Option	-	-	–	–	–	(Teso and Kersting 2019)	–	–
Lazy Lasso	–	-	–	(Liu et al. 2017)	–	–	–	–
Dimension Reduction	–	-	–	(Eiras-Franco et al. 2019)	–	(Karevan et al. 2015)	(Karevan et al. 2015)	–

Publication P4:

Table 45: Mathematical models for timeliness of data

Author(s)	Mathematical models	Variables
Ballou et al. (1998)	currency = (delivery time − input time) + age $timliness = \{\max[\left(1 - \frac{currency}{volatility}\right), 0]\}^{s}$	Currency (age of data): - Delivery date - Extraction date - Age at measurement Volatility (validity period): - Determined by data quality manager with user(s)
Hinrichs (2002)	$QZeit(\omega, A) = \frac{1}{upd(A)} \cdot age(\omega) + 1$	Timeliness of attribute: - Change in value (update) - Date of determination - Date of transaction - Current time
Even and Shankaranarayan (2007)	$t^{E}_{n,m}\left(g^{E}_{n,m}\right) = \exp\left\{-\eta g^{E}_{n,m}\right\}$	Novelty of data item in t: - Current time - Time of last update - 'Ageing rate' (η), defined by expert(s)
Heinrich and Klier (2011)	$Q_{Curr.}(\omega, A) := \exp(-decline(A) \cdot age(\omega, A))$	Currency (age of data): - Data age at measurement - 'Ageing rate', to be determined statistically

Table 46: Mathematical models for completeness of data

Author(s)	Mathematical models	Variables
Hinrichs (2002)	$NotNull(w) := \begin{cases} 0 & \text{falls } w = NULL \text{ oder } w \text{ zu } NULL \text{ äquivalent} \\ 1 & \text{sonst.} \end{cases}$ $Q_{Voll}(t) := \frac{\sum_{j=1}^{n} Q_{Voll}(t.A_j) g_j}{\sum_{j=1}^{n} g_j}$	Evaluation of completeness: - Non-availability value, 'unknown' (NULL) - value or deviating values - Relative importance for application context
Shankaranarayan et al. (2003)	$\mathbf{C_x} = \Sigma_{i=1,n}(c_i * C_i) / \Sigma_{i=1..n}(c_i)$	Assignment of completeness: - Availability of the data elements - Relative importance for application context
Heinrich and Klier (2015)	$Q_{Vollst.}(T) := \frac{\sum_{i=1}^{\lvert A \rvert} Q_{Vollst.}(T.A_i) g_i}{\sum_{i=1}^{\lvert A \rvert} g_i}$	Completeness in info-system: - Attribute values available vs. not available - Relative importance for application context
Aljumaili et al. (2016)	$completeness = 1 - \left(\frac{\text{no. of incomplete items}}{\text{total no. of items}}\right)$	Completeness checking: - Missing or unknown values of the real-world entity

Table 47: Mathematical models for accuracy of data

Author(s)	Mathematical models	Variables
Hinrichs (2002)	$Q_{Korr}(t,e) := \frac{\sum_{j=1}^{n} Q_{Korr}(t.A_j, e.A_j) g_j}{\sum_{j=1}^{n} g_j}$ $Q_{Gen}(t) := \frac{\sum_{j=1}^{n} Q_{Gen}(t.A_j, A_j) g_j}{\sum_{j=1}^{n} g_j}$	Correctness of data values: - Distance measure to modeled real-world entity - Relative importance for real-world entity Precision of data values: - Precision due to the number of decimal places - Digits in classification hierarchy (importance)
Shankaranarayan et al. (2003)	$A_x = [\Sigma_{i=1,n} (a_i * A_i)] / [\Sigma_{i=1,n} (A_i)]$	Accuracy of data element(s): - Number of incorrect data values - Total number of data values
Heinrich and Klier (2015)	$d_2(w_I, w_R) := \left(\frac{\lvert w_I - w_R \rvert}{\max\{\lvert w_I \rvert, \lvert w_R \rvert\}} \right)^{\alpha}$, $Q_{Fehl.}(w_I, w_R) := 1 - d(w_I, w_R)$	Accuracy in info-system: - Degree of conformity with real-world entity - Weighting factor for effect of deviation
Aljumaili et al. (2016)	accurancy = 1 - (no. of items in error / total no. of items)	Accuracy metrics: - Number of items in error - Total number of items

Figure 53: Excerpt of sustainability report Henkel AG (Henkel AG 2015, p. 54)

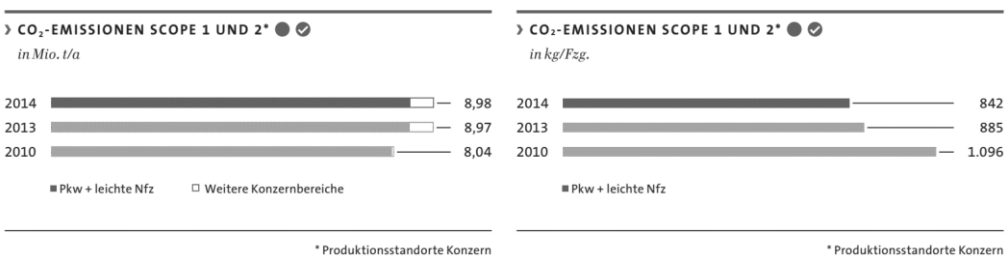


Figure 54: Excerpt of sustainability report Volkswagen AG (Volkswagen AG 2014, p. 127)

Publication P8:

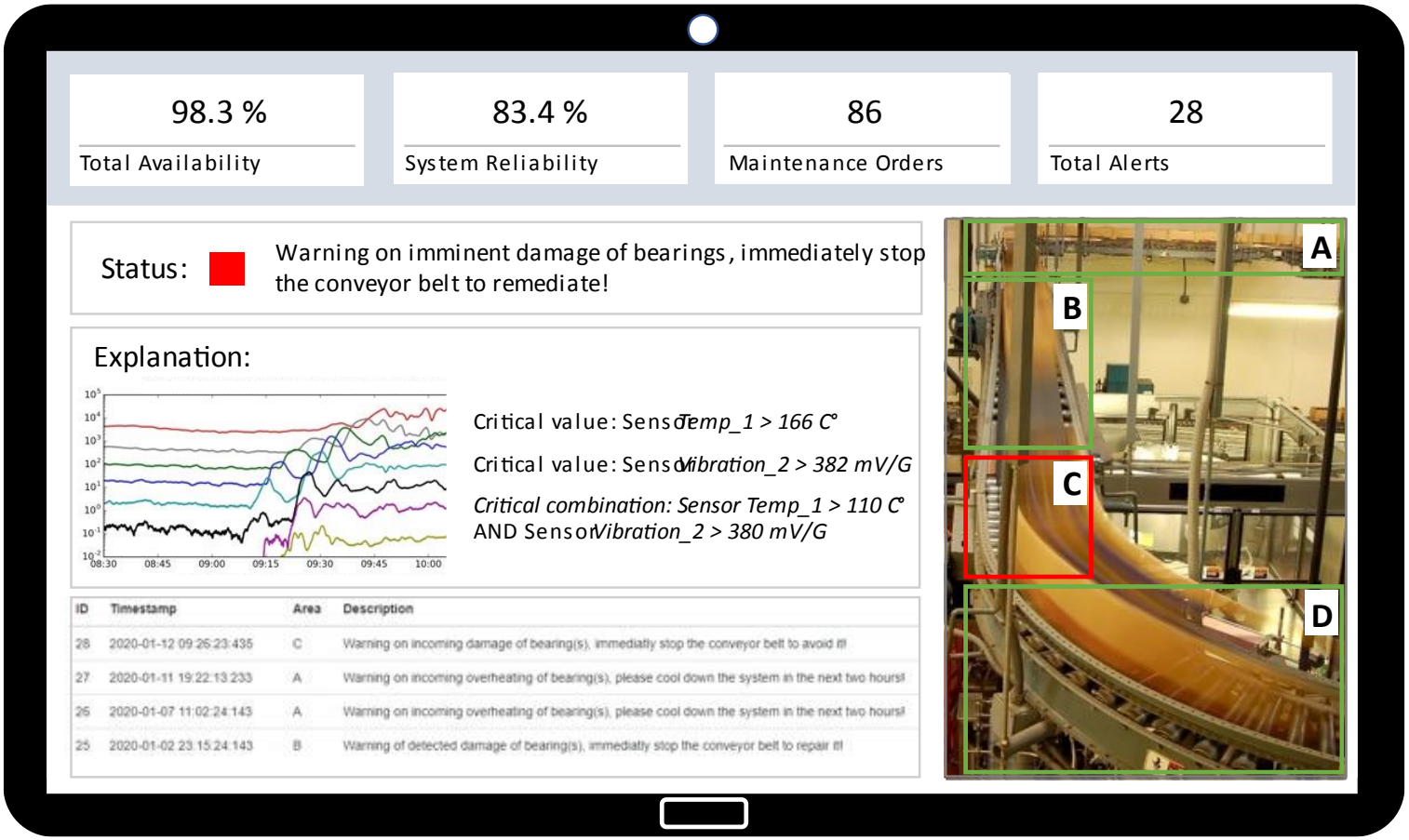


Figure 55: Dashboard Design

Table 48: Measurement Item Collection Procedure

Construct		Measurement Item	Abb.	Primary Source	Secondary Source	Sequential Reduction				
						1	*2*	*3*	*4*	*5*
PE	Perceived Usefulness	Using the system in my job would enable me to accomplish tasks more quickly.	PE1	Davis (1989)	Venkatesh et al. (2003)	•	•	•	•	•
		Using the system would improve my job performance.	PE2			•	•	•	•	•
		Using the system would enhance my effectiveness on the job.	-			•	•	•		
		Using the system would make it easier to do my job.	PE3			•	•	•	•	•
		I would find the system useful in my job.	PE4			•	•	•	•	•
	Job-fit	Use of the system will have no effect on the performance of my job (reverse scored).	-	Venkatesh et al. (2003)	Thompson et al. (1991)	•				
		Use of the system can decrease the time needed for my important job responsibilities.				•				
		Use of the system can significantly increase the quality of output on my job.				•	•	•		
		Using this system can significantly increase the quantity of output for the same amount of effort in my job				•	•	•		
		Use of the system can increase the effectiveness of performing job tasks.				•				
		Use can increase the quantity of output for the same amount of effort.				•	•	•		
		Considering all tasks. the general extent to which use of the system could assist on the job.				•	•	•		
	Relative Advantage	Using the system enables me to accomplish tasks more quickly.	-	Moore and Benbasat (1991)	Venkatesh et al. (2003)	•	•			
		Using the system improves the quality of the work I do.				•	•	•		
		Using the system makes it easier to do my job.				•				
		Using the system enhances my effectiveness on the job.				•				
		Using the system in my job would increase my productivity.	PE5			•	•	•	•	•
	Outcome Expectations - Performance	If I use the system I will increase my effectiveness on the job.	-	Venkatesh et al. (2003)	Compeau and Higgins (1995)	•				
		If I use the system I will spend less time on routine job tasks.				•	•	•		
		If I use the system I will increase the quality of output of my job.				•				
		If I use the system I will increase the quantity of output for the same amount of effort.				•	•	•		
		If I use the system my coworkers will perceive me as competent.				•	•	•		
		If I use the system I will increase my chances of obtaining a promotion.				•	•	•		
		If I use the system I will increase my chances of getting a raise.				•	•	•		

EE	Perceived Ease of Use	Learning to operate the system would be easy for me.	EE1	Venkatesh et al. (2003)	Davis (1989)	•	•	•	•	•
		I would find it easy to get the system to do what I want it to do.	EE2			•	•	•	•	•
		My interaction with the system would be clear and understandable.	EE3			•	•	•	•	•
		I would find the system easy to use.	EE4			•	•	•	•	•
		I would find the system to be flexible to interact with.	-			•	•	•		
		It would be easy for me to become skillful at using the system.	-			•				
	Complexity	Using the system takes too much time from my normal duties.	-	Venkatesh et al. (2003)	Thompson et al. (1991)	•	•	•		
		Working with the system is so complicated. it is difficult to understand what is going on.				•	•	•		
		Using the system involves too much time doing mechanical operations (e.g.. data input).				•	•	•		
		It takes too long to learn how to use the system to make it worth the effort.				•	•	•		
	Ease of Use	My interaction with the system is clear and understandable.	-	Venkatesh et al. (2003)	Moore and Benbasat (1991)	•				
		I believe that it is easy to get the system to do what I want it to do.				•				
		Overall. I believe that the system is easy to use.				•				
		Learning to operate the system is easy for me.				•				
ATT	Intrinsic Motivation	I find using the system to be enjoyable	-	Davis et al. (1992)	-	•				
		The actual process of using the system would be pleasant.	ATT1		Venkatesh et al. (2003)	•	•	•	•	•
		I have fun using the system.	-		-	•				
	Affect Toward Use	This system would make work more interesting.	ATT2	Thompson et al. (1991)	Venkatesh et al. (2003)	•	•	•	•	•
		Working with the system is fun.	-	Venkatesh et al. (2003)	-	•				
		The system is okay for some jobs. but not the kind of job I want. (R)		Thompson et al. (1991)		•	•	•		
	Affect	I would like working with the system.	ATT3	Compeau et al. (1999)	Venkatesh et al. (2003)	•	•	•	•	•
		I look forward to those aspects of my job that require me to use the system.	-			•	•	•		
		Using the system is frustrating for me. (R)				•	•	•		
		Once I start working on the system. I find it hard to stop.				•	•	•		
	Attitude Toward Behavior	Using the system is a good idea.	ATT4	Peters et al. (2020); Taylor and Todd (1995)	Venkatesh et al. (2003)	•	•	•		•
		I dislike/like the idea of using the system.	-			•				
		Using the system would be wise move.	ATT5			•	•	•		•

	Using the system is unpleasant/pleasant.	-			•	•	•		
Behavioral Intention	If this system was available to me. I would intend to use this system in the next months.	BI1	Venkatesh et al. (2003)	-		•	•	•	•
	If this system was available to me. I predict I would use this system in the next months.	BI2				•	•	•	•
	If this system was available to me I would plan to use this system in the next months.	BI3			•	•	•	•	•
System Transparency	I know what will happen the next time I use the system because I understand how it behaves.	-	Madsen and Gregor (2000)	-	•	•	•		
	I would understand how this system will assist me with decisions I have to make.	ST1			•	•	•	•	•
	Although I may not know exactly how the system works. I know how to use it to make decisions about the problem.	-			•	•	•		
	It is easy to follow what the system does.				•	•	•		
	I recognize what I should do to get the advice I need from the system the next time I use it.				•	•	•		
	I would understand why this system provided the decision it did.	ST2	Cramer et al. (2008)		•	•	•	•	•
	I would understand what this system bases its provided decision on.	ST3			•	•	•	•	
Trust Ability	This system would be competent in providing maintenance decision support.	TA1	McKnight et al. (2002)	Cheng et al. (2008)	•	•	•	•	•
	This system would perform maintenance decision support very well.	TA2			•	•	•	•	•
	In general. this system would be proficient in providing maintenance decision support.	TA3			•	•	•	•	•
Trusting Beliefs	It would be easy for me to trust this system.	TB1	Lee and Turban (2001)	Cheng et al. (2008); Wang and Benbasat (2007)	•	•	•	•	•
	My tendency to trust this system would be high.	TB2			•	•	•	•	•
	I would tend to trust this system. even though I have little or no knowledge of it.	TB3			•	•	•	•	•
	Trusting this system would be difficult for me.	TB4		Wang and Benbasat (2007)	•	•	•	•	

Legend: Sequential reduction of the item collection to fit the defined use case: 1) preliminary work; 2) authors' internal discussion; 3) expert survey; 4) pre-study; 5) main-study

Table 49: Validation and Reliability Testing Results Pre-Study

Cross-loadings*							
Factors	**ATT**	**BI**	**EE**	**PE**	**ST**	**TA**	**TB**
ATT1	**0.819**	0.436	0.521	0.518	0.180	0.658	0.580
ATT2	**0.581**	0.107	0.285	0.268	0.021	0.345	0.179
ATT3	**0.872**	0.269	0.622	0.482	0.110	0.565	0.453
BI1	0.498	**0.859**	0.500	0.536	0.325	0.458	0.589
BI2	0.190	**0.911**	0.250	0.321	0.343	0.264	0.318
BI3	0.229	**0.800**	0.276	0.330	0.361	0.315	0.275
EE2	0.476	0.208	**0.773**	0.313	0.002	0.480	0.495
EE3	0.366	0.331	**0.758**	0.177	0.214	0.285	0.198
EE4	0.686	0.437	**0.891**	0.452	0.203	0.520	0.449
PE1	0.327	0.443	0.207	**0.746**	0.396	0.398	0.371
PE2	0.461	0.497	0.281	**0.846**	0.228	0.432	0.429
PE3	0.509	0.300	0.342	**0.776**	0.129	0.454	0.347
PE4	0.483	0.219	0.386	**0.739**	0.132	0.342	0.255
PE5	0.530	0.437	0.376	**0.881**	0.305	0.404	0.348
ST1	0.188	0.225	0.263	0.211	**0.842**	0.269	0.268
ST2	0.091	0.445	0.235	0.309	**0.890**	0.239	0.105
TA1	0.677	0.421	0.524	0.522	**0.241**	**0.918**	0.731
TA2	0.521	0.215	0.328	0.338	0.222	**0.799**	0.558
TA3	0.520	0.399	0.463	0.356	0.260	**0.707**	0.419
TB1	0.637	0.410	0.503	0.405	0.191	**0.751**	0.929
TB2	0.507	0.436	0.475	0.440	0.103	0.632	**0.906**
TB3	0.213	0.412	0.335	0.254	0.267	0.339	**0.584**
TB4	0.014	-0.180	0.055	0.083	-0.093	-0.107	**-0.450**
Fornell-Larcker Criterion							
Factors	**ATT**	**BI**	**EE**	**PE**	**ST**	**TA**	**TB**
ATT	0.768	-	-	-	-	-	-
BI	0.391	0.858	-	-	-	-	-
EE	0.650	0.427	0.757	-	-	-	-
PE	0.576	0.486	0.393	0.799	-	-	-
ST	0.156	0.397	0.285	0.305	0.866	-	-
TA	0.710	0.423	0.540	0.509	0.291	0.813	-
TB	0.575	0.495	0.526	0.443	0.207	0.720	0.746

We conclude that the items for *EE* are well chosen, as these have been tested and verified in many studies based on the UTAUT model. In addition, *EE* does not fail any other criteria except indicator reliability (EE1). Thus, we retain all measurement items for *EE*. We conclude that items for ST are, in principle, well chosen. However, we conclude that an additional measurement item for *ST* must be added as it lacks internal consistency (CA < 0.7). Hence, we extend our items by ST3, which is derived from Cramer et al. (2008). Item loadings for TB3 (0.58) and TB4 (-0.45) are below the threshold of 0.7. TB4 seems to be particularly problematic, as the reverse wording suggested by Cheng et al. (2008) as well

as Wang and Benbasat (2007) causes convergence reliability issues. Removing TB4 leads to a higher CA (0.75), AVE (0.68), and CR (0.86). Since using reversed wording is not advised (Van Sonderen et al. 2013; Zhang et al. 2016), we decide to drop TB4. We decided to follow Lee and Turban (2001) and use the original wording in line with the other items for the main study (TB5). We decide to retain TB3 in the main study, as the loading is satisfactory and the construct itself is reliable if TB4 is dropped. As ATT2 performs subpar in terms of item loading, we decided to add additional items. Additionally, ATT has a low value for CA, indicating low internal consistency. Thus, we added ATT4 and ATT5 following Taylor and Todd (1995). It was recently used in a similar context by Peters et al. (2020).

Table 50: Fornell-Larcker Criterion Main Study

Factors	AGE	AGE-EE	AGE-PE	ATT	BI	EE	EX1-EE	EX1-PE	EXP2-EE	EXP3-PE	EXP3-EE	EXP3-PE	EPX1	EXP2	EXP3	GEN	GEN-EE	GEN-PE	PE	ST	TA	TB
Age	1.000	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
AGE-EE	0.030	1.000	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
AGE-PE	-0.003	0.515	1.000	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
ATT	-0.026	-0.053	-0.008	0.841	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
BI	0.075	-0.056	-0.084	0.634	0.951	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
EE	0.024	-0.283	-0.071	0.573	0.434	0.835	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
EXP1-EE	-0.019	-0.038	-0.022	0.056	0.086	0.053	1.000	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
EXP1-PE	0.073	-0.026	-0.066	0.076	0.039	0.019	0.630	1.000	-	-	-	-	-	-	-	-	-	-	-	-	-	-
EXP2-EE	0.098	0.043	-0.019	0.127	0.082	0.036	0.604	0.387	1.000	-	-	-	-	-	-	-	-	-	-	-	-	-
EXP3-PE	0.040	-0.056	0.004	0.110	0.065	0.037	0.353	0.561	0.321	1.000	-	-	-	-	-	-	-	-	-	-	-	-
Exp3-EE	-0.078	0.039	-0.053	0.027	0.000	0.005	0.546	0.347	0.506	0.520	1.000	-	-	-	-	-	-	-	-	-	-	-
Exp3-PE	0.144	-0.024	-0.066	0.039	-0.009	0.007	0.456	0.713	0.664	0.528	0.370	1.000	-	-	-	-	-	-	-	-	-	-
EXP1	0.023	-0.022	0.083	0.120	0.134	0.252	0.382	0.226	0.286	0.129	0.261	0.077	1.000	-	-	-	-	-	-	-	-	-
EXP2	0.079	0.121	0.149	0.097	0.059	0.216	0.303	0.071	0.235	0.001	0.168	0.107	0.571	1.000	-	-	-	-	-	-	-	-
EXP3	0.033	-0.097	0.048	0.082	0.143	0.158	0.279	0.138	0.170	0.047	0.049	0.001	0.536	0.429	1.000	-	-	-	-	-	-	-
GEN	-0.028	-0.070	0.048	0.027	-0.025	0.031	-0.018	0.020	-0.113	0.056	-0.047	-0.075	0.042	0.117	0.077	1.000	-	-	-	-	-	-
GEN-EE	-0.052	-0.126	-0.163	-0.139	-0.146	-0.227	0.066	0.067	0.163	0.153	0.244	0.124	-0.016	-0.106	-0.044	-0.023	1.000	-	-	-	-	-
GEN-PE	0.038	-0.170	-0.175	-0.153	-0.156	-0.176	0.061	0.139	0.101	0.090	0.148	0.185	0.017	-0.061	0.052	-0.040	0.633	1.000	-	-	-	-
PE	0.010	-0.073	-0.054	0.720	0.616	0.596	0.018	0.004	0.006	0.038	0.036	-0.127	0.202	0.139	0.105	0.053	-0.174	-0.191	0.860	-	-	-
ST	-0.024	-0.089	0.075	0.559	0.472	0.539	0.088	0.048	0.033	0.117	0.073	-0.016	0.170	0.105	0.040	-0.015	-0.098	-0.149	0.505	0.892	-	-
TA	0.025	-0.013	0.118	0.687	0.552	0.531	0.000	-0.027	-0.018	0.132	0.026	-0.078	0.115	0.093	0.105	-0.007	-0.173	-0.144	0.594	0.610	0.905	-
TB	-0.007	-0.040	-0.060	0.600	0.444	0.462	0.111	0.071	0.069	0.148	0.121	0.010	0.045	0.084	0.069	-0.005	-0.065	-0.131	0.528	0.411	0.656	0.877

Table 51: Cross-loadings Main Study

Factors	AGE	AGE-EE	AGE-PE	ATT	BI	EE	EXP1-EE	EXP1-PE	EXP2-EE	EXP3-PE	EXP3-EE	EXP3-PE	EXP1	EXP2	EXP3	GEN	GEN-EE	GEN-PE	PE	ST	TA	TB
AGE	1.000	0.030	-0.003	-0.026	0.075	0.024	-0.019	0.073	0.098	0.040	-0.078	0.144	0.023	0.079	0.033	-0.028	-0.052	0.038	0.010	-0.024	0.025	-0.007
ATU1	-0.125	-0.093	0.038	0.764	0.460	0.566	0.021	-0.021	0.053	0.029	-0.008	0.007	0.142	0.129	0.045	-0.047	-0.066	-0.148	0.510	0.454	0.530	0.372
ATU3	-0.038	-0.107	-0.017	0.856	0.557	0.490	0.116	0.137	0.146	0.166	0.088	0.080	0.132	0.166	0.055	-0.010	-0.068	-0.110	0.643	0.521	0.551	0.495
ATU4	0.091	-0.015	-0.025	0.881	0.557	0.462	0.016	0.074	0.126	0.078	0.009	0.026	0.089	0.028	0.110	0.059	-0.160	-0.124	0.646	0.463	0.650	0.603
ATU5	-0.036	0.030	-0.015	0.861	0.554	0.430	0.032	0.053	0.095	0.087	-0.004	0.015	0.047	0.012	0.063	0.079	-0.166	-0.137	0.613	0.445	0.576	0.531
BI1	0.026	-0.011	-0.085	0.610	0.953	0.421	0.028	-0.008	0.059	0.029	0.009	-0.047	0.132	0.056	0.120	-0.038	-0.141	-0.163	0.591	0.428	0.506	0.416
BI2	0.155	-0.077	-0.063	0.606	0.931	0.424	0.121	0.069	0.091	0.060	-0.030	0.017	0.141	0.079	0.142	-0.027	-0.130	-0.118	0.595	0.442	0.540	0.421
BI3	0.032	-0.072	-0.092	0.593	0.968	0.393	0.094	0.048	0.084	0.095	0.022	0.003	0.108	0.034	0.146	-0.008	-0.147	-0.166	0.572	0.477	0.527	0.429
EE1	0.017	-0.279	-0.053	0.373	0.273	0.814	0.060	-0.043	0.019	-0.022	-0.047	-0.038	0.212	0.190	0.182	0.067	-0.180	-0.186	0.423	0.339	0.291	0.279
EE2	0.001	-0.167	0.006	0.381	0.232	0.724	0.099	0.088	0.080	0.059	0.035	0.093	0.236	0.262	0.153	0.058	-0.135	-0.054	0.346	0.449	0.450	0.415
EE3	-0.042	-0.221	-0.109	0.582	0.466	0.893	0.026	0.013	0.012	0.062	0.050	-0.020	0.186	0.142	0.084	0.015	-0.271	-0.195	0.619	0.520	0.529	0.457
EE4	0.107	-0.284	-0.061	0.528	0.422	0.898	0.013	0.005	0.020	0.013	-0.035	-0.001	0.224	0.161	0.140	-0.013	-0.154	-0.142	0.546	0.466	0.465	0.372
PE1	-0.034	-0.106	0.002	0.514	0.447	0.518	-0.021	-0.009	0.008	0.028	0.075	-0.100	0.224	0.121	0.072	-0.020	-0.097	-0.127	0.838	0.421	0.449	0.361
PE2	0.012	-0.028	-0.048	0.661	0.505	0.459	0.075	0.061	0.068	0.063	0.056	-0.058	0.162	0.195	0.131	0.161	-0.160	-0.168	0.855	0.452	0.536	0.476
PE3	-0.020	-0.072	-0.048	0.659	0.545	0.577	0.009	0.002	-0.034	0.032	0.059	-0.141	0.181	0.109	0.082	-0.041	-0.164	-0.137	0.895	0.449	0.544	0.473
PE4	0.058	-0.019	-0.071	0.647	0.608	0.545	0.034	-0.002	0.025	0.021	-0.025	-0.104	0.144	0.087	0.060	0.025	-0.131	-0.125	0.853	0.404	0.509	0.484
PE5	0.018	-0.098	-0.060	0.595	0.529	0.460	-0.026	-0.039	-0.043	0.019	-0.001	-0.143	0.168	0.086	0.104	0.095	-0.188	-0.263	0.858	0.446	0.508	0.463
ST1	-0.032	-0.027	0.045	0.531	0.481	0.476	0.034	-0.023	0.008	0.089	0.062	-0.063	0.096	0.015	0.018	-0.060	-0.132	-0.176	0.469	0.854	0.600	0.400
ST2	-0.023	-0.076	0.111	0.472	0.401	0.470	0.040	-0.004	0.013	0.075	0.025	-0.044	0.159	0.143	0.045	0.012	-0.105	-0.173	0.430	0.920	0.524	0.335
ST3	-0.008	-0.140	0.046	0.486	0.373	0.496	0.166	0.162	0.070	0.150	0.109	0.070	0.206	0.132	0.046	0.014	-0.020	-0.044	0.448	0.902	0.501	0.358
TA1	-0.024	0.057	0.154	0.565	0.463	0.404	-0.029	-0.062	-0.076	0.097	-0.013	-0.167	0.104	0.093	0.096	0.038	-0.153	-0.169	0.507	0.554	0.899	0.537
TA2	0.055	-0.060	0.052	0.653	0.514	0.573	-0.007	-0.077	0.019	0.053	0.008	-0.047	0.124	0.132	0.111	-0.017	-0.157	-0.115	0.563	0.518	0.888	0.588
TA3	0.035	-0.028	0.115	0.643	0.519	0.466	0.031	0.056	0.004	0.200	0.070	-0.007	0.086	0.034	0.079	-0.037	-0.159	-0.111	0.543	0.582	0.926	0.649
TB1	-0.051	0.009	-0.031	0.596	0.449	0.456	0.097	0.093	0.083	0.144	0.139	0.038	0.057	0.081	0.067	0.006	-0.074	-0.157	0.519	0.419	0.628	0.937
TB2	-0.006	-0.065	-0.049	0.566	0.402	0.446	0.113	0.112	0.110	0.197	0.147	0.085	0.039	0.047	0.050	-0.015	-0.065	-0.121	0.497	0.397	0.606	0.935
TB3	0.060	-0.058	-0.091	0.393	0.300	0.291	0.080	-0.046	-0.036	0.022	0.006	-0.135	0.017	0.102	0.066	-0.005	-0.024	-0.051	0.355	0.240	0.477	0.744
AGE * EE	0.030	1.000	0.515	-0.053	-0.056	-0.283	-0.038	-0.026	0.043	-0.056	0.039	-0.024	-0.022	0.121	-0.097	-0.070	-0.126	-0.170	-0.073	-0.089	-0.013	-0.040
EE * EXP1	-0.019	-0.038	-0.022	0.056	0.086	0.053	1.000	0.630	0.604	0.353	0.546	0.456	0.382	0.303	0.279	-0.018	0.066	0.061	0.018	0.088	0.000	0.111
EE * EXP2	0.098	0.043	-0.019	0.127	0.082	0.036	0.604	0.387	1.000	0.321	0.506	0.664	0.286	0.235	0.170	-0.113	0.163	0.101	0.006	0.033	-0.018	0.069
EE *EXP3	-0.078	0.039	-0.053	0.027	0.000	0.005	0.546	0.347	0.506	0.520	1.000	0.370	0.261	0.168	0.049	-0.047	0.244	0.148	0.036	0.073	0.026	0.121
EE * GEN	-0.052	-0.126	-0.163	-0.139	-0.146	-0.227	0.066	0.067	0.163	0.153	0.244	0.124	-0.016	-0.106	-0.044	-0.023	1.000	0.633	-0.174	-0.098	-0.173	-0.065
PE- *AGE	-0.003	0.515	1.000	-0.008	-0.084	-0.071	-0.022	-0.066	-0.019	0.004	-0.053	-0.066	0.083	0.149	0.048	0.048	-0.163	-0.175	-0.054	0.075	0.118	-0.060
PE-*EXP1	0.073	-0.026	-0.066	0.076	0.039	0.019	0.630	1.000	0.387	0.561	0.347	0.713	0.226	0.071	0.138	0.020	0.067	0.139	0.004	0.048	-0.027	0.071
PE-*EXP2	0.144	-0.024	-0.066	0.039	-0.009	0.007	0.456	0.713	0.664	0.528	0.370	1.000	0.077	0.107	0.001	-0.075	0.124	0.185	-0.127	-0.016	-0.078	0.010
PE- * EXP3	0.040	-0.056	0.004	0.110	0.065	0.037	0.353	0.561	0.321	1.000	0.520	0.528	0.129	0.001	0.047	0.056	0.153	0.090	0.038	0.117	0.132	0.148
PE-*GEN	0.038	-0.170	-0.175	-0.153	-0.156	-0.176	0.061	0.139	0.101	0.090	0.148	0.185	0.017	-0.061	0.052	-0.040	0.633	1.000	-0.191	-0.149	-0.144	-0.131

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