The Internet of Things: Business Applications, Technology Acceptance, and Future Prospects

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Abstract

This dissertation explores the Internet of Things from three different perspectives for which three individual studies were conducted. The first study presents a business application within supply chain management. The second study addresses user acceptance of pervasive information systems, while the third study covers future prospects of the Internet of Things.

The first study is about wireless sensor technologies and their possibilities for optimizing product quality in the cold chain. The processing of sensor data such as temperature information allows for the construction of novel issuing policies in distribution centers. The objective of the study was to investigate the possible economic potential of sensor-based issuing policies in a cold chain. By means of simulation, we analyzed a three-echelon supply chain model, including a manufacturer, a distribution center, and a retail store. Our analysis shows that sensor-based issuing policies bear the potential to become an effective complement to conventional issuing policies. However, the results also indicate that important trade-offs must be taken into account in the selection of a specific issuing policy.

The second study deals with the increasing emergence of pervasive information systems and user acceptance. Based on the integration of the extended “Unified Theory of Acceptance and Use of Technology” (UTAUT2) and three pervasiveness constructs, we derived a comprehensive research model to account for pervasive information systems. Data collected from 346 participants in an online survey was analyzed to test the developed research model using structural equation modeling and taking into account multi-group and mediation analysis. The results confirm the applicability of the integrated UTAUT2 model to measure pervasiveness.

The third study addresses future prospects of the Internet of Things within the retail industry. We employed a research framework to explore the macro- as well as microeconomic perspective. First, we developed future projections for the retail industry containing IoT aspects. Second, a two-round Delphi study with an expert panel of 15 participants was conducted to evaluate the projections. Third, we used scenario development to create scenarios of the most relevant projections evaluated by the participants.

Zusammenfassung

Die vorliegende Dissertation untersucht das „Internet der Dinge" aus drei verschiedenen Perspektiven, wofür drei Studien durchgeführt wurden. Die erste Studie präsentiert eine kommerzielle Anwendung innerhalb des Supply Chain Managements. Die zweite Studie behandelt das Thema Nutzerakzeptanz im Kontext allgegenwärtiger Informationstechnologien, während sich die dritte Studie mit Zukunftsaussichten des Internets der Dinge im Einzelhandel befasst.

Die erste Studie evaluiert die Möglichkeiten kabelloser Sensortechnologien zur Optimierung der Produktqualität verderblicher Güter in der Kühlkette. Dabei ermöglicht die Verarbeitung von Sensordaten, wie bspw. Temperaturinformationen, neuartige Ansätze bei sog. Verbrauchsfolgeverfahren in der Lagerhaltung im Verteilzentrum. Das Ziel der Studie ist die möglichen ökonomischen Potenziale sensorbasierter Verbrauchsfolgeverfahren in der Kühlkette zu untersuchen. Mittels Simulation wurde eine dreistufige Lieferkette, bestehend aus einem Hersteller, einem Verteilzentrum und einem Einzelhandelsgeschäft, analysiert. Die Analyse verdeutlicht, dass sensorbasierte Verbrauchsfolgeverfahren das Potenzial besitzen sich zu einer wirkungsvollen Ergänzung zu üblichen Verbrauchsfolgeverfahren zu entwickeln. Die Ergebnisse zeigen jedoch auch, dass wichtige Kompromisse bei der Auswahl spezifischer Verbrauchsfolgeverfahren zu berücksichtigen sind.

Die zweite Studie behandelt das Thema Nutzerakzeptanz von sog. pervasiven Informationssystemen. Auf der Grundlage der Integration der erweiterten „Unified Theory of Acceptance and Use of Technology" (UTAUT2) und drei Konstrukten zu „Pervasiveness", wurde ein umfassendes Forschungsmodell entwickelt um pervasiven Informationssytemen Rechnung zu tragen. Hierzu wurden Daten von 346 Teilnehmern einer Onlineumfrage gesammelt und analysiert, um das Forschungsmodell unter Verwendung von Strukturgleichungsmodellierung zu testen. Weitere Bestandteile der Analyse waren eine Mehrgruppen-Moderation und Mediation. Die Ergebnisse bestätigen die Anwendbarkeit des integrierten UTAUT2-Modells um die Nutzerakzeptanz pervasiver Informationssysteme zu messen.

Die dritte Studie befasst sich mit den Zukunftsaussichten des Internets der Dinge im Einzelhandel. Vor dem Hintergrund makro- und mikroökonomischer Faktoren wurden zunächst Zukunftsprojektionen im Kontext des Internets der Dinge im Einzelhandel erstellt. Anschließend wurde eine zweistufige Delphi-Studie mit einer 15 Teilnehmer umfassenden Expertengruppe durchgeführt zur Bewertung der Projektionen. Im letzten Schritt stand die Szenarioentwicklung im Vordergrund, in der potenzielle Zukunftsszenarien aus den relevantesten Projektionen, basierend auf den Expertenmeinungen, entwickelt wurden.

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List of Abbreviations

AMT	Amazon Mechanical Turk
AMOS	Analysis of Moment Structures
AVE	Average Variance Extracted
BI	Behavioral Intention
CAW	Context Awareness
CB-SEM	Covariance-based Structural Equation Modeling
CFA	Confirmatory Factor Analysis
CFI	Comparative-Fit Index
CI	Confidence Interval
CR	Composite Reliability
DC	Distribution Center
EE	Effort Expectancy
EFA	Exploratory Factor Analysis
FC	Facilitating Conditions
FG	Functional Group
FDFO	First Delivered First Out
FEFO	First Expiry First Out
FIFO	First In First Out
FPFO	First Produced First Out
GPS	Global Positioning System
HIT	Human Intelligence Task
HM	Hedonic Motivation
HQFO	Lowest Quality First Out
ICT	Information and Communication Technologies
ID	Identifier
IDT	Innovation Diffusion Theory
IoT	Internet of Things
IoT-A	Internet of Things Architecture
IoT ARM	Internet of Things Architectural Reference Model
IQR	Interquartile Range
IS	Information Systems
IT	Information Technology
LBS	Location-based System
LEFO	Last Expiry First Out
LIFO	Last In First Out
LSFO	Least Shelf-life First Out
LQFO	Lowest Quality First Out
MSV	Maximum Shared Variance

NFC	Near-field Communication
NNFI	Non-normed Fit Index
OUFO	Oldest Unit First Out
PE	Performance Expectancy
PEST	Political/Economic/Social/Technological
PIS	Pervasive Information Systems
PV	Price Value
RAND	Research and Development
RFID	Radio-Frequency Identification
RMR	Root Mean Square Residual
RMSEA	Root Mean Square Error of Approximation
RS	Retail Store
SCM	Supply Chain Management
SD	Standard Deviation
SEM	Structural Equation Modeling
SI	Social Influence
SIRO	Service In Random Order
SRMR	Standardized Root Mean Square Residual
SRSL	Shortest Remaining Shelf Life’
SPSS	Statistical Package for the Social Sciences
SQL	Structured Query Language
TAM	Technology Acceptance Model
TLI	Tucker-Lewis Index
TPB	Theory of Planned Behavior
TRA	Theory of Reasoned Action
TTI	Time-Temperature Indicator
UBI	Ubiquity
UNO	Unobtrusiveness
UTAUT	Unified Theory of Acceptance and Use of Technology
VE	Virtual Entity
VIF	Variance Inflation Factor
WSN	Wireless Sensor Network

1. Introduction

The upward trend of connected objects and the resulting information networks promise to provide a huge range of business and socio-economic benefits as new services for businesses and consumers are being connected by intelligent networks. In what's called the Internet of Things (IoT), sensors and actuators embedded in a variety of pervasive physical objects are seamlessly interconnected through wired and wireless networks. These uniquely identifiable objects are given virtual representations which are linked to a plethora of IoT services enabled by their embedded technologies. The vision is to create a transition from the current era of many "Intranets" of Things towards an integrated "Internet of Things" (Zorzi et al., 2010), with the ultimate goal to merge the physical and digital world with the integration of people (see Figure 1). An important challenge arising thereby are scalability requirements in the IoT to be met with the increasing pervasiveness through new applications and wider adoption (Uckelmann et al., 2011).

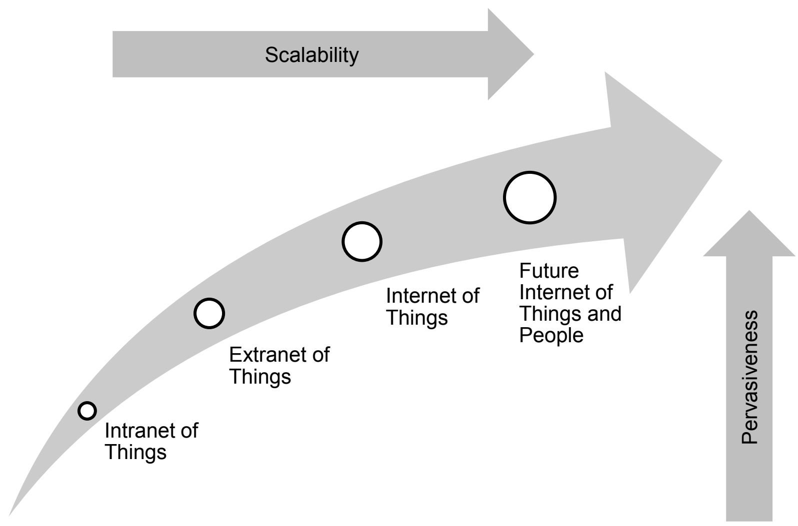

Figure 1. Evolution from an Intranet of Things to a Future Internet of Things. (Uckelmann et al., 2011)

Certainly, the Internet is one of the most disruptive inventions whereas the IoT is the next evolutionary step in which data is automatically generated and analyzed to trigger events. By means of Radio-Frequency Identification (RFID), Near-field Communication (NFC), sensors, or actuators, the IoT provides the capabilities to process, analyze, aggregate, and combine information from virtual worlds. Based on a sheer number of interconnections among things, the IoT contributes in the transformation from processed data into information through to knowledge. The increased value of information and knowledge, in turn, is made available to applications such as decision support systems which require relevant and accurate basis for supporting decision makers in identifying and solving problems.

The term "Internet of Things" originated at the Massachusetts Institute of Technology's Auto-ID[1] Labs. It made its first public appearance when Kevin Ashton coined the term as the title of a presentation in 1999 (Ashton, 2009). As a member of the Auto-ID Labs, he formed part of a world-wide and independent network of academic research laboratories with the objective to conduct research and to develop new technologies for revolutionizing global commerce. Their research laid the foundation of the IoT with their initial proposals on how to build a networked physical world (Sarma et al., 2000). In the early stages of the IoT, RFID was considered as the main driver for further IoT evolution, however, the too expensive RFID tag price at that time was the reason for researchers to advocate for the "5¢ Tag" to drive industry adoption (Sarma, 2001). But only recently, RFID tags reached low tag prices for industry to consider them in industrial applications at a reasonable cost (Ashton, 2011).

The IoT is not only relevant for industry, but also for end-users since more and more network-capable consumer electronics are available. Often termed "smart" devices, they offer services for consumers that either already are or soon will become indispensable. One current trend and potential future service is mobile payment to serve next-generation consumers who demand seamless payments at all touch points where they do purchases. Consequently, payment service companies expect major gains through increased non-cash transactions and greater access to data. However, the latter is related to important issues among consumers, these are, data security and privacy. In cases where sensitive information is processed, a main focus must be on secure exchange of data to protect

[1] Auto-ID Labs, http://www.autoidlabs.org/

information about about consumers such as financial transactions or personal health information.

In the near and remote future, industry will be faced with a number of opportunities and challenges with the growing emergence of the IoT. A variety of future development analyses assume a continuous trend towards an interconnection not only among humans via social networks but also among objects. A well-known and often-cited source for technology trend analysis is Gartner's "Hype Cycle for Emerging Technologies" (Gartner, 2014).

It shows, for a broad aggregate of technologies, the degree of expectation of the specific technologies for certain periods of time divided into five stages from technology innovation through to productive use. In 2012, the IoT was located in the first stage in the hype cycle, that is, the "technology trigger" stage, even though it was already borderline to the subsequent stage. Figure 2 depicts the hype cycle for the year 2014 in which the IoT progressed to the second stage, namely the "Peak of Inflated Expectations." While it indicates that the IoT is in the midst of its evolutionary process, it has hardly found its way into business or society for a variety of reasons, among them a lack of or because of slow standardization processes (Davenport and Sarma, 2014) or privacy and security issues (Whitmore et al., 2014).

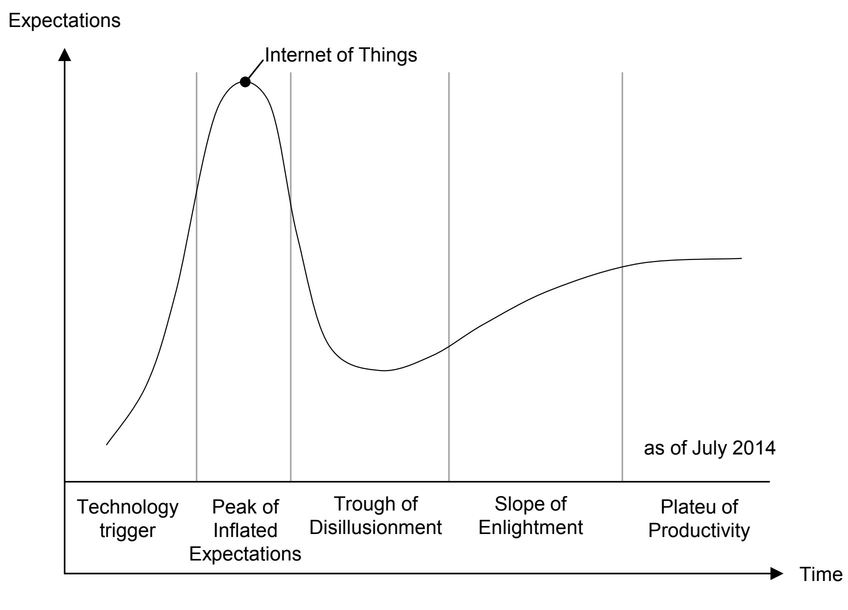

Figure 2. Gartner Hype Cycle for Emerging Technologies 2014.

Despite these obstacles, the IoT is on its way to a decisive breakthrough as becomes clear when following current discussions in politics and industry. One recurring topic is related to "Industry 4.0", which will have a significant impact on the German industry as an industrial nation and world market leader in many industry sectors (Spath et al., 2013). Not least because countries such as Germany and their industries cannot afford to fall behind their global competitors, they make serious efforts to implement the vision of the IoT.

1.1 Concept and architecture of Internet of Things

The term IoT is used as an umbrella keyword for describing different aspects in conjunction with the extension of the Internet where the integration of the physical world plays a key role (Miorandi et al., 2012). We provide a brief insight into the concept of the IoT including IoT abstraction levels and a novel concept of IoT system development based on the so-called IoT Architectural Reference Model. This introduction forms a basis for the understanding of how an IoT system works and might be developed from a technical point of view.

1.1.1 IoT abstraction levels

To familiarize the reader with the concept of IoT, we explain the different abstraction levels of the physical world and an IoT system that are illustrated in Figure 3.

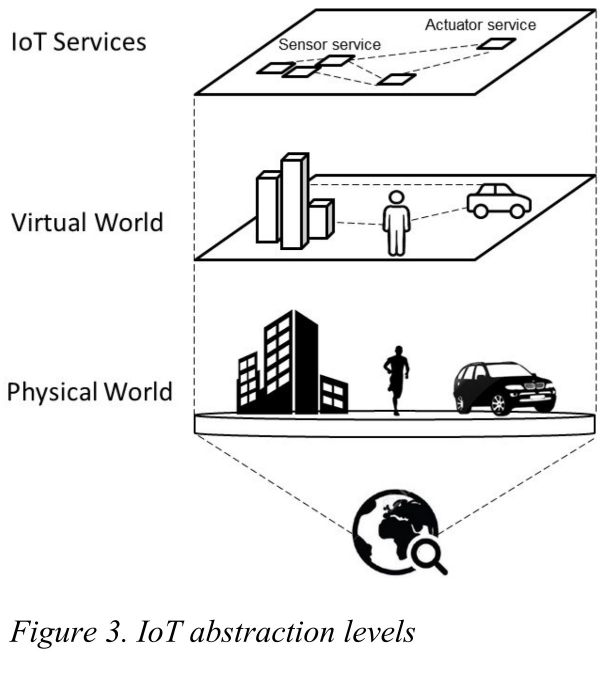

Figure 3. IoT abstraction levels

The physical world consists of real world objects including humans, buildings, or cars. These objects might have a variety of sensors or actuators attached to them that capture changes of certain aspects in the physical world, be it a room temperature sensor in case of a building or a heart rate monitor in case of a runner. These sensors or actuators are connected to the internet to enable interoperability on a higher level such as an IoT system. The virtual world together with the IoT service level define an IoT system. The virtual world contains the virtual representations of the physical objects, each of which is also known as virtual entity (VE). The resources associated to the sensors and actuators are exposed as IoT services on the IoT service level.

A concrete example for the interaction between an application and an IoT service can be the request of the temperature information provided by a certain temperature sensor to adjust the heating in a room, e.g. “Give me the value of Sensor-123” and the answer is “20”. In this context it is important to note that an application needs to interpret the semantics correctly to process the information in a meaningful way, that is, the application needs to know that the information provided is the indoor temperature of the room of interest. While this use case is common for applications that are configured for specific environments, another type of application might make use of suitable IoT services to react on changing environmental conditions without knowing the specific sensor or actuator which provides the information requested. For example, if a distributor in a supply chain wants to know the actual inside temperature of an awaiting container to plan the further processing, he can make a request such as “Give me the inside temperature of container XYZ-478”. As can be seen, he only knows the container number which refers to a VE, but not the associated sensor service. In this case, the virtual world models higher-level aspects of the physical world, which can be used for service discovery enabled by associations which bring VE in relation to IoT services. In our example, the association includes the information that the inside temperature of container XYZ-478 is provided by Sensor-354 so that the temperature request can be answered by the IoT service.

These abstraction levels have implications on how IoT systems are developed. This includes the underlying system architecture and functional groups related to it, which is further explained in the following section.

1.1.2 IoT Architectural Reference Model

The concept of IoT requires new approaches in the development process of IoT systems. This has been addressed by the European project "Internet of Things Architecture", in which an "IoT Architectural Reference Model" (IoT ARM) was developed. The IoT ARM constitutes an IoT Reference Model and IoT Reference Architecture that can be used for building concrete domain-specific IoT architectures with full interoperability (Carrez, 2013). We briefly describe the main content of the IoT ARM, however, the interested reader is referred to Carrez (2013) for an in-depth look into the results of the project.

The first part of the IoT ARM is the IoT Reference Model, that provides the concepts and definitions on which IoT architectures can be built (see Figure 4). It consists of a number of sub-models that are required to address architectural views and perspectives.

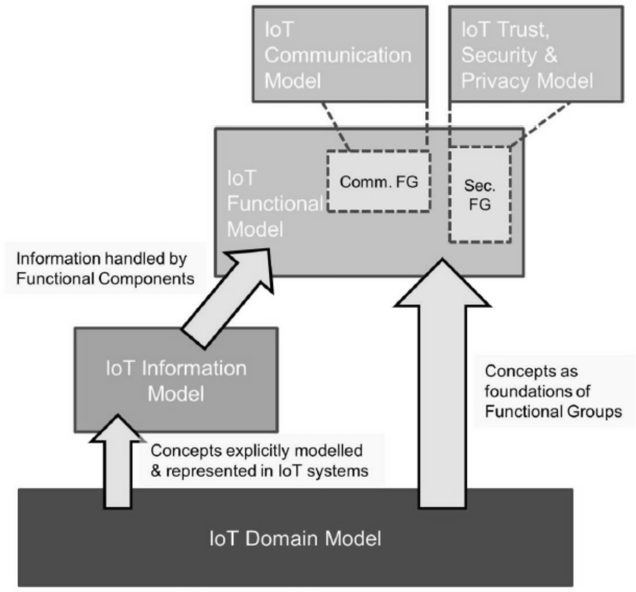

Figure 4. Interaction of the sub-models in the IoT Reference Model. (Carrez, 2013)

The baseline forms the Domain Model, which outlines the concepts that are essential to the IoT such as devices, IoT services, and virtual entities. This foundation is mandatory in the development process of an IoT system as all other models in the IoT Reference Architecture are based on it. The IoT Information Model is based on the Domain Model and defines the structure (e.g. relations, attributes) of IoT-related information in an IoT system on a conceptual level. The information related to the concepts of the IoT Domain Model is modelled in the IoT Information Model, i.e. the information which is gathered, stored, and processed in an IoT system. The IoT Functional Model identifies functional groups (FG) of functionalities, of which most are grounded in key concepts in the IoT Domain Model. Two FGs are highlighted in the IoT Functional Model that highlight key functionalities which are relevant to most IoT systems. First, the Communication FG points out a key functionality of any distributed system – the communication between components. It provides concepts to manage the heterogeneity of communication technologies employed in IoT systems. Second, the Security FG contains an IoT Trust, Security and Privacy model, which provides functionalities to ensure data security and privacy.

The second part of the IoT ARM is the IoT Reference Architecture, that consists of the Functional, Information, Deployment & Operation View together with several perspectives related to non-functional requirements of IoT architectures. We focus on introducing briefly the individual parts of the IoT Reference Architecture without describing them in detail and again refer to Carrez (2013) for more insights.

The Functional View describes the functional building blocks of the architecture (see Figure 5). They were identified as crucial to almost any IoT system. Each FG has a couple of functional components and is represented between the device and application layer.

The IoT Process Management FG refers to the integration of traditional process management systems with the IoT ARM. The objective of this FG is to provide the functional concepts and required interfaces to redefine traditional (business) processes by accounting for the peculiarities of the IoT. The Process Modelling functional component provides an environment for the modelling of IoT-aware business processes that will be serialized and executed in the Process Execution functional component.

The Service Organisation FG works as a communication hub between the different FGs. The notion of a service is the primary concept of communication within the IoT ARM, thus the Service Organisation is used for composing and orchestrating services of different levels of abstraction.

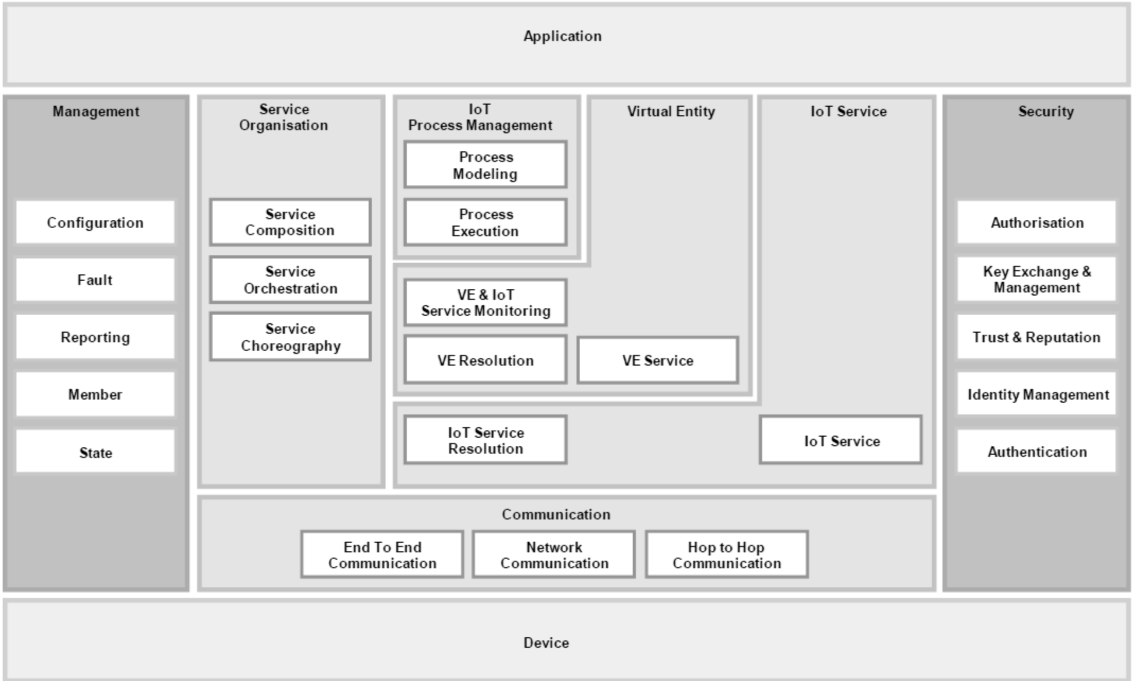

Figure 5. Functional-decomposition view of the IoT Reference Architecture. (Carrez, 2013)

The Virtual Entity FG includes functions for interacting with the IoT system based on VEs. It provides features for discovering and looking up services that can give information about VEs, or which control the interaction with VEs. Moreover, it contains all the required functionality for managing associations and dynamically finding new associations. More specifically, the VE & IoT Service Monitoring functional component is in charge for automatically finding new associations, which are then inserted into the VE Resolution functional component. The VE Resolution functional component provides the functionalities to the IoT user to retrieve associations between VEs and IoT services. The last functional component VE Service deals with entity services, which represent an overall access point to a particular entity to enable reading and/or updating the value(s) of the entities' attributes via operations.

The IoT Service FG includes IoT services and associated functions for discovery, look-up, and name resolution of IoT services. The IoT Service component is responsible for (1) returning information provided by a resource, (2) accepting information sent to a resource in order to either store the information or to configure the resource or to control an actuator device, and (3) subscribing to information, i.e. return information provided by a resource. The IoT Service Resolution functional component provides all the functionalities required by the user to find and reach IoT Services.

The Communication FG is an abstraction layer, which models the variety of interaction schemes derived from the many technologies belonging to IoT systems and provides a common interface to the IoT Service FG. The Hop To Hop Communication functional component provides an abstraction to enable the usage and the configuration of any different link layer technology. The main function of the Network Communication functional component is to enable communication between networks through locators and ID Resolution. The End To End Communication functional component is in charge of the whole end-to-end communication abstraction, i.e. transmitting a message from the Network Communication functional component to the End To End Communication functional component and from IoT Service to the End To End Communication functional component.

The Security FG defines concepts for ensuring the security and privacy of IoT systems. It consists of basic security mechanisms such as authentication, authorization, trust & reputation, identity management, and key exchange & management.

Finally, the Management FG consists of the functionalities Configuration, Fault, Reporting, Member, and State, which are mainly related to the composition, tracking, and administration of actions that involve other core FGs.

Based on the IoT Information Model described above, the Information view gives more details about how the relevant information needs to be represented and the information flow through an IoT system. It also describes the components that handle the information and the life cycle of information in the IoT system.

The purpose of the Deployment and Operation View is to provide users of the IoT Reference Model with a set of guidelines to support them through the different design choices while designing the actual implementation of their services.

1.2 Key drivers of the Internet of Things

The IoT can be defined as bringing together people, technology, data, and processes to make networked connections more important and valuable than ever before for both private and business purposes. Based on meaningful information, appropriate actions can be taken that create new capabilities, richer experiences, and unprecedented economic opportunity for businesses, individuals, and countries. Figure 6 depicts the key drivers that are essential to the IoT and that are described in the following.

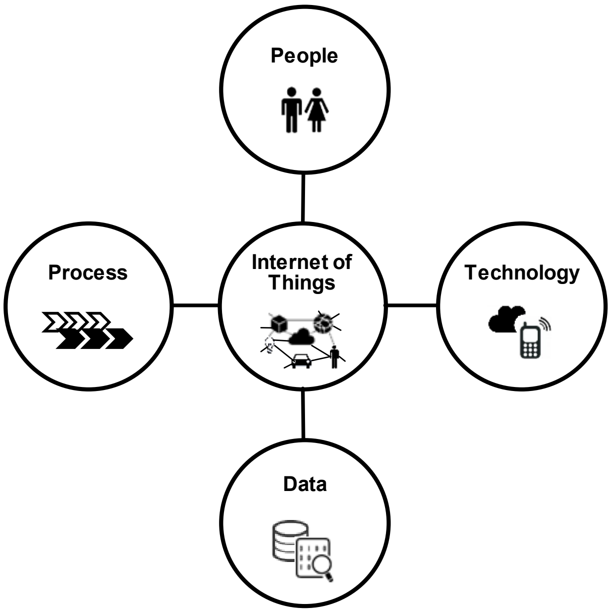

Figure 6. Key drivers of the Internet of Things

The important role assigned to people in the context of IoT originates from the vast amount of IoT services in human-centred environments. For example, the IoT augments social networks by connecting people in more relevant and useful ways using environmental information from everyday devices which has been termed "Social Internet of Things" (Atzori et al., 2012). By offloading data capture and information transfer to the background, devices and applications can actually improve human relationships. The gathered information is merged with social networking principles, to facilitate useful "social-driven" human to device interaction. Another application which might become common in the future is the intelligent shopping system due to the popularity of smart phones or the increasing deployment of RFID technology. It provides context-aware information to customers in such a way as to generate values for both customers and sellers. Against this backdrop, information from user tracking is an essential condition for personalized services which might be of value for customers. On the one hand, for example, this kind of service makes a user aware of general or personalized special offers in a retail store which might be of interest from a customer perspective. On the other hand, a retailer monitors specific users' purchasing habits to be able to provide personalized services, e.g. by tracking their smart phone via a location-based service. These examples of applications focus on the user of IoT services which is why user acceptance of IoT devices and services is of paramount importance to application providers and device manufacturers. We address the topic user acceptance in Chapter 3, where we present a technology acceptance study. In Chapter 4, we show the importance of general societal factors such as demographic change or data security in the context of IoT.

Technology has an enabling function in the IoT, i.e. it aims at closing the gap between the real and virtual world to prevent media breaks between physical processes and the associated information processing (Fleisch and Thiesse, 2007). Basic technologies related to IoT encompass auto-id technologies (e.g. RFID), communication technologies (e.g. NFC, ZigBee) or sensor infrastructures (e.g. Wireless Sensor Networks). As prices for technology decline steadily and standardization issues are resolved continuously, the wide-spread deployment is only a matter of time and value-adding business cases. Furthermore, smart devices such as smart phones or wearables are already pervasive or well on their way there. These kinds of devices become smart as a result of the interplay between the embedded hardware (e.g. GPS) and software (e.g. navigation). We investigate the potential of smart devices in Chapter 2, where we consider smart sensors in the perishables supply chain. In relation to smart devices, we consider Google Glass as subject to evaluation in the light of user acceptance in Chapter 3.

In an IoT application, data is typically gathered by (smart) devices and transferred to and stored in the cloud or in any high-performance repository, where it is analyzed and processed automatically to useful information (Gubbi et al., 2013). With the technological progress, the capabilities of things connected to the Internet continue to advance so that real-time data integration and processing together with an increase in information accuracy will become reality. Rather than just reporting raw data, connected smart objects will be able to send higher-level information back to machines, computers, and people for further evaluation and decision-making. This transformation from raw data to valuable information becomes important because it will support people in making prompt and more intelligent decisions in critical situations, as well as control our environment more effectively. The benefit from sensor information becomes clearer in Chapter 2, where we discuss its relevance in the management of perishable goods.

Process has an important function in how these entities – people, technology, and data – work together to increase the value of connections and networks in the IoT. Data and the information obtained from it through data analysis is a main source of value creation in the IoT and are leveraged to support various processes. For example, decision-making processes become more effective and efficient, provided that the right information is delivered, in the right format, at the right time and place, and for the right people. Processes are also a key element of optimizing automation and control. Taking data as the basis for process automation implies analyzing data and converting it into information that is fed back through the network to actuators that in turn modify processes. That way systems can adjust automatically to new and complex situations that render many human interventions unnecessary. The transformation from a conventional process used today in logistics to an innovative process potentially used in the future is described in Chapter 2, where we compare different logistical processes with and without support of sensor technology to show their advantages and disadvantages.

1.3 Scope and structure of the thesis

The structure of the present thesis is summarized in Figure 7. The introduction chapter provides a brief introduction to the concept of IoT and explains the scope and structure of the thesis. Chapter 2, 3, and 4 embody the main part of the thesis. Each of these chapters presents a self-contained study on certain aspects of the IoT which are further explained below. Finally, chapter 5 summarizes all findings of the thesis.

In the first study, we focus on the benefits of novel issuing policies using wireless sensor technologies for optimizing product quality in the perishables supply chain. It addresses the issue of temperature variations during goods transport for which we advocate a consideration of quality-based apart from expiry-based issuing of goods. In this respect, we take account of the technological possibilities of novel devices used in supply chains for processing sensor data such as temperature monitoring. The objective of the study is to examine the economic potential of sensor-based issuing policies in a supply chain for fresh or frozen goods. By means of computer simulation, we analyze a three-echelon supply chain model, including a manufacturer, a distribution center, and a retail store. We investigate the impact of different combinations of issuing policies and customer withdrawal behaviors on the quality of sold goods, spoilage, and holding costs.

The second study deals with the increasing emergence of pervasive technologies and their acceptance by its users. In particular, emerging pervasive technologies such as smart glasses are regarded as becoming a constant companion in everyday life. Against this background, we examine to what extent a pervasive technology, namely Google Glass, is accepted by potential end-users. Therefore, we integrate the extended "unified theory of acceptance and use of technology" (UTAUT2) and three pervasiveness constructs and derive a comprehensive research model to account for pervasive information systems. In a next step, we analyze the data collected from an online survey to test the developed model using structural equation modeling and taking into account multi-group and mediation analysis.

The third study investigates the future potential of the IoT in the retail industry. We conducted a Delphi study to obtain expert opinions on the probable future in the retail industry. First, we develop future projections based on the expert opinions. These projections are structured according to a research framework that covers macro- as well as micro-environment perspectives. Second, these projections are evaluated statistically to distill the most influential projections. Third, we focus on the projections with a medium to high impact on the economy and a high probability of occurrence. These projections form the input for scenario development in which we analyze the expert opinions and conclude probable future scenarios.

Chapter 1: Introduction

Concept and architecture of the Internet of Things
Scope and structure of the thesis

Chapter 2: Sensor-based Issuing Policies in the Perishables Supply Chain

Content: Investigation of the economic benefits of novel issuing policies based on wireless sensor technologies and comparison with traditional issuing policies.
Methodology: Simulation

Chapter 3: Extending UTAUT2 to Explore Pervasive Information Systems

Content: Integration of UTAUT2 and pervasiveness constructs in a research model to measure user acceptance of pervasive technologies.
Methodology: Structural Equation Modeling

Chapter 4: Towards a Future Internet of Things in Retail

Content: Development of future projections in the retail sector which formed the basis for the scenario development of probable future scenarios.
Methodology: Delphi Method, Scenario Development

Chapter 5: Summary

Summary of the findings

Figure 7. Structure of the thesis

2. Sensor-based Issuing Policies in the Perishables Supply Chain

2.1 Introduction

Globalization and the increasing complexity of today's value networks have a profound impact on many business domains. In particular, this holds true for the area of food logistics, which faces the challenge of efficiently managing the flow of goods while keeping costs low and product quality high. In order to uphold their competitive position, organizations worldwide depend on innovative tools for the management of their supply chains. The handling of perishable goods in cold chains provides a typical example, where the combination of new technology and appropriate management concepts can help to avoid shipments becoming damaged or otherwise compromised. Herein, the term "cold chain" refers to a temperature-controlled supply chain in which specialized packaging (e.g., all-insulated shipping containers) and transportation means (e.g., refrigerator trucks) are used to maintain the quality and value of a shipped good (Bogataj et al., 2005). Thus, monitoring environmental parameters during transportation and storage is of particular importance for perishables.

Apart from other environmental parameters, the monitoring of temperature is of utmost importance as it effects product quality due to its direct influence on microbial growth (Jedermann et al., 2009). To put it plainly, the greater the deviation between actual and nominal temperature values, the higher the potential for microbial growth and thus the increased risk of spoilage or food safety issues. Herein lies another problem — customers can only estimate the product quality of many perishables according to their printed expiry date (e.g. dairy goods). In fact, this static information ignores potential temperature variations during transportation and storage which might lead to inaccurate quality estimations by customers (Grunow and Piramuthu, 2013; Wang and Li, 2012).

Moving goods through the cold chain under adequate conditions requires particular attention because temperature is one of the most detrimental factors for perishables. It is imperative for a retail company to establish a comprehensive logistical process to avoid temperature anomalies causing both food safety issues and economic losses. Nevertheless, critical temperature deviations from optimal conditions in cold chains are a widespread phenomenon in practice to date (Laguerre et al., 2013), and grocery retailers have a keen interest in reducing the amount of spoilage as it constitutes a major determinant of the total turnover and profit margin (Rodríguez-Bermejo et al., 2007). In addition, spoilage poses a financial loss including not only the value of the goods in question, but also the associated costs for transportation (e.g. labor) in the supply chain. Besides its food safety and economic impacts, spoilage also attracts increasing attention in society as it constitutes an ethical and environmental concern (Kummu et al., 2012). Despite that, supply chain managers are still struggling in their attempt to reduce spoilage in their logistical processes. In a study of global food waste, Gustavsson et al. (2011) found that approximately one third of food produced for human consumption is lost or wasted globally, which amounts to about 1.3 billion tons per year. A high proportion of the food spoilage already happens before products arrive at the customer (Parfitt et al., 2010), which is why there is an evident potential for further efficiency gains in today's cold chain operations.

In order to achieve this objective, novel technologies such as wireless sensor networks (WSN) may be deployed for monitoring perishables in the supply chain (Amador et al., 2009; Ruiz-Garcia et al., 2009). The hope and expectation among practitioners is that these technological means will allow them to guarantee seamless product quality control in real-time from the manufacturer to the point-of-sale. Figure 8 exemplifies how a "smart" supply chain can be established by considering wireless temperature sensors throughout the entire supply chain to provide temperature information to all supply chain parties. The temperature information obtained during shipment or storage is exchanged via a commonly accessible information system (IS) which might be an inventory management or decision support system in praxis. It starts at the manufacturer where the goods being shipped must be equipped with some kind of temperature sensor capable of communicating within a WSN. Examples for such a technology are provided in section 2.2.1. At the manufacturer, the information about the initial state of the goods being shipped is transferred to the IS. The conditions are then tracked and exchanged with the IS during shipment between the manufacturer and the distribution center. At the distribution center, when the goods arrive, a goods inspection is performed either manually or automatically and damaged goods are disposed of. The remaining goods are then stored until further distribution and the temperature information about the goods is exchanged on a regular basis. When goods are transported to a retail store, again the temperature information is transmitted to and received from the IS. At the retail store, the goods inspection is conducted just as at the distribution center. Finally, the received goods are stored to be available for sale when necessary.

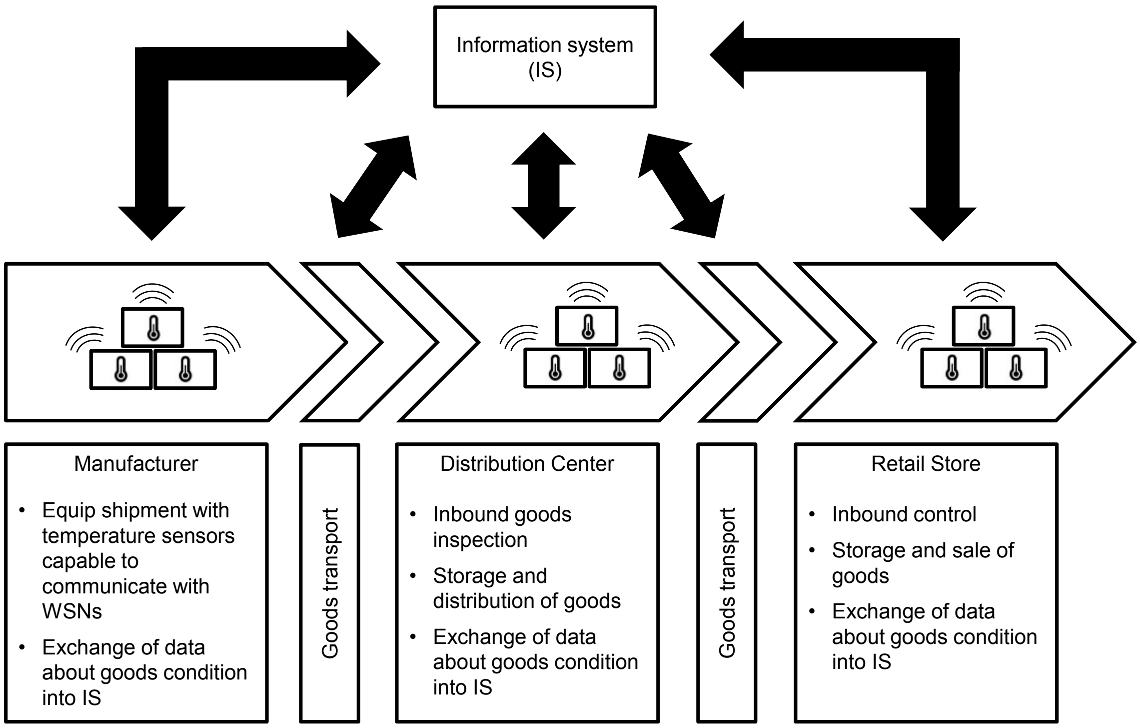

Figure 8. Smart supply chain

However, to leverage the data quality offered by a sensor infrastructure, the introduction of new technologies needs to be accompanied by changes on an organizational level (Luo et al., 2012). The present study considers the use of sensor technology in combination with issuing policies for control of the physical flow of goods along a cold chain. In this context, an issuing policy determines a selected order in which the products are removed from inventory and is often referred to a picking, withdrawal, or dispatching policy in the literature (Haijema, 2014). We focus on sensor-based issuing policies used in distribution centers when products are selected to fulfill an incoming order from a retail store. Our objective is to compare the performance of this class of policies with conventional policies (e.g., "First In First Out") relating to performance metrics, such as product quality, spoilage, and holding costs by means of simulation.

The remainder of this chapter is organized as follows. Section 2.2 provides the conceptual background with the technological foundation and the related work. In section 2.3, we develop our simulation model followed by an explanation of the computational implementation in section 2.4. The experimental design, the simulation results, and a sensitivity analysis are provided in section 2.5, while section 2.6 discusses the results and opportunities for further research. Finally, section 2.7 summarizes the main findings.

2.2 Background

2.2.1 Technological foundations

The quality of perishable products can deteriorate in many different ways depending on environmental factors such as humidity and brightness or product mishandling (e.g. shocks during transportation). Among all possible factors, the exposure to an out-of-the-optimum temperature range during transportation and storage has the highest negative influence on product quality (Hafliðason et al., 2012; Montanari, 2008). Hence, data concerning the temperature that a perishable good was exposed to provides the most important information for estimating its quality. For this purpose, a variety of solutions for temperature monitoring in supply chains is available on the market (Raab et al., 2011). In the following, we give an overview of existing technologies in use and highlight their main advantages as well as disadvantages.

Chart recorders are the traditional means for temperature monitoring in logistics. These electromechanical devices record the temperature over time resulting in a graph or chart of the data printed on paper. The paper feature also presents its major disadvantage in that the data must be processed and interpreted manually (Ruiz-Garcia and Lunadei, 2011).

Temperature data loggers are smaller and cheaper compared to chart recorders and have become a substitute in many areas of application. They are equipped with integrated sensors for measuring and tracking temperature data over time and are able to store digital or analogue data in a built-in memory (Raab et al., 2011). A cable connection (e.g., via USB) is usually required to obtain the data from the device.

The simple form of a *Time-Temperature Indicator (TTI)* is a small, inexpensive label used during shipment, storage, or processing to ensure cold-chain compliance (Smolander et al., 2004). These easy-to-use labels indicate exposure to excessive temperature and signal when product quality should be checked. The underlying functional principle is an incorporated dye that diffuses or a color-changing chemical substance that begins to flow along the quality-indicating range (Heising et al., 2014), indicating a significant difference between nominal and out-of-range temperature by the rate of flow of a chemical substance. While a TTI can visually indicate if a temperature limit overrun has occurred, it does not show when and where it happened (Jedermann et al., 2014). It only monitors the cumulative deviation from optimal temperature exposure but not the estimated present quality level (Urien and Piramuthu, 2013). A further disadvantage is the preset temperature response limit, which requires having various labels available in the event that the shipped products have different temperature thresholds (Sahin et al., 2007). Last but not least, TTI labels have no means to communicate with a reading device to automatically transfer data to an information system; manual data acquisition is required (Piramuthu and Zhou, 2013; Qi et al., 2014).

In recent years, significant technological progress can be observed in the area of wireless sensor technologies. Domains such as retail (Zhou et al., 2009) and healthcare (Pietrabissa et al., 2013) increasingly recognize the benefits of adopting novel technologies such as Radio-Frequency Identification (RFID). The most frequent deployment, however, can be observed in logistics (Miorandi et al., 2012). So-called "smart sensors" or "smart tags" – a combination of integrated sensors equipped with RFID technology – are being researched as prototypes (Abad et al., 2009; Abarca et al., 2009; Frank, 2013) as well as being available as off-the-shelf systems from various technology suppliers (Badia-Melis et al., 2014; Grunow and Piramuthu, 2013). A detailed taxonomy of this type of integrated sensors is provided by Liu et al. (2008).

Besides the well-known characteristics of RFID (Finkenzeller, 2010), smart sensors have a number of advantages over today's widely used technologies in cold chains, e.g. the extensibility by further sensors such as humidity, shock, motion, or pressure sensors to monitor additional environmental parameters apart from temperature (Delen et al., 2011). Recent promising developments, such as the AiroSensor from SenseAnywhere, show that smart sensors can be manufactured cost-effectively under the favorable condition of a constant price decline for sensors and tags, overcoming one of the frequently mentioned arguments against smart sensors – their high costs compared to commonly used technologies such as barcodes and/or TTIs. However, this view mostly neglects the additional benefits in contrast to barcodes, e.g. the reusability of smart sensors (Abad et al., 2009), and as a result, the amortization over the course of time so that the higher initial investment cost will pay off after a certain number of re-uses (Delen et al., 2011).

Furthermore, the connection between wireless sensor technology and RFID allows for transmitting both the product's identification and the collected sensor data wirelessly to a reader device. Thus, having a person to scan barcodes or visually control objects' product quality is no longer required, with the consequence of significant labor cost savings (Asif and Mandviwalla, 2005). It is also possible to identify the current location of a shipment by an integrated GPS sensor (Grunow and Piramuthu, 2013) or by knowing the location of the RFID readers (Ni et al., 2011), which enables traceability. This is of particular importance when issues in the supply chain are known but cannot be traced back to a specific supply chain party. Information about the exact location and the time interval of a deviation from the nominal temperature range is necessary to reduce the time spent in detecting defects in the supply chain. This provides the basis for accounting for the liability costs of the responsible supply chain party (Piramuthu et al., 2013).

2.2.2 Issuing policies and perishable goods

Inventory management for perishable goods has been studied extensively in the operations management literature since the 1960s. It has been given much attention not only in the re-emerging literature review articles (Bakker et al., 2012; Goyal and Giri, 2001; Li et al., 2010; Nahmias, 1982; Raafat, 1991), but also because of its prevalence in industry. Against this backdrop, a substantial body of literature exists on (near-)optimal policies for inventory control as well as for replenishment for inventory systems with deterioration. However, comparatively few take the factor of perishability of products into account affecting the issuing of goods.

In early studies, the focus was on traditional issuing policies such as FIFO and/or LIFO examining how to manage perishable and aging inventories. For an overview of early works we refer to Nahmias (1982) and Karaesmen et al. (2011). In recent research, Stanger et al. (2012) and Haijema (2014) address the blood bank problem of decreasing blood quality during the course of time. Stanger et al. (2012) investigate the management of perishable inventories and the trade-off of shortages and lost sales against wastage and spoilage. They conducted seven case studies with hospital transfusion laboratories in the UK blood supply chain in order to explore how perishable inventories are managed. Based on their results they conclude that all hospitals implement a strict age-based "Oldest Unit, First Out" (OUFO) policy to keep the stock as fresh as possible. Haijema (2014) examines the impact of the FIFO and LIFO issuing policy on optimal disposal and ordering policy for perishables. He conducted a simulation using Markov decision problem models, for which the results show that both the FIFO and LIFO issuing policy positively affect the optimal disposal and ordering policy under certain conditions.

The value of information and information sharing was studied by Ferguson and Ketzenberg (2006). They assume a supplier that provides information about product age to a retailer. The authors concluded that a retailer benefits most from information sharing when (i) the variability of either demand or the remaining lifetime of items to be replenished is high, (ii) product lifetimes are short, and (iii) the cost of the product is high. Furthermore, the value of information was tested against the issuing policies SIRO (Service In Random Order), FIFO, and LIFO with the result that the average improvement from information sharing is best for FIFO followed by SIRO and LIFO. Ketzenberg et al. (2014) examine the use and value of time and temperature information for a retailer. Two heuristics, a base case using a FIFO issuing and a RFID case using a FEFO (First Expired, First Out) issuing, were developed. They show that the value of this information is highest for a medium shelf life of 6.5 days and that the cost for the RFID case is generally lower than for the base case, with a convergence towards higher shelf life.

Beyond the traditional FIFO and LIFO policies, researchers developed their own approaches in the context of issuing policies. Huq et al. (2005) examined a heuristic model developed to evaluate an issuing policy for a single perishable product with a fixed shelf life in a single-echelon inventory system. They compared their proposed model with FIFO and a random allocation approach and could demonstrate that their heuristic model performs significantly better with regard to revenue generation. A further work by Thron et al. (2007) investigated the advantageousness of specific issuing policies, namely “First Produced, First Out” (FPFO) and “First Delivered, First Out” (FDFO), against SIRO, FIFO, and LIFO. By means of a simulation study, they obtain performance measures for level of safety inventory, customized product expiration schedules, and frequency and place of expiration control, among others. Based on the results they conclude that particularly FPFO has a strong potential for supply chain improvements.

It was only with the arrival of novel technologies, which opened new opportunities for research to examine the impact on supply chains. In particular, the grocery industry depends on monitoring technology as many perishables must be handled under temperature-controlled conditions throughout the entire supply chain. Hence, temperature monitoring is of utmost importance and is frequently enabled by the TTI technology. The applicability of TTIs was studied for different reasons, including supply chain safety (Koutsoumanis et al., 2005; Sahin et al., 2007), dynamic pricing (Herbon et al., 2012, 2014; Wang and Li, 2012), or shelf life prediction (Kouki et al., 2010; Mai et al., 2011). In particular, the latter constitutes an essential part of new forms of issuing policies. Likewise, Labuza and Taoukis (1990) introduced the quality-based issuing policy "Least Shelf-life, First Out" (LSFO) for which a TTI is considered. They suggested a transition from FIFO to LSFO by providing a consumer indicator (i.e., a TTI) which reveals products' proper handling and reduces customer dissatisfaction. On this basis, Giannakourou and Taoukis (2003) assessed the applicability of the TTI technology for the cold chain in a field study. After providing evidence of TTI effectiveness, they conducted a numerical simulation to investigate the potential of a LSFO system facilitated by TTI. They conclude that the application of LSFO provides acceptable quality and minimization of rejected products at the consumer end.

As a result of recent technology advances, smart sensors and WSNs are becoming increasingly important. Due to their ability to identify objects in close proximity and to specify the environmental condition, smart sensors enable an ever-increasing number of interconnected objects, creating the Internet of Things (Atzori et al., 2010), and leading to the concept of virtual supply chains (Verdouw et al., 2013). A prerequisite is, however, that developments towards and deployments of intelligent packing (Heising et al., 2014) or intelligent transportation containers (Jedermann et al., 2010; Lang et al., 2011; Rodríguez-Bermejo et al., 2007) are pushed forward by industry. While research activities frequently examine smart sensors and WSNs only technologically, their impact on business operations is of equal importance. Against the background of supply chains, recent studies by Piramuthu and Zhou (2013) and Grunow and Piramuthu (2013) consider an item's shelf life estimated via smart sensors to show that it has positive economic implications under certain circumstances. Jedermann and Lang (2007) compare different types of RFID-supported data loggers and smart sensors and their impact on quality tracing in the food chain. Another study from Hafliðason et al. (2012) considers WSNs in that they examine different types of methods and criteria to establish temperature alerts in decision support systems. Based on a simulation study, Aung and Chang (2014) conducted an experiment with WSNs for temperature monitoring and found that sensor-based methods for real-time quality monitoring outperform visual assessment methods.

Nonetheless, only a few researchers take smart sensors or WSNs into account in the issuing of perishable goods, including Qi et al. (2014), Lang et al. (2011), and Dada and Thiesse (2008). Qi et al. (2014) analyze an implemented system called “Cold Chain Shelf Life Decision Support System” which is based on WSN-based TTI nodes. A system test and evaluation confirm that the system functions properly from a technological point of view and user requirements were met. However, even though their study describes the advantages of LSFO over FIFO provided by their system, they do not substantiate their assertion by conducting a performance comparison. The concept of FEFO issuing policy in the context of an intelligent container was studied by Lang et al. (2011). The so-called “dynamic FEFO” makes use of an online monitoring and decision support system enabled by a sensor network, which improves the performance of FEFO and promises minimum waste of perishables. To our knowledge, Dada and Thiesse (2008) are the first to compare sensor-based issuing policies in a supply chain of perishables. They conduct a simulation study in which they consider seven different issuing policies. The examined performances are average quality of sold items plus their standard deviations, unsold items, and low quality sales. Overall, the issuing policy “Lowest Quality First Out” (LQFO) proves to be a reasonable compromise according to the simulation results, although “First Expiry First Out” performs even better in many cases or only slightly behind. The other issuing policies underperform particularly in the light of spoilage.

Table 1 provides a chronological overview of the recent studies including issuing policies as presented above. It becomes obvious that issuing policies for perishables are the subject of research, but in most cases it is limited to traditional issuing policies (e.g. FIFO and LIFO) and, if at all, to only one technology (e.g. TTI or smart sensors). We take the work in the area of issuing policies for perishables one step further in that we draw on the work from Dada and Thiesse (2008) but take additional issuing policies, combinations thereof with different customer withdrawal behaviors, and the financial perspective into consideration.

Table 1. Overview of recent studies considering issuing policies

Author(s)	**Problem context**	**Methodology**	**Issuing policies**
Giannakourou and Taoukis (2003)	Examination of the applicability of TTIs for frozen chain management.	Field test, Simulation	FIFO LSFO
Huq et al. (2005)	Development of a heuristic model which considers the remaining shelf life of the in-stock inventory and the expected time that the product will spend in inventory.	Simulation	Heuristic algorithm Random Allocation FIFO
Ferguson and Ketzenberg (2006)	Exploration of the value of information (VOI) in the context of FIFO and LIFO.	Simulation	SIRO FIFO LIFO
Thron et al. (2007)	Performance comparison of FPFO and FDFO against traditional issuing policies. They consider performance measures such as level of safety inventory, customized product expiration schedules, and frequency and place of expiration control.	Simulation	SIRO FIFO LIFO FPFO FDFO
Dada and Thiesse (2008)	Investigation of the potential of sensor-based issuing policies on product quality in the supply chain of perishables.	Simulation	SIRO FIFO LIFO FEFO LEFO LQFO HQFO
Lang et al. (2011)	Performance comparison between a common cargo container and an “Intelligent Container” based on a decision support tool.	System performance test	Dynamic FEFO
Stanger et al. (2012)	Investigation of the management of perishable inventories in the UK blood supply chain.	Case study	FIFO OUFO
Haijema (2014)	Evaluation of cost reductions that can be achieved by an optimal stock-age dependent ordering or disposal policy.	Simulation	FIFO LIFO
Ketzenberg et al. (2014)	Analytical investigation of the use and value of time and temperature information for a retailer.	Analytical model	FIFO FEFO
Qi et al. (2014)	System analysis of a “Cold Chain Shelf Life Decision Support System” based on WSN and TTI.	System performance test	FIFO LSFO

2.3 Model development

2.3.1 General framework

In this work, we aim to fill a gap in the literature regarding policies for the issuing of perishable goods enabled by wireless sensor technologies. Our primary objective is to gain a better understanding of the specific characteristics of these policies in comparison to policies that rely on established technologies, for example, the barcode. In contrast to prior research summarized in section 2.2.2, our study is not limited to a comparison of FIFO/LIFO vs. quality-based issuing policies; in fact, we make a finer distinction between issuing policies that rely on different forms of product quality measures. Moreover, we consider not only product quality, but also spoilage and holding costs as the performance criteria of interest. In order to circumvent some of the simplifications that become necessary in analytical modeling to achieve mathematical tractability, we make use of the simulation method as our means of investigation.

We examine a three-echelon supply chain model including a manufacturer of perishable goods, a distribution center (DC), and a retail store (RS) as depicted in Figure 9. An overview of the notation used in the following is given in Table 2.

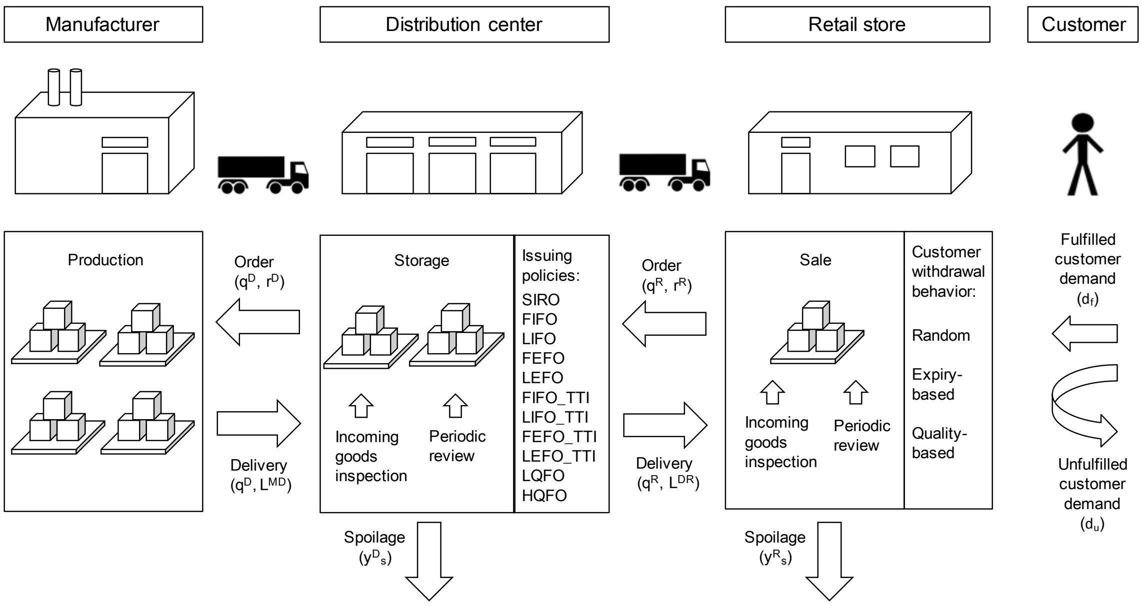

Figure 9. The supply chain model for simulation

Despite its limited complexity, the supply chain model captures the essential elements of a cold chain and allows us to conduct meaningful experiments with a broad variety of issuing policies. We distinguish between different conventional issuing policies with and without TTI based on the time of arrival at the DC and those based on product age (see section 2.3.2). Furthermore, we consider novel sensor-based issuing policies for which the product quality is the primary criterion. The purpose of our model is to enable a rigorous comparison between the performances of different issuing policies at the DC in combination with different customer withdrawal behaviors at the RS. To this end, the performance measures product quality, spoilage, and holding costs are reported to identify the strengths and weaknesses of each issuing policy.

Table 2. Notation overview

Notation	Description
$c^D{}_h$	Holding cost rate at DC
$c^R{}_h$	Holding cost rate at RS
c_h	Total holding costs
$I^D{}_p$	Physical inventory level at DC
$I^R{}_p$	Physical inventory level at RS
$I^D{}_r$	Recorded inventory level at DC
$I^R{}_r$	Recorded inventory level at RS
$y^D{}_s$	Number of spoiled items at DC
$y^R{}_s$	Number of spoiled items at RS
y_s	Total spoilage rate
d_f	Number of fulfilled customer demands
d_u	Number of unfulfilled customer demands
p_q	Quality of an item
p_a	Age of an item
q^D	Order quantity at the DC
q^R	Order quantity at the RS
r^D	Reorder point at DC
r^R	Reorder point at RS
L^{MD}	Lead time from manufacturer to DC
L^{DR}	Lead time from DC to RS
T	Simulation horizon
λ	Customer demand rate
θ	Shelf life of an item
β	Service level

We make the following assumptions regarding the simulated supply chain:

- We consider a single perishable product, which in most of the inventory control studies is common practice due to the high complexity of a multi-item model (Bakker et al., 2012). The product has a fixed shelf life, which is indicated by an expiry date associated with each item by the manufacturer.
- Product deterioration depends on product age (p_a) as well as on product quality (p_q). The latter is characterized by a daily calculated deterioration rate. This two-fold consideration of product deterioration sets time (p_a) apart from quality (p_q), which are usually interdependent, but might differ in certain scenarios (e.g. cooling system failure or careless storage). A given quality threshold defines the minimum quality level below which it is considered as spoiled. If an item with a lower quality is found during a periodic review, it is disposed of.
- The retailer operates the supply chain under a service level constraint to reduce the occurrence of stock-outs.
- The manufacturer has ample production capacity to fulfill any incoming order from the DC.
- The DC and the RS use the (Q,r) inventory control policy. When the inventory position drops below the reorder point r, a replenishment order of size Q is placed. Q is exogenously given (e.g. by long-term contracts between the retailer and the manufacturer) and is not subject to optimization. The (Q,r) policy is commonly used in practice and is considered as a generally good replenishment policy (Berk and Gürler, 2008; Kouki et al., 2010).
- L^{MD} is a uniformly distributed random variable, whereas L^{DR} is constant, given that the product is available at the DC. The fixed length of L^{DR} reflects the fact that the delivery frequency of perishables is usually about one day (Broekmeulen and van Donselaar, 2009). The variable L^{MD} might lead to order crossover, i.e. some orders arrive out of sequence in contrast to how they left the manufacturer. The potential occurrence of order crossovers does not pose an issue in our simulation.
- All incoming goods at the DC and the RS are inspected for sufficient product quality if technically feasible. In addition, we assume periodic reviews of all stored items

within the DC and the RS once a day as this procedure is most common in the grocery industry (Ferguson and Ketzenberg, 2006).

- The daily customer demand rate at the RS is probabilistic. In case of stock-outs, demand is not backlogged, i.e. sales are lost.

A detailed flow chart describing the sequence of simulated events is depicted in Figure 10. In the beginning, the respective issuing policy is set together with the initialization of all relevant input parameters. The first step in the simulation run is the arrival of a shipment at the DC. The shipment is received and the incoming goods are inspected for product quality. If any spoiled items are detected, $y^D{}_s$ is incremented, otherwise the items are stored in the inventory and $I^D{}_p$ increases according to the stored amount. Subsequently, the same procedure takes place at the RS. If a shipment arrives, it is inspected for product quality, too. In case of spoiled items, $y^R{}_s$ is incremented whereas all acceptable goods are stored and $I^R{}_p$ is updated. So far, the daily shipments for the DC and the RS are processed and the inventory is replenished.

In the following step, the daily customer demand is calculated. We use a truncated normal distribution for demand which sets the demand to zero in case negative demand occurs. If enough stock is on hand, d_f is incremented, otherwise d_u is incremented. After the customer demand has been fulfilled, the periodic review at the RS is conducted. Depending on the issuing policy and the technology used, the review detects spoiled items either by product age p_a or by product quality p_q. If any spoilage is detected, $y^R{}_s$ is incremented. Next, the RS's recorded inventory $I^R{}_r$ is checked against the reorder point r^R if replenishment is necessary. In case $I^R{}_r$ is below r^R, an order of q^R is placed and $I^R{}_r$ is updated accordingly. In the next step, the same sequence of periodic review and inventory inspection is conducted at the DC. For detected spoiled items $y^D{}_s$ is incremented. Given that $I^D{}_r$ is below r^D, an order of q^D is sent to the manufacturer and the recorded inventory position $I^D{}_r$ is increased accordingly. At the end of a simulation period, the product deterioration is calculated which affects the product quality p_q and the product age p_a of each item in the supply chain. In addition, the holding costs $c^D{}_h$ and $c^R{}_h$ are calculated.

If the finite time horizon T has been reached, the simulation starts another replication with the same parameter settings or continues with a new set of settings until all combinations of issuing policies and input parameters have been simulated.

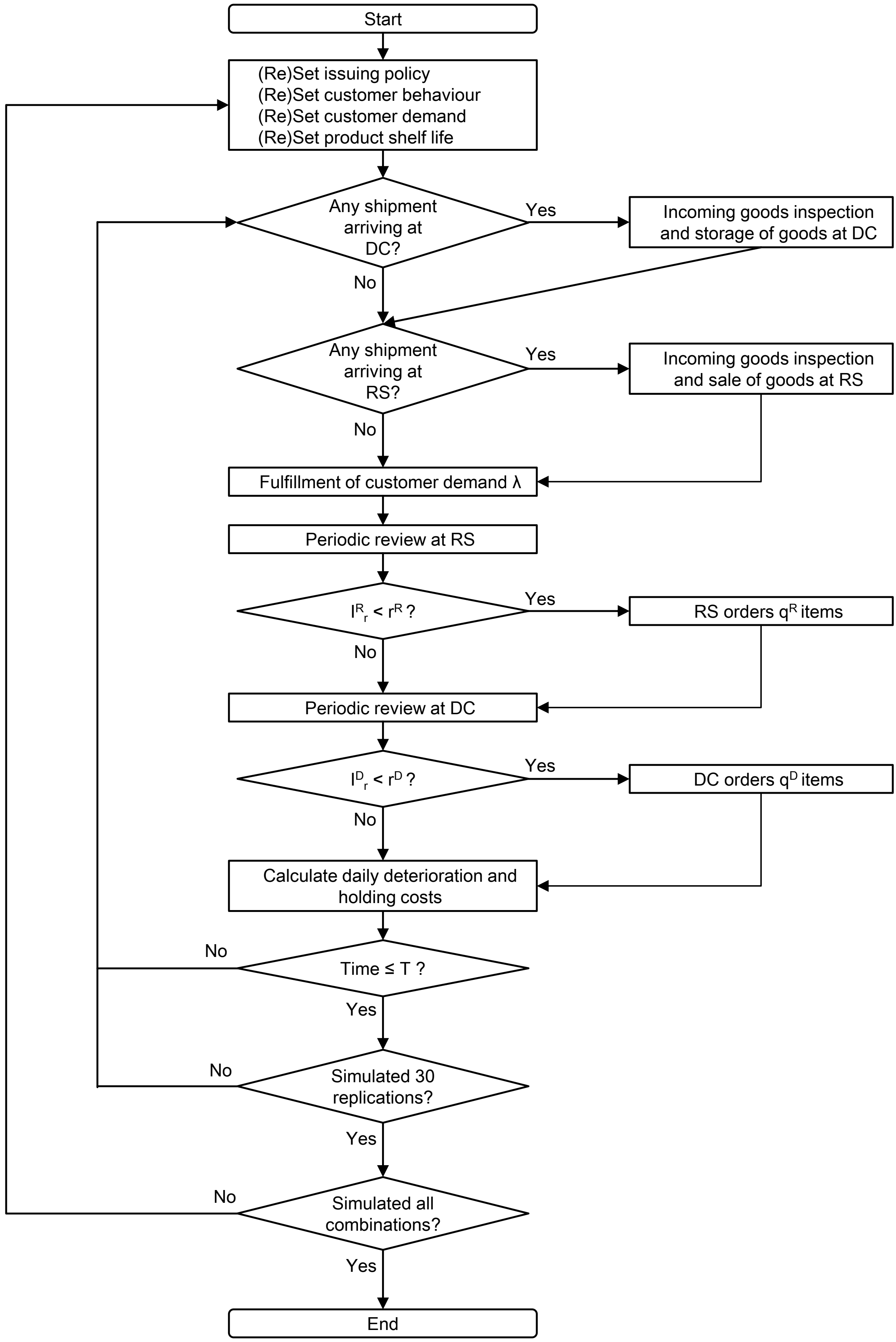

Figure 10. Simulation flowchart

2.3.2 Issuing policies

An issuing policy corresponds to a selected order of goods issuance in the inventory in case of an incoming demand (Haijema, 2014). We draw on the work from Dada and Thiesse (2008) and extend the set of proposed issuing policies each based on one of the item withdrawal criteria “arrival time,” “product age,” or “product quality” at the DC. The considered issuing policies are characterized as follows:

- *Service In Random Order (SIRO)* provides the benchmark to which all other issuing policies are compared. Under this policy, the DC selects products to be shipped to the RS randomly and completely independent of their product age or quality.
- *First In, First Out (FIFO)* issues products according to their arrival time, that is, the items which arrived first in the DC are shipped first to the RS.
- *Last In, First Out (LIFO)* issues products according to their arrival time, that is, the items which arrived last in the DC are shipped first to the RS.
- *First Expired, First Out (FEFO)* follows an age-based issuing strategy with the items which were manufactured earlier being the first to be shipped to the RS.
- *Last Expired, First Out (LEFO)* follows an age-based issuing strategy with the items which were manufactured later being the first to be shipped to the RS.
- *Highest Quality, First Out (HQFO)* relies on the estimated quality of items with the highest quality being shipped before any other items.
- *Lowest Quality, First Out (LQFO)* relies on the estimated quality of items with the lowest quality being shipped before any other items.

In addition, we consider enhanced variants of FIFO, LIFO, FEFO and LEFO using a TTI label that allows for a simple form of quality inspection. It indicates whether a particular item should be disposed of when its quality level is below the acceptable minimum. Thus, the four policies FIFO_TTI, LIFO_TTI, FEFO_TTI, and LEFO_TTI include quality inspections for both the incoming goods and the periodic review at the DC and the RS. Altogether, we consider eleven issuing policies in our simulation study.

With the exception of SIRO, all considered policies depend on some kind of identification or technology. In the case of FIFO/LIFO, the retailer must be able to identify items by a unique identification number, which is associated with the item’s arrival time at the DC.

Note that in our scenario neither SIRO nor FIFO/LIFO have means to evaluate the product age or product quality, which implies that spoiled products remain in the cold chain when they are expired.

FEFO/LEFO depend on the existence of a database that stores the items' expiry dates and links this information to a unique identification number. Both types of policies require that shipments are labeled with barcodes – the predominant technology in the food supply chain (Hafliðason et al., 2012) – or any other kind of auto-id technology, such as RFID.

In contrast, HQFO/LQFO make use of information gathered by sensor technology (e.g. "smart sensor"), which allows an item's time-temperature history to be determined during storage and transportation, and to calculate a sufficiently precise estimate of its current product quality (Wang and Li, 2012).

FIFO_TTI/LIFO_TTI and FEFO_TTI/LEFO_TTI provide a compromise of the aforementioned issuing policies. On the one hand, they combine the ability of product identification through an auto-id technology and the detection of spoiled goods based on product quality. On the other hand, they lack a temperature history, so that the actual issuing decision-making is according to either arrival time or product age as for the same policies without TTI.

2.3.3 Customer withdrawal behavior

Customers follow different strategies in their product withdrawal behavior. Ishii and Nose (1996) consider two types of customers (high and low priority) in their study, whereby high customers choose always the newest products in terms of remaining shelf life while low customers not only buy the newest but also old ones. In some cases, the quality of perishable goods may be judged easily by their visual appearance; in other cases, customers may only have the expiry date at their disposal. To reflect this situation, we consider three different types of customer withdrawal behaviors:

- *Random*. This behavior describes a customer who is unable or unwilling to judge an item's product quality. Consequently, items are taken arbitrarily off the shelf, no matter whether their product quality is satisfactory or not.

- *Expiry-based*. This behavior describes a customer who withdraws a product depending on its age as given by the expiry date. In this case, the customer always chooses the "youngest" item.
- *Quality-based*. This behavior describes a customer who withdraws a product depending on its product quality. Hereby, the customer takes the item's product quality estimation (e.g. through "smart sensor") into account, and always chooses the item that shows the best quality.

2.4 Simulation implementation

This section describes the technical implementation of the simulation algorithm depicted in Figure 10 in more detail. The algorithm was coded using the object-oriented programming language C# and the integrated development environment Microsoft Visual Studio. Integrated development environments present a single program in which all development is done; particularly the full integration of SQL in Visual Studio enabled us to efficiently interact with the Microsoft SQL Server. The collected simulation output data was stored in a database in SQL Server and analyzed with Microsoft SQL Server Management Studio and Microsoft Excel. We adhere to the sequence of the simulation algorithm in Figure 10 and explain for each step the underlying code snippets (see Appendix A). Note that these are only abstracts from the entire source code and might not work as specified.

The program starts with the simulation parameter initialization which uses a foreach-loop to run the same algorithm repeatedly but with different parameter settings (Appendix A.1). Our parameters were stored in an enumerator list as a set of named constants. The foreach-loop is used to iterate through an array or object collection such as an enumerator list. To ensure all combinations of parameters are processed, we nested all foreach-loops to iterate through all enumerator lists. The following for-loops iterate over the reorder point at the DC (rdc) and the reorder point at the store (rstore), again in a nested loop structure. The last for-loop iterates over the replications and provides the input parameters for each replication.

At close of day when all the daily events have been passed through in the simulation algorithm, the next day only starts if the simulation horizon has not been reached, which is implemented by means of a while-loop. If the simulation horizon has been reached, a check is made as to whether the pre-defined 30 replications were processed by using a for-loop. The simulation terminates when all parameter combinations were simulated.

The source code for the actual simulation starts with the arrival of a shipment at the DC takes place (Appendix A.2). In case of a shipment arriving, an incoming goods inspection is conducted. Here, we distinguish between quality-based and age-based issuing policies. The actual quality level of items under quality-based issuing policies, to which all policies using a TTI and LQFO/HQFO belong, is tested against the minimum quality level of 40%. In case of approval, the items are stored in the inventory of the DC, otherwise they are disposed of. The items under age-based issuing policies, to which FEFO and LEFO belong, undergo the test of actual age against predefined shelf life. Again, in case of approval, the items are stored in the inventory of the DC, otherwise they are disposed of. The inventory is coded as a list, in which for each item its arrival time, age, and quality is recorded. In the next step of the algorithm, the arrival of a shipment at the RS is processed (Appendix A.3). Basically, this step includes the same course of action as the preceding step of an arrival of a shipment at the DC, with the main difference of distinct inventories. Upon completion of the warm-up period, the spoiled items are recorded. Figure 11 summarizes the sequence of actions in the event of shipment arrival at the DC and RS.

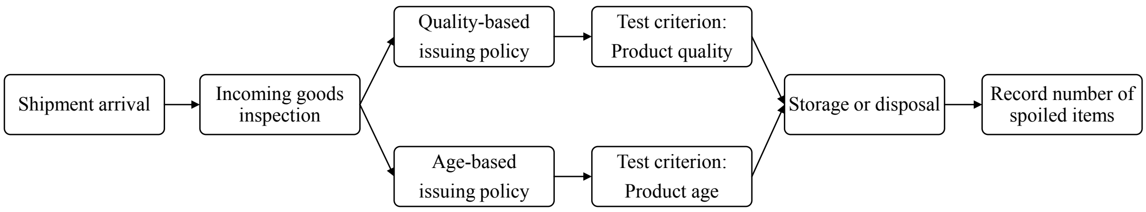

Figure 11. Process of shipment arrival at DC and RS

Following the shipment arrival, the daily customer demand is computed (Appendix A.4). After the definition of necessary variables, two switch statements follow for sensitivity analysis purposes (see section 2.5.3).

In the first switch statement, the standard deviation is changed to adjust it to the different demand rates. Further, the daily customer demand is calculated by using a (truncated) normal distribution. The actual value for customer demand depends on the input parameter for customer demand (e.g. mean of 50 items in the base case) and its standard deviation (e.g. 10 in the base case). In the unlikely event of a negative customer demand, the actual value for customer demand is set to zero.

In the second switch statement, the three different customer withdrawal behaviors are taken into account as explained in section 2.3.3. The procedure for each customer withdrawal behavior resembles one another so that we describe their common parts and point to the differences. Each switch statement for the different withdrawal behaviors starts with the definition of a variable that specifies the items to be withdrawn from inventory according to the criteria of each behavior. The three criteria are random, product age, and product quality. Subsequently, a for-loop (random behavior) or foreach-loop (expiry-based and quality-based behavior) serves as iteration loop for selecting individual items from inventory until customer demand is fulfilled as per the actual value calculated before. In case of a random withdrawal behavior, the variable value is based on a uniform distribution, i.e. all items in inventory are equally likely to be withdrawn. In case of an expiry-based withdrawal behavior, product age is the selection criterion according to which a customer selects a product, i.e. the customer selects the youngest item. In case of a quality-based withdrawal behavior, product quality is the selection criterion for a customer, i.e. the customer selects the item with the highest quality.

After an item has been selected and the warm-up period has elapsed, the product quality of each item is recorded in one of the product quality categories used for data analysis (see section 2.5.2). Then it is removed from the physical as well as from the recorded inventory. Additionally, the number of customers and stock-outs are recorded to allow for a calculation of the service level in the aftermath of the simulation. Figure 12 depicts the whole process for customer demand.

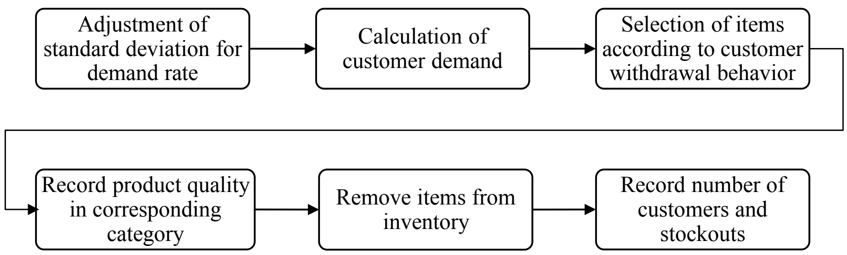

Figure 12. Customer demand process

The source code for the periodic review at the RS closely resembles the incoming goods inspection, in that the items in inventory are checked depending on the issuing policy (Appendix A.5). If a quality-based issuing policy is set, the test criterion is product quality, for which the actual quality of an item must exceed the minimum quality level of 40%. If an age-based issuing policy is set, the test criterion is product age, for which the actual age of an item must be below the predefined shelf life. In case an item has still enough product quality or is below its shelf life, it is kept in inventory, otherwise it is disposed of. Once the warm-up period is over, the spoiled items are recorded. The algorithm for the periodic review at the DC functions analogously, with the only difference that it happens at the DC instead of the RS (Appendix A.7). Figure 13 shows the periodic review process at the RS and DC.

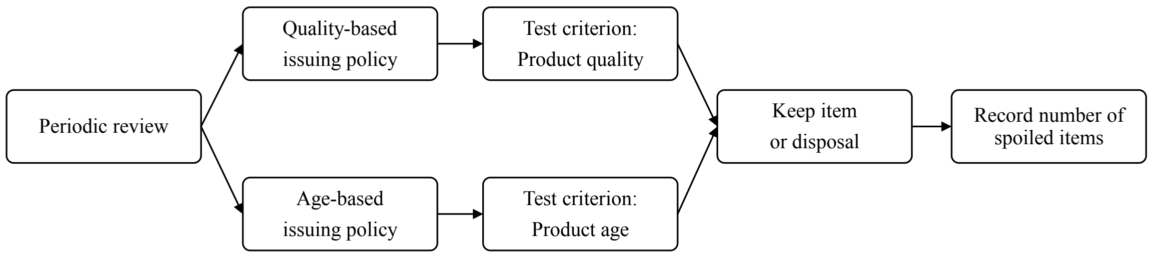

Figure 13. Periodic review at RS and DC

After the inventory has been reviewed to detect spoilage, the recorded inventory level is checked against the reorder point to determine whether stocks must be replenished or not (Appendix A.6). If the inventory level exceeds the reorder point, the process of order placement is stopped and the algorithm continues with the next step. In case the inventory level has fallen below the reorder point, an order is placed immediately. Once the warm-up period is over, all orders are recorded. Figure 14 illustrates the sequence of order placement at the RS.

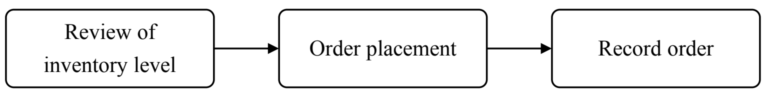

Figure 14. Order placement at RS

The order placement process at the DC is slightly different to the one at the RS (Appendix A.8). First, the recorded inventory level is checked against the reorder point to assess if inventory must be replenished. If so, then an order is placed and the lead time and product quality are assigned to each item. For this purpose, a for-loop is processed until the order quantity for the DC is reached.

In this for-loop, the lead time is assigned by using a uniform distribution, with a minimum value of 1 day and a maximum of 3 days. Subsequently, the product quality and product age at the manufacturer are specified by using a normal distribution. In case of product quality, the value is derived from the pre-defined mean quality and standard deviation (see section 2.5.1). If a negative value or a value above 100% is calculated, the value is set to 0% or 100%, respectively. The product age is calculated with a pre-defined mean and standard deviation, however, in the event of a negative value for product age, the value is set to zero.

Finally, the items are stored in a queue representing the transportation from the manufacturer to the DC. After the for-loop and if the warm-up period has ended, the order is recorded. Figure 15 shows the whole process of order placement at the DC.

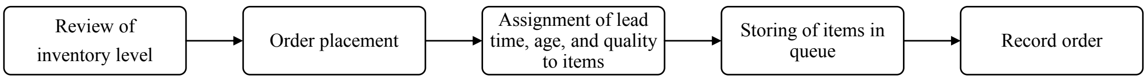

Figure 15. Order placement at DC

At the end of the day in the simulation, the daily deterioration of items and the holding costs are calculated (Appendix A.9). Figure 16 describes this part of the simulation. First, those items being transported from the manufacturer to the DC (transportation queue 1), are subject to an update of product age and product quality due to deterioration. The loss of product quality is calculated by using a normal distribution with specific values for the mean and the standard deviation (see section 2.5.1). To avoid "negative" product loss, which would result in an increase of product quality, the value is set to zero if a negative value was calculated. The product age is measured in days, i.e. it increases by one day at the end of every day. The items in the transportation queue from DC to RS (transportation queue 2) undergo the same process as described previously. Next, all items in inventory at the DC and RS are subject to deterioration. Again, the process of updating product quality and product age is identical to the first process step.

Finally, the daily holding costs are calculated based on the number of items in inventory. When the warm-up period is over, the total holding costs are incremented by the calculated daily holding costs as per function 3 in section 2.5.2.

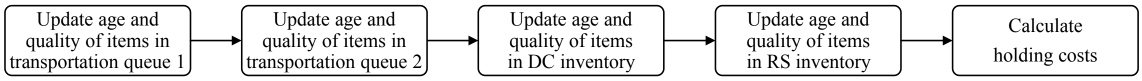

Figure 16. Update of product age/quality and calculation of holding costs

2.5 Simulation study

2.5.1 Experimental design

The simulation algorithm was run on a computer with an Intel Quad-Core i5-4690S processor and a clock speed of 3.20GHz. Each parameter setting was simulated in an individual simulation run, which consisted of an adequate number of 30 independent replications for meaningful conclusions at the 95% confidence level.

For the base case of our simulation experiment, we consider a perishable product with a fixed shelf life of 15 days (e.g. yogurt), which corresponds to a "weeks fresh" perishable (van Donselaar et al., 2006). Once a product exceeds its shelf life, it is regarded as spoiled. The product age upon leaving the manufacturer is normally distributed with a mean of p_a = 2 days and a standard deviation of 0.5, and the product quality is normally distributed with a mean of p_q = 90% and a standard deviation of 1, which approximates a common initial product quality level (Rong et al., 2011).

The order quantity of the DC is q^D = 600 items per order, while the order quantity of the RS is q^R = 150 items. We argue that a DC usually orders more items than a RS, thus we assume a value four times as much as a RS. Furthermore, small to medium size grocery stores usually do not receive daily deliveries (Ferguson and Koenigsberg, 2007), so that we assume the store to receive an order quantity to supply customer demand for about three days. In contrast to these given values, the reorder points r^D and r^R may be optimized freely.

The daily customer demand rate at the RS follows a normal distribution with a mean of λ = 50 items and a standard deviation = 10. The lead time from the manufacturer to the DC

(L^{MD}) is uniformly distributed with lower bound = 1 and upper bound = 3 days, while the lead time from the DC to the RS is fixed with L^{DR} = 1 day.

Product deterioration is determined by both the time spent in transit (L^{MD} and L^{DR}) or in storage affecting p_a and the quality deterioration rate affecting p_q, which follows a normal distribution with a mean of 4% and a standard deviation of 1. The minimum quality level below which products are regarded as spoiled is 40%.

The holding costs per item are for the DC $c^D{}_h$ = 0.05$/day and for the RS $c^R{}_h$ = 0.15$/day, which reflects the fact that shelf space in a RS is more expensive than storage space in the DC and cooling of products can be managed more efficiently.

The simulation horizon of T = 500 days splits up into an initial simulation warm-up period of 50 days to reduce the initialization bias, and a run period of 450 days for the effective performance measures.

In total, we compared 33 different combinations of (i) the eleven issuing policies and (ii) the three customer withdrawal behaviors. The two reorder points r^D and r^R were optimized under a service level constraint of at least 95%, which is in the range of observed service levels in practice (Broekmeulen and van Donselaar, 2009; Ketzenberg and Ferguson, 2008). The RS service level β is defined as the fraction of served customers as compared to the total annual customer demand:

$$\beta = \frac{d_f}{d_f + d_u} \tag{1}$$

Optimizations were conducted with three different objective functions, these are, (i) maximizing product quality, (ii) minimizing spoilage, and (iii) minimizing holding costs. The results of these optimizations are presented in the following section.

2.5.2 Simulation results

We first consider the performance of the eleven issuing policies that can be achieved when we seek to maximize the average quality of sold products for the base case. Figure 17, Figure 18, and Figure 19 show the distribution of product quality categories for each combination of issuing policy and customer withdrawal behavior. In the following we refer to low-quality sales with a quality below 40%, average-quality sales with a quality of 40-69%, and high-quality sales with a quality of 70% and above. The quality category 90-100% does not appear as no sales were recorded for this category.

Figure 17 shows the results for a random customer withdrawal behavior. It can be observed that SIRO, FIFO, and LIFO perform similarly and inferior to the other issuing policies. We also see that except for LEFO, all issuing policies not using quality monitoring solutions have a remarkably high share of low-quality sales, even though the spoilage threshold is set to 40% of product quality. This can be explained by the missing technological means to determine the product quality. In contrast, this does not apply to the other issuing policies, which is why they show no or only a comparatively small amount of low-quality sales. LQFO sets its focus on average quality sales, while FIFO_TTI and FEFO_TTI perform similarly but have a higher share of high-quality sales. Among all issuing policies, LIFO_TTI, LEFO_TTI, and HQFO perform best with HQFO outperforming the others.

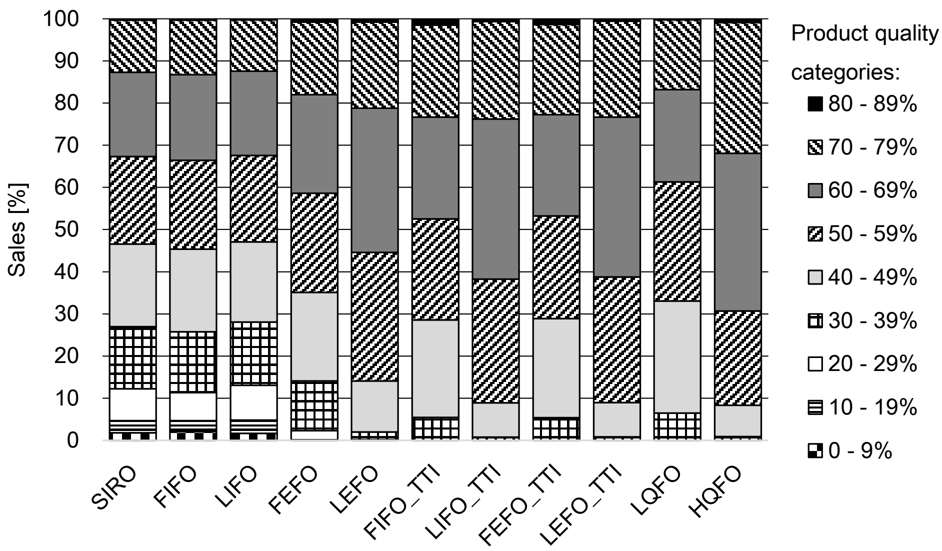

Figure 17. Distribution of product quality for random customer withdrawal behavior

Figure 18 shows the results of the distributions of product quality categories for a customer withdrawal behavior based on expiry date. As can be seen, a shift towards higher quality sales becomes obvious across all issuing policies. SIRO, FIFO, and LIFO show only minor improvements towards higher quality sales, however, the share of low-quality sales remains high with about 25-28%. In the case of FEFO, the low-quality sales drop significantly from about 14% to about 7% compared to the customer withdrawal behavior before. The low-quality sales of FIFO_TTI, FEFO_TTI, and LQFO are reduced to the benefit of average-quality sales as compared to the random customer withdrawal behavior. LEFO, LIFO_TTI, LEFO_TTI, and HQFO gain substantially in high-quality sales, making them again the issuing policies performing best, whilst low-quality sales disappear almost completely.

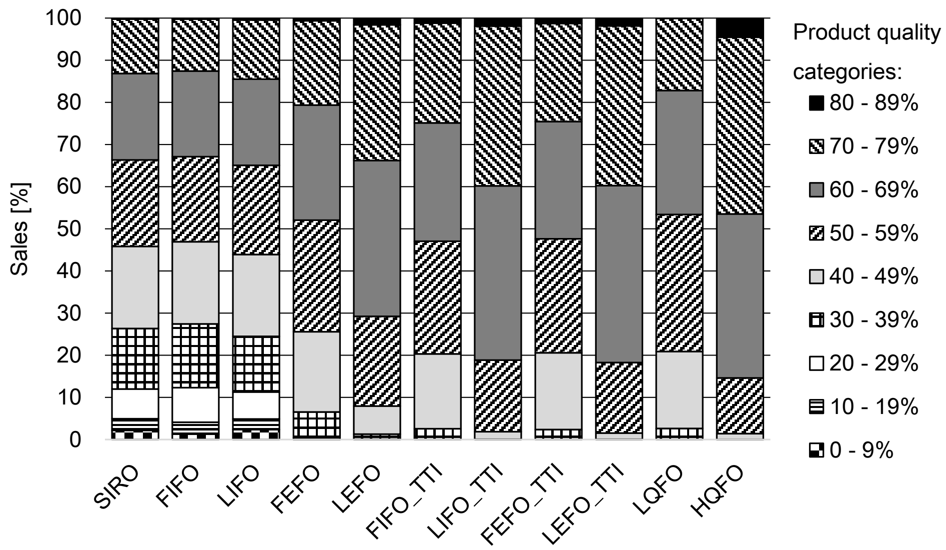

Figure 18. Distribution of product quality for customer withdrawal behavior based on expiry date

Figure 19 depicts the results for a customer withdrawal behavior based on product quality. Again, a general shift towards higher quality sales becomes apparent, with increases across all issuing policies. More specifically, all issuing policies show significant increases in high-quality sales, with the exception of SIRO, FIFO, LIFO. In addition, low-quality sales are reduced almost completely for these policies. In this customer withdrawal behavior the advantage of issuing policies using quality monitoring means becomes apparent. They have the highest increases in the highest product quality category, and the sales of spoiled products fall almost to zero. LEFO represents the only exception to this rule as it has no means for quality monitoring but prioritizes young products.

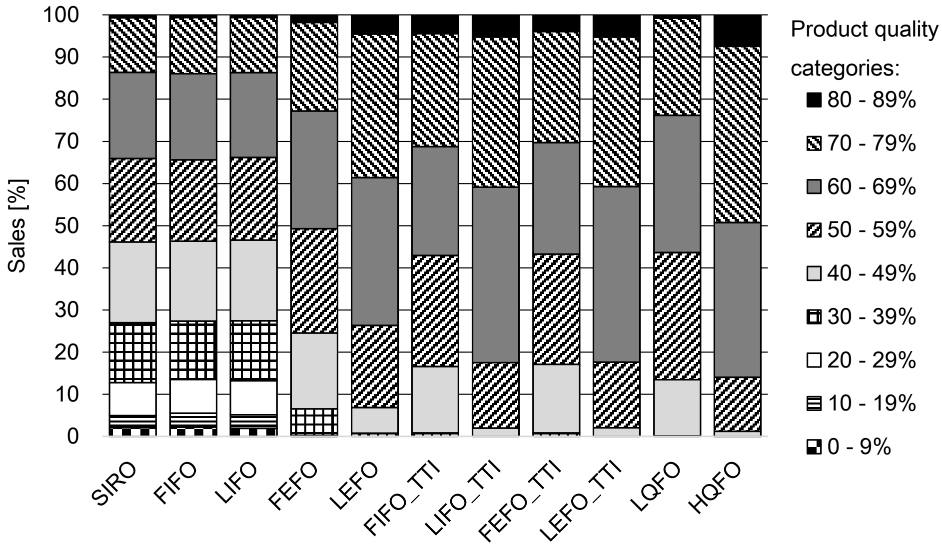

Figure 19. Distribution of product quality for customer withdrawal behavior based on product quality

Table 3 outlines the numerical simulation results for all combinations of customer withdrawal behavior and issuing policy. We provide the mean values from 30 replications and the corresponding confidence intervals at 95% significance level in brackets. For analyses regarding spoilage, we exclude SIRO, FIFO, and LIFO, as these issuing policies are conceptually not able to detect spoilage; neither by product age nor by product quality. It also prevents the optimization regarding spoilage, thus the results for these issuing policies are not reported.

When optimizing for maximum product quality, the afore-mentioned improvements of product quality levels across the customer withdrawal behaviors become evident as a consequence thereof. With regard to product quality, LIFO_TTI, LEFO_TTI, and HQFO perform better than the other policies with HQFO showing the best performance. The results also indicate only marginal differences between FIFO_TTI/FEFO_TTI and LIFO_TTI/LEFO_TTI, respectively. The issuing policies without quality monitoring means show the lowest mean quality values with the exception of LEFO.

A further important insight can be derived from the spoilage values. Here, HQFO shows the worst performance followed by LEFO_TTI, LIFO_TTI, and LEFO as they prioritize either young or high-quality items, whereas old items or those with lower quality are sold late or spoil before they ever reach the customer. SIRO, FIFO, and LIFO show no spoilage

Table 3. Numerical simulation results for objective functions

Customer withdrawal behavior	Issuing policy	Quality maximization			Spoilage minimization			Holding costs minimization		
		Quality [%]	Spoilage [%]	Holding costs [$]	Quality [%]	Spoilage [%]	Holding costs [$]	Quality [%]	Spoilage [%]	Holding costs [$]
Random	SIRO	50.1 (± 0.6)		9452 (± 106)				49.3 (± 0.4)		9036 (± 50)
	FIFO	50.5 (± 0.7)		9333 (± 125)				49.0 (± 0.6)		9065 (± 87)
	LIFO	49.9 (± 0.6)		9006 (± 85)				49.9 (± 0.6)		9006 (± 85)
	FEFO	55.9 (± 0.3)	9.4 (± 0.9)	9742 (± 87)	55.1 (± 0.2)	7.1 (± 0.9)	8717 (± 69)	55.5 (± 0.3)	8.0 (± 1.1)	8659 (± 77)
	LEFO	61.1 (± 0.2)	43.6 (± 0.5)	14699 (± 86)	57.2 (± 0.1)	10.4 (± 0.9)	8340 (± 76)	57.2 (± 0.1)	10.4 (± 0.9)	8340 (± 76)
	FIFO TTI	58.8 (± 0.3)	12.1 (± 1.5)	8498 (± 197)	58.8 (± 0.3)	12.1 (± 1.5)	8498 (± 197)	58.5 (± 0.1)	13.5 (± 0.8)	8140 (± 84)
	LIFO TTI	62.6 (± 0.2)	50.5 (± 0.5)	16360 (± 69)	58.8 (± 0.1)	11.4 (± 0.8)	8037 (± 88)	58.8 (± 0.1)	11.4 (± 0.8)	8037 (± 88)
	FEFO TTI	58.7 (± 0.2)	11.5 (± 0.9)	8606 (± 131)	58.7 (± 0.2)	11.5 (± 0.9)	8606 (± 131)	58.5 (± 0.1)	13.5 (± 1)	8155 (± 109)
	LEFO TTI	62.5 (± 0.2)	50.6 (± 0.4)	16395 (± 80)	58.8 (± 0.2)	11.5 (± 1)	9196 (± 146)	58.7 (± 0.1)	12.4 (± 0.9)	8069 (± 84)
	LQFO	56.6 (± 0.2)	11.4 (± 0.8)	9522 (± 84)	56.1 (± 0.2)	9.1 (± 0.6)	8123 (± 55)	56.1 (± 0.2)	10.4 (± 0.9)	8115 (± 50)
	HQFO	64.3 (± 0.2)	52.4 (± 0.4)	17542 (± 97)	59.9 (± 0.1)	15.1 (± 1)	9276 (± 108)	60.2 (± 0.1)	15.4 (± 0.8)	8508 (± 103)
Expiry-based	SIRO	50.0 (± 0.8)		9436 (± 136)				49.6 (± 0.9)		8966 (± 145)
	FIFO	50.1 (± 0.7)		8990 (± 125)				50.1 (± 0.7)		8990 (± 125)
	LIFO	50.4 (± 0.6)		10000 (± 108)				49.3 (± 0.8)		9042 (± 121)
	FEFO	58.6 (± 0.3)	23.2 (± 0.5)	14527 (± 78)	56.3 (± 0.3)	8.9 (± 0.8)	8532 (± 95)	56.3 (± 0.3)	8.9 (± 0.8)	8532 (± 95)
	LEFO	64.7 (± 0.2)	51.6 (± 0.3)	22101 (± 71)	57.8 (± 0.1)	11.8 (± 1)	8352 (± 108)	58.0 (± 0.2)	12.0 (± 0.7)	8276 (± 69)
	FIFO TTI	60.7 (± 0.2)	24.3 (± 0.6)	13940 (± 115)	59.2 (± 0.1)	12.3 (± 0.8)	8581 (± 109)	58.9 (± 0.2)	12.9 (± 0.8)	8011 (± 73)
	LIFO TTI	67.2 (± 0.1)	55.4 (± 0.3)	22675 (± 74)	59.2 (± 0.1)	12.4 (± 0.8)	8573 (± 110)	58.9 (± 0.1)	13.3 (± 0.8)	8102 (± 74)
	FEFO TTI	60.5 (± 0.2)	24.4 (± 0.7)	13933 (± 112)	59.1 (± 0.1)	12.5 (± 0.9)	8552 (± 112)	59.1 (± 0.1)	13.2 (± 0.7)	7992 (± 88)
	LEFO TTI	67.2 (± 0.1)	55.3 (± 0.3)	22615 (± 65)	58.8 (± 0.1)	12.0 (± 0.7)	8190 (± 86)	58.9 (± 0.2)	12.5 (± 1.1)	8038 (± 114)
	LQFO	59.1 (± 0.3)	24.1 (± 0.4)	14448 (± 103)	56.1 (± 0.2)	9.2 (± 0.7)	8129 (± 64)	56.1 (± 0.2)	9.2 (± 0.7)	8129 (± 64)
	HQFO	68.5 (± 0.1)	56.1 (± 0.3)	22725 (± 73)	60.5 (± 0.1)	15.9 (± 0.6)	8448 (± 64)	60.5 (± 0.1)	15.9 (± 0.6)	8448 (± 64)
Quality-based	SIRO	50.1 (± 0.3)		9423 (± 64)				49.1 (± 0.4)		9154 (± 93)
	FIFO	50.1 (± 0.5)		8982 (± 82)				50.1 (± 0.5)		8982 (± 82)
	LIFO	50.2 (± 0.4)		8975 (± 45)				50.2 (± 0.4)		8975 (± 45)
	FEFO	59.4 (± 0.2)	22.5 (± 0.4)	14814 (± 43)	56.1 (± 0.1)	7.5 (± 0.5)	8677 (± 36)	56.1 (± 0.2)	8.8 (± 0.6)	8616 (± 78)
	LEFO	65.9 (± 0.2)	51.8 (± 0.3)	22282 (± 72)	57.7 (± 0.1)	10.9 (± 0.5)	8744 (± 65)	57.6 (± 0.1)	12.2 (± 0.3)	8400 (± 41)
	FIFO TTI	62.5 (± 0.1)	25.6 (± 0.6)	13466 (± 123)	60.0 (± 0.1)	14.6 (± 0.6)	7865 (± 74)	60.0 (± 0.1)	14.6 (± 0.6)	7865 (± 74)
	LIFO TTI	67.7 (± 0.1)	55.3 (± 0.3)	22252 (± 77)	60.1 (± 0.1)	14.2 (± 0.9)	8408 (± 80)	59.7 (± 0.1)	15.4 (± 0.5)	8014 (± 59)
	FEFO TTI	62.3 (± 0.1)	26.1 (± 0.9)	13600 (± 137)	60.1 (± 0.1)	14.7 (± 0.4)	8138 (± 65)	59.8 (± 0.1)	15.7 (± 0.5)	8059 (± 60)
	LEFO TTI	67.7 (± 0.1)	55.3 (± 0.3)	22291 (± 70)	59.7 (± 0.1)	14.9 (± 0.4)	8056 (± 48)	59.7 (± 0.1)	14.9 (± 0.4)	8056 (± 48)
	LQFO	61.9 (± 0.1)	25.7 (± 0.2)	13883 (± 45)	57.7 (± 0.1)	10.8 (± 0.3)	8020 (± 25)	57.5 (± 0.1)	11.5 (± 0.5)	8003 (± 49)
	HQFO	69.2 (± 0.1)	56.1 (± 0.3)	22476 (± 70)	61.4 (± 0.1)	17.9 (± 0.6)	9132 (± 54)	61.2 (± 0.1)	19.0 (± 0.5)	8795 (± 74)

at all, however, this is also the determining factor for the worst product quality since spoiled items remain in the inventory.

With regard to holding costs, the interrelationship between spoilage and holding costs is clearly visible. Again, LEFO, LIFO_TTI, LEFO_TTI, and HQFO show consistently the worst performance across all customer withdrawal behaviors. In summary, the result reveals that despite the use of quality monitoring means, a trade-off exists between superior product quality on the one hand and low spoilage and holding costs on the other hand.

We continue with the optimization of spoilage for all combinations of issuing policy and customer withdrawal behavior. The spoilage on the part of the DC and RS that we consider for optimization purposes in our simulation is the total spoilage rate, which is given as:

$$y_s = \frac{y_s^D + y_s^R}{y_s^D + y_s^R + d_f} \tag{2}$$

In terms of spoilage minimization, FEFO performs best followed by LQFO across all customer withdrawal behaviors. Besides its low spoilage values, LQFO shows low holding costs for all customer withdrawal behavior. As a drawback, FEFO and LQFO have a lower product quality compared to the other issuing policies. In contrast, HQFO shows the best value for product quality, however, once more at the expense of the highest values for spoilage and holding costs. In sum, LQFO appears to be the best compromise across all customer withdrawal behaviors. It shows the second best value for spoilage in combination with low holding costs and reasonable product quality.

Finally, we optimized for holding costs for all combinations of issuing policy and customer withdrawal behavior. The costs on the part of the DC and RS that we consider for optimization purposes in our simulation are the total holding costs c_h, which are given as:

$$c_h = I^D{}_p \, c^D{}_h + I^R{}_p \, c^R{}_h \tag{3}$$

Since it exits an interrelationship between spoilage and holding costs, the values do not differ significantly from the previous scenario of spoilage optimization with some exceptions. SIRO, FIFO, and LIFO show the highest holding costs as a consequence of their inability of detecting spoiled items, which leads to a large number of spoiled products that remain undetected along the entire supply chain. These items incur holding costs while they are soon be detected and removed under LQFO/HQFO and the TTI policies. LIFO_TTI incurs the lowest holding costs for a random customer withdrawal behavior. FIFO_TTI shows the lowest values for an expiry-based and a quality-based customer withdrawal behavior with only a small increase of spoilage as opposed to the scenario of spoilage minimization. In the case of a random customer withdrawal behavior, LIFO_TTI shows the best trade-off when taking all performance measures into account, while for an expiry-based customer withdrawal it holds true for FIFO_TTI. In the case of a quality-based customer withdrawal, LQFO has a good performance in terms of holding costs and represents the best trade-off.

2.5.3 Sensitivity analysis

The analyses in the previous section refer to a predefined base case. To better understand the impacts of variations in the different input parameters, we conducted a sensitivity analysis. For this purpose, we varied the parameters shelf life, customer demand rate, and service level to observe their effects on product quality, spoilage, and holding costs (see Table 4). These parameter variations were done taking into account the three customer withdrawal behaviors as described in section 2.3.3.

Table 4. Parameter variations

Parameter	**Symbol**	**Base Case**	**Variations**
Shelf life	θ	15 days	12 days (deterioration rate 5%) 18 days (deterioration rate 3%)
Customer demand	λ	50 items	40 items (standard deviation = 8) 60 items (standard deviation = 12)
Service level	β	95%	93% 97%

2.5.3.1 Random customer withdrawal behavior

Figure 20 shows the impact of parameter variations on product quality for a random customer withdrawal behavior. In the case of SIRO, FIFO, and LIFO, it can be observed that a decrease and increase of shelf life result in lower and higher product quality of up to ±20%, respectively (see Figure 20a). These issuing policies without means to determine the product age or product quality show the highest sensitivities of this parameter variation. The underlying reason is inability to detect spoiled products which consequently remain in inventory and are offered to the customers. Conversely, when products have a longer shelf life, the above-mentioned issuing policies are impacted positively. In this case, products spoil slower and are sold earlier relative to the base case due to the unchanged customer demand.

A similar trend is clearly recognizable when customer demand is varied (see Figure 20b). Although the effect is not as high as for shelf life variation, the same three issuing policies are impacted the most, namely SIRO, FIFO, and LIFO. A decrease/increase in customer demand results in a decrease/increase in product quality, respectively. Again, SIRO, FIFO, and LIFO are the issuing policies which are largely impacted by this parameter variation. In the case of a lower customer demand, products stay longer in inventory at the DC and thus deteriorate over a longer period before they are eventually dispatched to the RS. In the case of a higher customer demand, products stay shorter in inventory at the DC because the rate of turnover is accelerated for dispatching to the RS.

When the service level is varied, only negligible effects on certain issuing policies can be observed (see Figure 20c). A reduction in service level causes an increase in product quality of about 0.3%. On the other hand, an increase in service level impacts FIFO_TTI the most with a decrease in product quality of about 0.4%. Those issuing policies without any effects already had service levels of 97% or higher when we optimized for product quality.

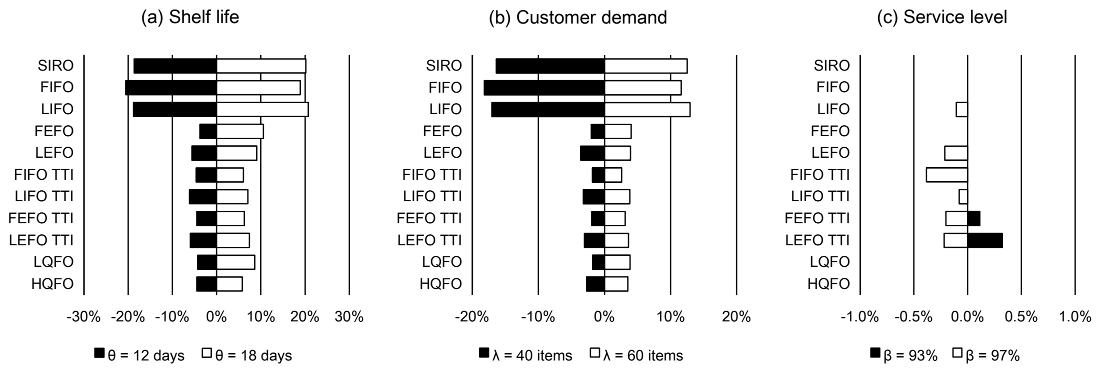

Figure 20. Impact of parameter variations on product quality for random customer withdrawal behavior

Figure 21 shows the results of the impact on spoilage for the different parameter variations. In this case, SIRO, FIFO, and LIFO are not listed because they don't record spoilage as explained in section 2.3.2. A shorter shelf life causes more spoilage because products spoil earlier. This impacts all issuing policies and specifically applies to FEFO with a more than twice as high spoilage as in the base case (see Figure 21a). On the other hand, a longer shelf life reduces spoilage almost completely across all issuing policies.

A variation of customer demand has high impacts on spoilage, too (see Figure 21b). In the case of a lower customer demand, spoilage increases by at least 60% (HQFO) and up to more than 160% (FEFO). The reason is similar to the variation of shelf life in that products remain longer in inventory before they are sold or eventually spoil. If customer demand is higher than in the base case, spoilage decreases by at least 50% (HQFO) up to approximately 70% (FEFO).

The impact of a service level variation on spoilage can be observed in Figure 21c. While a lower service level has no effect on the amount of spoilage of any issuing policy, a higher service level impacts some of the issuing policies. In particular, LIFO_TTI and LEFO are impacted significantly by 5% and about 7.5%, respectively.

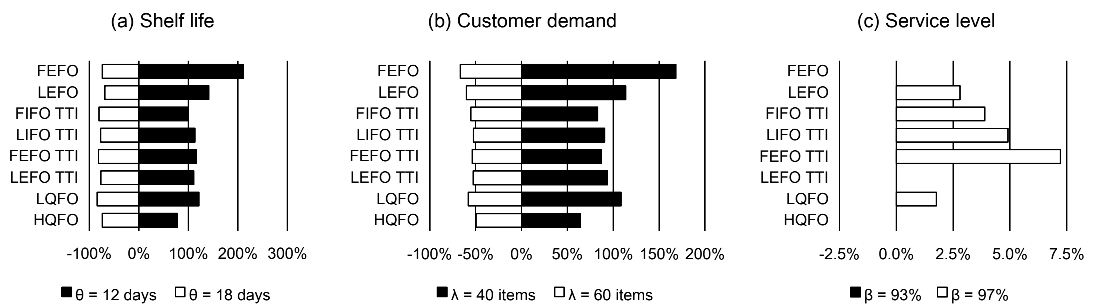

Figure 21. Impact of parameter variations on spoilage for random customer withdrawal behavior

Figure 22 shows the impact on holding costs when the different input parameters are varied. If product shelf life is decreased, holding costs increase under all issuing policies except for SIRO, FIFO, LIFO, LQFO which show a small decrease (see Figure 22a). In the case of SIRO, FIFO, and LIFO, this outcome is unsurprising due to the inability of detecting spoiled items and the interrelationship of spoilage and holding costs. LQFO and HQFO show contrasting developments in that LQFO/HQFO incurs less/more holding costs, respectively. LQFO has the highest decrease in holding costs of about 3%. This is the result of a decrease in average inventory at the DC, while in the case of HQFO, the average inventory at the DC increases. In general, when shelf life is decreased, it causes a substantial increase in spoilage. This, in turn, generates an increase of orders by the DC and RS. Even though this happens in both cases (LQFO and HQFO), the increase in orders at the DC is much higher for HQFO than for LQFO. Hence, the reason is that despite of a small increase of items in the supply chain in the case of LQFO, the holding costs decrease because of the higher number of spoiled products. The highest increase in holding costs can be observed for FEFO and LEFO with about 15%. When shelf life is increased, products can remain longer in inventory before they spoil. Thus, the holding costs increase for most of the issuing policies. Generally products spent more time in inventory even though less orders are made by the DC and RS. Only in the case of FIFO, the holding costs decrease due to a lower average inventory at the DC. In all other cases, the average inventory at the DC and/or RS increases, which causes a rise in holding costs.

A variation in customer demand results in a consistent pattern as can be seen in Figure 22b. A reduction in customer demand leads to higher holding costs under all issuing policies as a result of less orders by the DC and RS and fewer products in the supply chain. Those issuing policies which prioritize "younger" products, either by their arrival time at the DC or their expiry date, or "high-quality" products such as LIFO, LEFO, and HQFO are worst affected by a reduction of customer demand with the exception of FEFO. An increase in customer demand causes a reduction in holding costs under all issuing policies. LQFO shows the lowest decrease in holding costs of about 2%, while the other issuing policies show similar decreases between 6% and 9%.

The third parameter to be varied is the service level (see Figure 22c). A lower service level has no or little impact on holding costs in the case of SIRO, FIFO, LIFO, and LQFO, while the other issuing policies show a reduction in holding costs of up to 5%. A higher service level generates higher holding costs under all issuing policies between 1% (FEFO) and about 7% (HQFO).

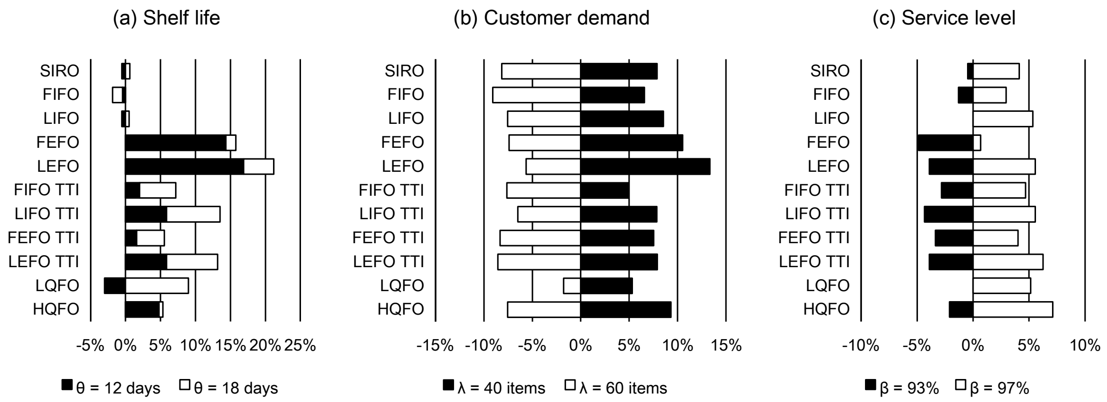

Figure 22. Impact of parameter variations on holding costs for random customer withdrawal behavior

2.5.3.2 Expiry-based customer withdrawal behavior

Figure 23 sets the focus on the impact on product quality when the different parameters are varied for an expiry-based customer withdrawal behavior. First, the shelf life is varied, according to which all policies show sensitivities (see Figure 23a). In general, a lower/higher shelf life means a lower/higher average quality, respectively, because of the same initial product age and product quality at the manufacturer but the different quality deterioration rates. As a result, it can be concluded that issuing policies based on randomness (SIRO) and arrival time without quality monitoring means (FIFO/LIFO) are impacted the most when shelf life is varied with sensitivities of about ±20%.

Second, the customer demand rate is varied leading to substantial impacts on SIRO, FIFO, and LIFO (see Figure 23b). First, a decrease in customer demand leads to a loss in average product quality of approximately 17-18%. Again, the root cause for this phenomenon is the lack of product quality inspection under SIRO, FIFO, and LIFO; any single item is shipped to the RS and sold to a customer regardless of its product quality. It means that if customer demand decreases, the average time that an item spends in the supply chain increases, which causes a lower average quality of the sold goods. This has a strong effect on SIRO, FIFO, and LIFO, as these never filter out spoiled products before they reach the customer. All other issuing policies are less impacted with decreases in product quality by about 1-4%. Second, if customer demand increases, the average product quality increases up to approximately 14% in the case of SIRO, FIFO, and LIFO. The other issuing policies show an increase in product quality by about 2-5%.

A lower service level has no impact when we optimized for product quality, while a higher service level has only an insignificant impact on FIFO with a decrease in product quality of about 0.3% (see Figure 23c).

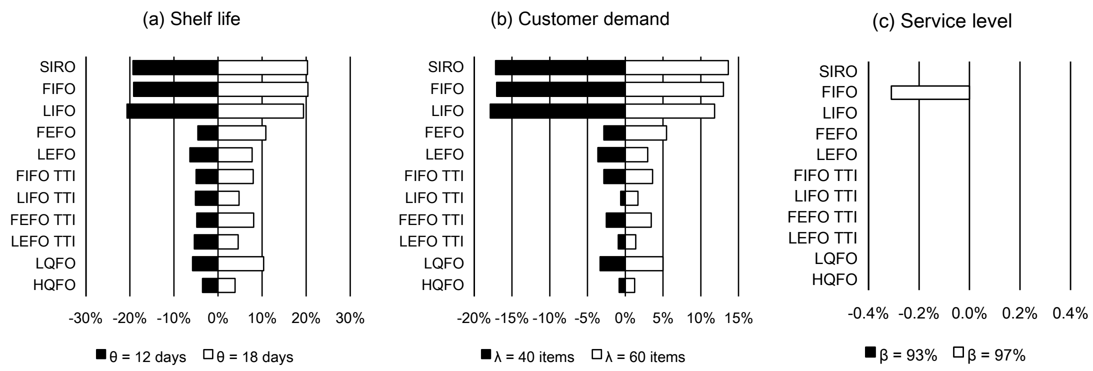

Figure 23. Impact of parameter variations on product quality expiry-based customer withdrawal behavior

Figure 24 sets the focus on the impact on spoilage when the different parameters are varied. First, a shorter shelf life has an overall high impact on all issuing policies with at least a doubling in spoilage except for HQFO (see Figure 24a). In contrast, we observe that a longer shelf life leads to a significant reduction in spoilage for all issuing policies resulting in a very low amount of spoilage. The reason is that products can stay longer in inventory, before they are disposed of because of product age or product quality during goods inspection.

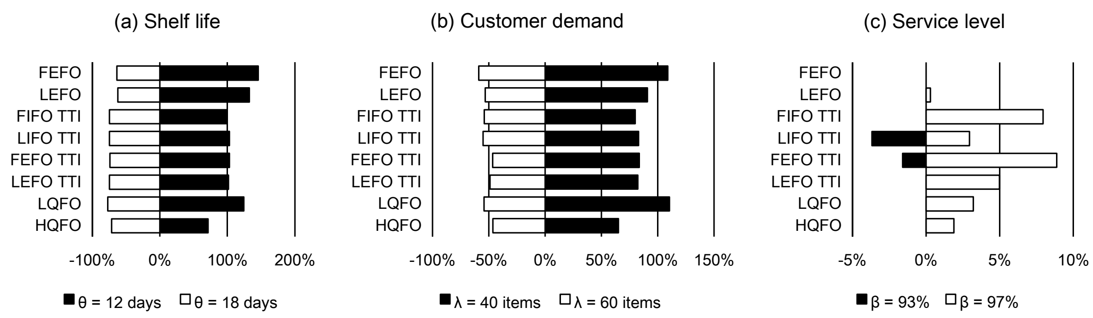

Figure 24. Impact of parameter variations on spoilage expiry-based customer withdrawal behavior

Second, in the case of a decreased customer demand rate, all issuing policies suffer higher spoilage compared to the base case, with FEFO and LQFO showing a more than twice as high spoilage rate (see Figure 24b). Although there are fewer items in the supply chain due to fewer orders by the DC and RS, a higher amount of spoiled items can be observed. The reason is a longer time an item spends in inventory as a consequence of the lower customer demand. An increase of customer demand rate causes a decrease in spoilage of about 50% under all issuing policies.

Third, a lower service level has a low impact only on LIFO_TTI and FEFO_TTI, with a decrease in spoilage of approximately 4% and 1.5%, respectively (see Figure 24c). The reason is that less inventory is needed in the supply chain to uphold the desired service level. Consequently, the average time products spend in the supply chain decreases. A higher service level has the highest effect on those issuing policies using TTI labels, with an increase in spoilage of up to 9%. These issuing policies are sensitive to an increased number of products in the supply chain caused by a higher service level. Since the customer demand rate remains constant, a higher proportion of spoiled items occurs. FEFO and LEFO show no or only very small impacts, while LQFO and HQFO are impacted with an increase in spoilage of 3% and 2%, respectively.

Figure 25 depicts the impact on holding costs when the different input parameters are varied. First, if product shelf life is decreased it shows similar impacts on holding costs as in the scenario before of a random customer withdrawal behavior (see Figure 25a). The holding costs are reduced marginally under SIRO, FIFO, LIFO, and LQFO, while they increase under the other issuing policies, especially in the case of LEFO. The reason is that when shelf life is decreased, more orders are placed by the DC and RS. As a consequence, the average inventory increases at the DC and/or RS except for SIRO, FIFO, LIFO, and LQFO. This results in more items in the supply chain and thus higher holding costs. On the other hand, an increase in shelf life causes an increase in holding costs under all issuing policies except for SIRO and LIFO. The longer shelf life implies that products can remain longer in inventory and spoilage decreases significantly, which, in turn, leads to less orders by the DC and RS. It also means that the average inventory at the DC decreases, while it is kept to a minimum at the RS to uphold the service level.

Second, if customer demand rate is decreased, it causes an increase in holding costs under all issuing policies (see Figure 25b). In this scenario, both the DC and RS place fewer orders, which leads to less items in the supply chain and lower holding costs according to expectation. However, it also leads to higher spoilage rates and a higher average inventory at the RS at a higher holding cost rate because the service level must be upheld, which outweighs the reduced orders. In sum, this circumstance leads to an increase in holding costs. In the case of an increased customer demand rate, the impact on all issuing policies shows a decrease in holding costs as expected. Despite the rise in orders by the DC and RS to fulfill customer demand, the lower spoilage rate and the shorter time items spend in inventory have a total effect of decreasing holding costs.

Third, Figure 25c shows that a lower service level causes a reduction in holding costs under all issuing policies with the exception of SIRO, FIFO and LIFO. The optimized results for the latter issuing policies achieve a service level of 95% or higher after the parameter variation, which is why they show no effect on a service level reduction. The other issuing policies are impacted by a decrease in holding costs between 1% and 5%. In contrast, a higher service level causes higher holding costs for all issuing policies except for FEFO, which already achieves a service level of 97% in the base case. The higher service level requires more items in the supply chain, which, in turn, implies higher holding costs. In this scenario, the holding costs increase between 4% and 7.5%.

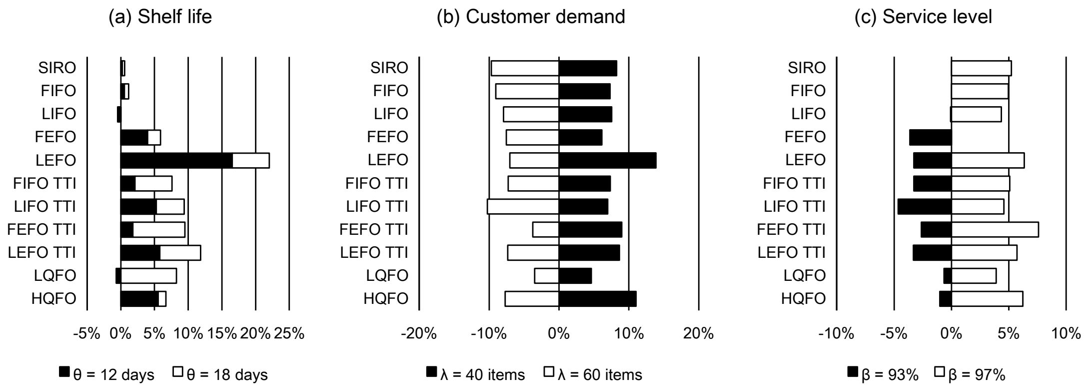

Figure 25. Impact of parameter variations on holding costs for expiry-based customer withdrawal behavior

2.5.3.3 Quality-based customer withdrawal behavior

The impacts of parameter variations on product quality in the context of a quality-based customer withdrawal behavior are depicted in Figure 26. The effects of a parameter variation of shelf life can be seen in Figure 26a. In the case of a reduction of shelf life, the pattern of effects of the individual issuing policies resembles the scenario of an expiry-based customer withdrawal behavior. SIRO, FIFO, and LIFO are the most affected issuing policies with decreases in product quality of up to 20%. Unlike the scenario of a random customer withdrawal behavior, however, the decrease in product quality is significantly lower as customers choose only best-quality products. When shelf life is increased, all issuing policies gain in average product quality. Here, SIRO, FIFO, LIFO, and FEFO benefit the most in terms of product quality with increases between 10% and 20%.

Figure 26b shows the impacts of customer demand variation on product quality. A lower customer demand causes a significantly lower product quality of up to 17.5% under SIRO, FIFO, and LIFO. The other issuing policies show only marginal effects of about 1% to 4%. On the contrary, a higher customer demand induces a higher product quality across all issuing policies. Again, SIRO, FIFO, and LIFO together with FEFO are most influenced by the variation with increases in product quality between 5% and 12.5%. In summary, it can be stated that the issuing policies using a TTI or temperature sensor and LEFO are least sensitive to a variation of customer demand impacting product quality.

A variation in service level has only small effects on the issuing policies (see Figure 26c). While a lower service level has no impact on any issuing policy, a higher service level causes a minor reduction in product quality of about 0.2% and 0.4% under FIFO and LIFO, respectively.

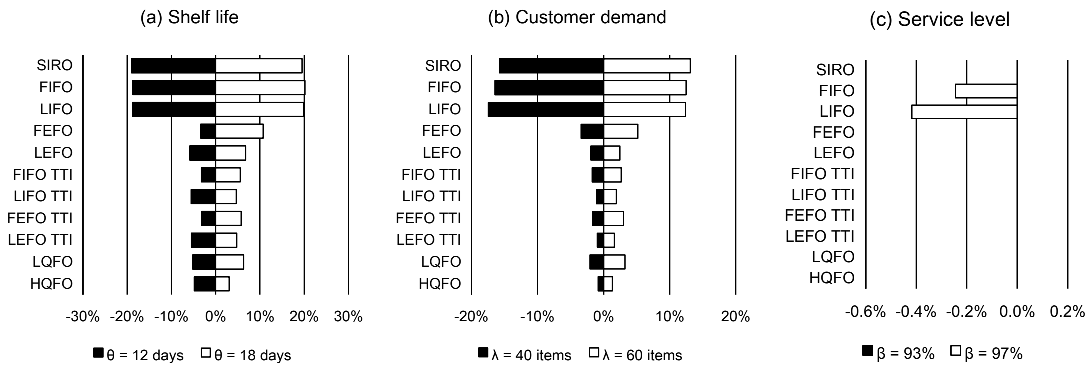

Figure 26. Impact of parameter variations on product quality for quality-based customer withdrawal behavior

The next set of parameter variations reveals the impact on spoilage for a quality-based customer withdrawal behavior (see Figure 27). The impact of a variation of shelf life on spoilage can be observed in Figure 27a. A shorter shelf life has the highest impact on

FEFO and LEFO, so issuing policies not using technical means for temperature measurement. Both issuing policies show a major difference in spoilage as compared to the other issuing policies and as a consequence less orders by the DC and RS. On the other hand, a longer shelf life signifies a relatively uniform reduction in spoilage of about 70% across all issuing policies. The simple reason for this result is that products can remain longer in inventory before they either spoil or are sold to customers.

The effect of a customer demand variation on spoilage can be seen in Figure 27b. In the case of a lower customer demand, spoilage increases between 65% (HQFO) and more than 150% (FEFO). Products are sold slower and remain for a longer time in inventory, which eventually causes spoilage when products are not sold in time prior to expiration. A higher customer demand induces less spoilage as compared to the base case with decreases of about 50% across all issuing policies. Products are sold faster which means more orders are placed by the DC and RS and items spend less time in inventory due to the rapid goods turnover.

In the case of a service level variation, we observe effects on spoilage for most of the regarded issuing policies (see Figure 27c). In particular, when the service level is decreased, only FEFO_TTI and LEFO_TTI show less spoilage with decreases of 0.3% and 6%, respectively. An increase in service level effects all issuing policies but FEFO and LIFO_TTI. The increases in spoilage are between 2.5% and more than 10%.

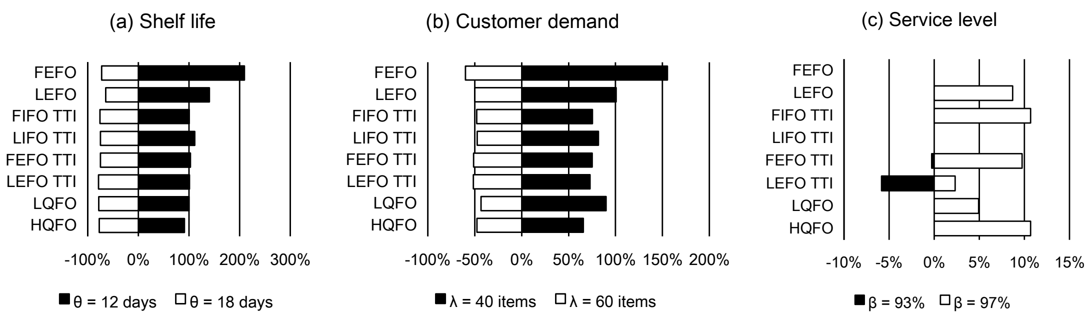

Figure 27. Impact of parameter variations on spoilage for quality-based customer withdrawal behavior

The parameter variations in the light of holding costs is depicted in Figure 28. First, when shelf life is varied, a mixed pattern can be observed similar to a random and expiry-based customer withdrawal behavior (see Figure 28a). In the case of a shorter shelf life, holding costs increase under all issuing policies except for SIRO and LQFO of which they decrease. When shelf life is decreased, an increase of orders by the DC and RS is necessary to uphold the service level under all issuing policies. In particular, FEFO and LEFO show a high increase in holding costs due to a relatively high increase in spoilage which causes more replenishment orders by the DC and RS as compared to the other issuing policies. A longer shelf life has a significant impact on holding costs only on FIFO_TTI and LQFO, with an increase by about 7.5% and 9%, respectively. According to expectation, the orders by the DC and RS decrease in both cases due to the longer shelf life and less spoilage. An interesting observation is the decrease in holding costs in the case of HQFO. The main reason is the difference in average inventory at the DC and RS. At the DC, the longer shelf life leads to a higher average inventory, while the average inventory is lower at the RS as compared to the base case. Since holding costs are more expensive at the RS compared to the DC, the total holding costs decrease in the case of HQFO.

Figure 28b shows the impact of a variation in customer demand on holding costs. A lower customer demand means higher holding costs under all issuing policies. FEFO and LEFO show the highest differences from the base case with values of 10% and 13%, respectively. On the other hand, a higher customer demand causes lower holding costs under all issuing policies. Here, SIRO and HQFO benefits the most from the variation with a decrease in holding costs by about 11% and 13%, respectively.

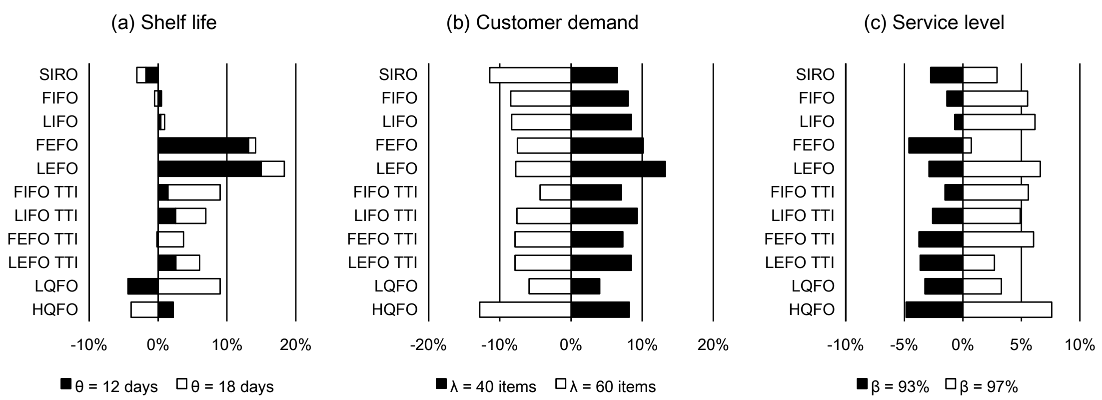

Figure 28. Impact of parameter variations on holding costs for quality-based customer withdrawal behavior

The impact of a service level variation on holding costs is depicted in Figure 28c. First, when the service level is decreased, all issuing policies show a decrease in holding costs of about 0.5% to 5%. Second, when the service level is increased, the holding costs increase by about 0.5% and 7.5% across all issuing policies.

2.6 Discussion

The simulation study presented was set out to unveil the potential of sensor-based issuing of perishables based on the performance measures product quality, spoilage, and holding costs. Our analysis has the following key findings.

2.6.1 Managerial implications

First, from a retailer's perspective, the results support companies in pursuing specific issuing strategies. Different retailers might have different priorities, such as offering high-quality/high-cost or low-quality/low-cost perishables depending on their customer base. For example, in the case of HQFO, the high average product quality of sold items comes at the expense of a high number of spoiled items and high holding costs. In fact, when the retailer's focus is set on low spoilage, FEFO and LQFO are the best-performing issuing policies, while still providing a decent product quality level. From a holding costs point of view, the issuing policies using TTI and LQFO were identified as cost-effective. Naturally, the well-known benefits of smart sensors must be balanced against the costs of a sensor infrastructure deployment, which might be a primary decision criterion whether or not to introduce sensor-based issuing policies.

Second, quality-based issuing might also induce novel concepts of dynamic distribution planning at the distribution center. For example, perishable products are often transported via a cross docking system at the distribution center (Agustina et al., 2014). The inbound trucks are scheduled to arrive at the inbound docks in order to match their loadings with the outbound trucks delivering to retail stores. The process flow at the cross docking center starts with the arrival of an inbound truck and its unloading. The loading is either processed to be consolidated with other loadings or it is temporarily stored. In the former case the consolidated loading goes into the outbound truck, which departs from the cross docking center with a pre-defined route and departure time calculated by the cross dock manager. In case a cross dock manager is able to make use of additional parameters such as product quality in the decision making process, the optimization process of scheduling and routing of vehicles might be improved. A possible improvement could be the coordination of truck loadings in such a way that products with a higher remaining product quality are delivered to distant retail stores, while those with lower remaining product quality are delivered to nearby retail stores. This promotes a uniform quality level for all receiving retail stores. An even more sophisticated scenario is the vision of a self-aware and autonomous transportation unit. It is capable of acting proactively on the basis of sensor data gathered throughout the transportation process and supporting the transportation flow by itself in that it provides the sensor data necessary for optimization. These are only a few common and visionary scenarios, in which the consideration of sensor data in the cross docking center process might generate further value for a retail company.

Third, novel concepts such as sensor-based issuing require changes in the packaging process. This implies that when perishables are packed for transportation the sensor-enabled device (e.g. smart sensor) must be considered by the staff. Existing staff will be faced with restructured packaging methods that rely on intelligent packaging (Heising et al., 2014), for which additional staff training might be necessary. Processes such as reading/writing of the sensor device need to be part of the practical skills of each employee handling intelligent packaging. Thus, the introduction of sensor-based issuing policies requires adequate staff training at the DC.

Fourth, our results might also impact branches of trade such as online grocery shopping (Boyer and Hult, 2006). Online customers expect higher product quality and product freshness when perishables are issued at the DC rather than a RS due to a shortened supply chain. In this case, a complete stage in the supply chain is saved (Boyer and Hult, 2005). Yet, this does not enable a customer to check for product quality. This is where the value of information and its sharing come into play in order to improve the overall product freshness level of perishables (Ferguson and Ketzenberg, 2006). However, it is not sufficient to share the sensor data between a supplier and a retailer, rather the customer must be included. Only if a retail company is able to integrate the sensor data in their online grocery shopping platform in order to display the product quality or freshness of perishables, it increases customer trust and potentially stimulates the demand for buying groceries online.

Fifth, the potential of quality-based issuing of perishables in terms of a higher average product quality could be supported in our study. Thus, the next step in evaluating perishables is the accurate determination of product quality based on sensor data instead of an expiry date and the integration of sensor data in information systems. For example, suppose a quantity of a perishable product is delivered to a DC with an actual shelf life of 15 days, but the predicted shelf life indicated by the expiry date is only 14 days. In this case, if the expiry date has been reached and the product has not been sold, the product is considered spoiled, although sensory observation would reveal that the product is still consumable. This prevents unnecessary product loss due to inaccurate quality estimation. Conversely, if the actual shelf life is 14 days, but the predicted shelf life is 15 days (e.g. due to adverse transport conditions), the spoiled quantity of products will be removed from inventory in time prior to putting consumer health at risk. In other words, if no under- or overestimation of shelf life occurs, it might lead to a more accurate order quantity and adequate inventory level, and eventually less spoilage for more consumer safety.

2.6.2 Theoretical implications

From a research perspective, our study not only extends the number of issuing policies provided by Dada and Thiesse (2008), but also considers holding costs as an economic metric. The consideration of the TTI technology in our study is important as it is widely used in food logistics for shelf life estimation and provides an alternative to the more advanced smart sensor. A striking observation we find across the experimental results is the high performance of the TTI-based relative to the sensor-based issuing policies. Unlike our initial assumption, the actual product quality estimation by smart sensors seems not to be a key advantage over the static shelf life information provided by an expiry date. Certainly, one reason might be our simplifying assumption of a nearly linear degradation rate that may differ from reality as each perishable good has its specific quality degradation (Zanoni and Zavanella, 2012). Nonetheless, for the vast majority of experiments, the general tendency of quality-based issuing policies being superior to the other issuing policies is significant.

Second, further limitations of our study should not go unmentioned. The consideration of only a single product leaves a static view since a retailer usually deals with a number of perishable goods for which the issuing policies might perform differently. The omission of cost factors such as spoilage cost and order cost prevent the consideration of total costs which in contrast to holding costs might better reflect the differences between the issuing policies.

Third, we see a number of opportunities for future research. We considered the customers' product withdrawal behavior as the only environmental condition in the retail store; other researchers may consider additional factors, such as the influence of product types with different shelf lives. The serial three-echelon supply chain as used in our study may be extended in order to verify our findings using a more realistic setup (e.g., including several retail stores). Moreover, further issuing policies might be developed and tested that make use of sensor data in a different way than LQFO/HQFO. Finally, we are convinced that empirical research will be necessary to better understand the reasons for the low diffusion rate of wireless sensors in practice. These empirical results could then be used to further refine models of the cold chain based on the one presented in this study.

2.7 Conclusion

We studied the performance of eleven different issuing policies at the distribution center based on either the issuing criterion "arrival date," "product age," or "product quality" in a perishables supply chain. Our primary aim was to analyze under which conditions sensor-based issuing policies using sensor technology perform best and how their characteristics differ from other conventional policies with or without TTI technology. For this purpose, we conducted a computer-based simulation study. Our results indicate that LQFO and HQFO enable a retailer to pursue two different goals, however, the results also show that a sensor-based policy does not provide a silver bullet since a number of trade-offs regarding further performance metrics must be taken into account. Nevertheless, LQFO turns out to be a reasonable trade-off among all issuing policies as it shows good performance for spoilage and holding costs together with acceptable product quality levels. In sum, information gathered from sensor technology poses a powerful means to improve the economic performance throughout the supply chain of perishables. At the same time we clarify that sensor-based policies should be regarded less as substitutes and more as useful complements to existing issuing policies. They enlarge the retailer's scope of action in a distribution center if the objective is to increase the quality of products offered to the customer.

3. Extending UTAUT2 to Explore Pervasive Information Systems

3.1 Introduction

"The most profound technologies are those that disappear. They weave themselves into the fabric of everyday life until they are indistinguishable from it" (Weiser, 1991). Things that are taken for granted today, namely ubiquitous mobile technologies, were only available as experimental innovations representing an ambitious vision at the time of this statement. In fact, it paved the way for a new paradigm shift towards "Ubiquitous Computing" (Weiser, 1991), "Pervasive Computing" (Estrin et al., 2002; Saha and Mukherjee, 2003), "Nomadic Computing" (Lyytinen and Yoo, 2002b), or the "Internet of Things" (Ashton, 2009). All these concepts share the vision of a future world with everyday physical objects equipped with digital logic, sensors, and networking capabilities (Fleisch and Thiesse, 2007). Due to the continuous and relentless technological progress, these interconnected devices will become omnipresent, not least because of the miniaturization of microelectronic components together with a price decline as a result of advances in the development and manufacturing processes.

This future vision dawns a new era, one in which today's internet gives way to tomorrow's Internet of Things. In such a scenario, everything from aircraft engines through to toothbrushes will communicate in some form or another. Today, we are in the middle of this paradigm shift, still facing a number of challenges. Among these is the enabling of full interoperability of interconnected devices by implementing uniform standards, allowing them a seamless automatic adaptation and autonomous behavior in all kinds of environments. The widespread employment of the IoT will also depend on mechanisms that ensure trust, security, and privacy, which are often challenging in their implementation (Miorandi et al., 2012). To name a single example, wireless communications must be secured against eavesdropping taking into account the constraint of low-power devices not being capable of processing complex security mechanisms.

As an integral part of the IoT, pervasive information systems (PIS) will play an increasingly important role. While artifacts such as smartphones are already ubiquitous in society today, wearables are classified as to be likely the next "big thing" that will radically change our society and the mobile consumer market (Hyman, 2013). In general, mobile devices have become the preferred way for many people to keep in touch with friends, and family and are used to access a variety of services (e.g. internet and social media). Wearables can be seen as a further evolutionary step to enable a networked world of humans and things. They offer enhanced means in comparison to smartphones in terms of accessibility, services, or wearing comfort. Figure 29 shows different types of wearables today.

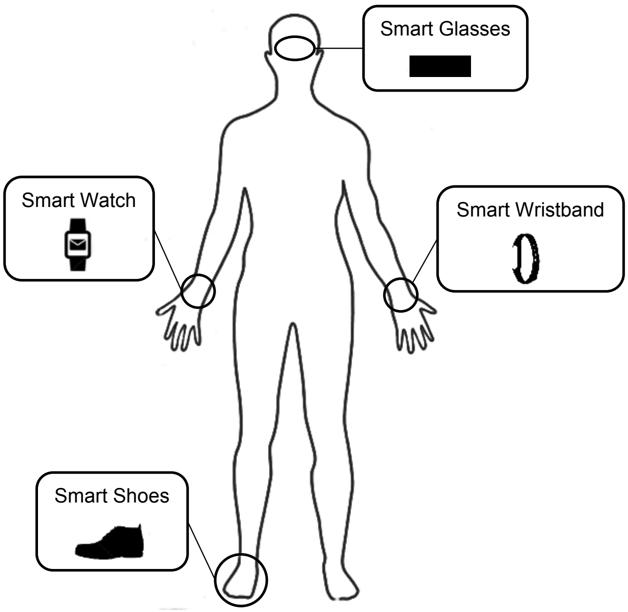

Figure 29. Smart wearables

Smart shoes with embedded sensors are mostly relevant to sportsmen to log biomechanical data and to monitor training while jogging. For example, data about foot position when the foot hits the ground is health relevant to identify an incorrect foot position and to avoid injuries or long-term effects on the jogger. In most cases, this data is transmitted to a smartphone or a smart watch. The latter is a further emerging smart technology that is gaining attention among potential users of wearables. Smart watches are computerized wristwatches that have essentially the same capabilities as smartphones. Today, big consumer electronics companies such as Apple Inc. or Samsung Electronics announced or released their first consumer version of their smart watches. A further wearable is the smart wristband with the Fitbit Flex as one its most prominent representatives. It is a 24-hour activity tracker able to track steps, distance, calories burned, and sleep. Data is transferred wirelessly to a computer or a smartphone to discover certain trends of a user analyzed by an online tool or a mobile application.

Smart glasses were the first popular wearable to have seen significant early attention from society due to the early public announcement of Google Glass in April 2012. The first prototype was made available to a selected group of developers in April 2013. It is a web-enabled wearable computer with an optical head-mounted display that is intended to decrease user attention significantly when performing certain tasks. In many cases this might be supported by its augmented-reality capability. One of its main advantages is its capability of performing microinteractions — an interaction that gets the user in and out as quickly as possible by using appropriate interfaces (Starner, 2013). As compared to smartphones, Google Glass users have virtually immediate access to their applications since it is worn on the head and is always ready for use with an always-on connectivity. Smartphones are typically carried in a pocket or bag which delays the performance of a task as it must be taken out before it is ready for use. Furthermore, Google Glass provides continuous access to a variety of known services, be it emails or social networks, with the novel control concept of natural language voice commands. In summary, Google Glass includes the important characteristics of a pervasive technology so that it fits perfectly in our research context for testing technology's pervasiveness and is the pervasive IT artifact being investigated in our study.

However, certain characteristics of pervasive technology might challenge the interaction between humans and things. Today, many people own a multitude of mobile devices which are nearly always at hand, be it mobile phones or tablets, and often struggle to handle all their devices in an effective manner. Closely connected with the ubiquity of devices, user attention is a critical resource in today's digital world. It's often considered as more precious in mobile computing than energy, wireless bandwidth, or other computational resources (Satyanarayanan, 2011). A further important characteristic of mobile devices is context awareness and adaptation of the system to current information requirements. These features are crucial for devices to act smartly since they use necessary information within their environment in order to adapt services to the user's current situation and needs (Byun and Cheverst, 2004). It's evident that not only technology, but also humans play a crucial role in the evolution of the IoT.

In this context, PIS may be considered as the post-desktop era, in which smart devices act in a smart environment (Saha and Mukherjee, 2003). This transition towards PIS not only becomes evident with the recent emergence of smart devices in the media, such as smart glasses or watches, but also with the progressive extinction of so-called feature phones being replaced by smartphones. Even though the idea of PIS is not a new one, the IoT makes such systems increasingly useful as a consequence of a continuously improving network coverage and integrated internet services. However, success or failure of pervasive technologies highly depends on its users, which is why users' adoption is of paramount importance for establishing a widely used IoT. This gives rise to questions of how this kind of smart devices will be adopted by users and sustain in an IoT world.

It is against this background that the present study is concerned with the acceptance of PIS and pervasive technologies by end-users. For this purpose, we consider the example of an everyday object such as Google Glass. Based on the integration of the extended "Unified Theory of Acceptance and Use of Technology" (UTAUT2) proposed by Venkatesh et al. (2012) and the pervasiveness constructs proposed by Karaiskos (2009), we develop and empirically test a structural model for the explanation and prediction of users' intention to utilize a pervasive technology. This research contributes to the IS literature in that we investigate the applicability of the UTAUT2 model extended by the pervasiveness perspective to the domain of PIS and confirm its explanatory power for a new class of pervasive IT artifacts.

The remainder of this chapter is organized as follows. In section 3.2, we first provide a review of related work on technology acceptance and pervasiveness and explain the concept of PIS and smart wearables, particularly Google Glass, on which our study is based. This review guides the development of our research model in section 3.3 followed by the formation of a set of hypotheses to be tested in section 3.4. Subsequently in section 3.5, we describe our research methodology before we present the data analysis process and results in section 0. The discussion of results is provided in section 3.7 and followed by the conclusions in section 3.8.

3.2 Related work

3.2.1 Theoretical background

Over more than two decades, the research field of individual-level technology acceptance has attracted numerous researchers among the information systems (IS) community (Venkatesh et al., 2007). Today's acceptance models date from the work of Fishbein and Ajzen (1975), who published the Theory of Reasoned Action (TRA). Their theory posits that attitudes toward a behavior and subjective norms predict intention, which further impacts behavior. Another cornerstone can be seen in the Theory of Planned Behavior (TPB) (Ajzen, 1991), which fundamentally has a common structure with the TRA, but integrates perceived behavioral control as an additional predictor for intention. Based on the TRA, the Technology Acceptance Model (TAM) emerged, which was one of the first models considering technology acceptance (Davis et al., 1989). A key purpose of TAM is to subsume external variables, attitudes and perceptions into use intention, which predicts actual system use. In this context, use intention is directly affected by perceived usefulness and users' attitudes toward using a system, while the last two are affected by perceived ease of use. This construct, in turn, together with perceived usefulness is impacted by external variables. Later modifications on the widely applied TAM lead to TAM2 (Venkatesh and Davis, 2000) and TAM3 (Venkatesh and Bala, 2008), which introduce additional external variables that influence perceived usefulness and ease of use.

The Unified Theory of Acceptance and Use of Technology (UTAUT) arose out of a synthesis of eight previous theories/models, including the aforementioned, capturing the essential factors and contingencies to predict behavioral intention and actual use behavior predominantly in an organizational context (Venkatesh et al., 2003). The resulting parsimonious model consists of four core determinants, these are, *Performance Expectancy*, *Effort Expectancy*, *Social Influence*, and *Facilitating Conditions* together with four key moderators (*Gender*, *Age*, *Voluntariness*, and *Experience*) predicting *Behavioral Intention* and *Use Behavior*. UTAUT's particular strength is its explanatory power, i.e. it is able to account for about 70 percent of the variance (adjusted R^2) in *Behavioral Intention* to use a technology and about 50 percent of the variance in technology use, thus outperforming any of the eight original models. As such, it has been applied in a plethora of technology acceptance studies and proved to be valuable in enhancing our understanding of technology adoption (Venkatesh et al., 2012). In contrast to its predecessor, the extended UTAUT (UTAUT2) lays the focus on the consumer use context and includes three new constructs, these are: *Hedonic Motivation*, *Price Value* and *Habit* (Venkatesh et al., 2012). Further modifications comprise the removal of the moderator *Voluntariness* and a new relationship between *Facilitating Conditions* and *Behavioral Intention*. As compared to UTAUT, the variance explained of UTAUT2 remains considerable for both *Behavioral Intention* (74 percent) and technology use (52 percent). The UTAUT2 research model is depicted in Figure 30.

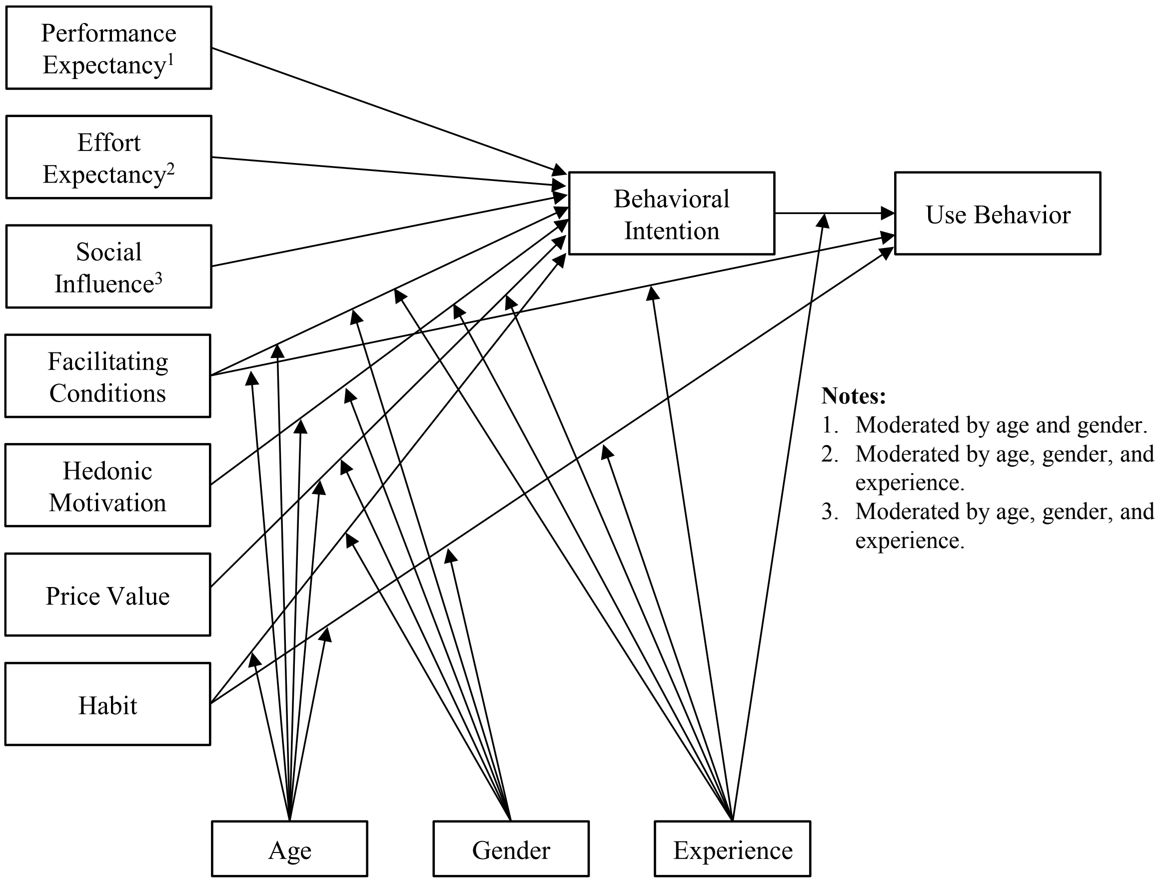

Figure 30. UTAUT2 research model

IT adoption models follow a general fashion to account for a large variety of IT/IS artifacts. In many cases researchers have to modify or adopt subsets of these models to make them accurately predict user acceptance of the IT/IS artifact at hand. Emerging paradigms to which this holds true are pervasive/ubiquitous computing and PIS. In this context, an early work from Garfield (2005)¸who investigated the factors related to the use of a tablet PC and their impact on the acceptance within organizations by employing a qualitative field study. The results show that this type of IT artifact presents technical as well as organizational challenges to be addressed. Within the retail domain, the effects of PIS on user shopping experience were examined with the result that a number of dimensions were affected suggesting pervasive technologies to be integrated in customer shopping processes (Kourouthanassis et al., 2007). A further study considering PIS evaluated user acceptance of an RFID-based ticketing system by employing a lab experiment (Karaiskos et al., 2007). The theoretical constructs were drawn from TAM and the innovation diffusion theory (IDT) along with constructs related to privacy and switching costs. Compatibility lacked construct reliability. The findings indicate that in accordance with other studies, usefulness and ease of use were the strongest predictors of *Behavioral Intention*.

A first attempt towards a technology acceptance model dedicated to pervasive technologies emerged from Connelly (2007), who named the developed model pervasive TAM. The model consists in parts of TAM2 and other models, while new constructs relevant to pervasiveness were added. However, the lack of measurement instruments for the new constructs leaves the model as a theoretical rather than an applicable contribution. This issue was addressed by Karaiskos (2009), who outlined the important technological factors of PIS and provided robust measurement instruments for assessing them. His work not only comprises extensive development efforts to obtain valid measurement scales for pervasiveness constructs but also the validation thereof. Altogether, 16 measurement items could be validated, each associated with one of three pervasiveness constructs, these are, *Ubiquity*, *Unobtrusiveness*, and *Context Awareness*. His research model integrated those constructs as antecedents of the acceptance factors, which essentially are used in UTAUT with the exception of *Facilitating Conditions*. The latter was replaced by perceived monetary value, while two additional factors — perceived enjoyment and personal innovativeness — were included.

The literature described above reveals that only a few studies considered technology acceptance in the light of pervasive technologies. However, the growing number of this type of technology requires a consideration in technology acceptance models. Against this background, we take the work in this area one step further in that we draw on the work from Karaiskos (2009) and integrate the pervasiveness constructs into the recently published UTAUT2. First, the predictors of *Behavioral Intention* used in Karaiskos (2009) and UTAUT2 are similar, which is why we assume compatibility. Second, the consumer context of UTAUT2 makes this model appropriate to apply it in relation to Google Glass, which is primarily intended for end consumers and fulfills the requirements of a pervasive technology. Third, we integrate moderators in the relationships between the pervasiveness constructs and the key constructs influencing *Behavioral Intention* in UTAUT2.

3.2.2 Pervasive Information Systems

The term “Pervasive Information Systems” is still scattered across different research streams covering aspects of technology and management. Most of the related research disciplines are considering their research from an engineering perspective, thus they predominantly focus on the technological capabilities and technology-driven output of pervasive IT artifacts. However, the inclusion of applications and services allows for taking a broader view of PIS. In this context, Kourouthanassis and Giaglis (2008) provide a definition for PIS as “interconnected technological artifacts diffused in their surrounding environment, which work together to sense, process, store, and communicate information ubiquitously and unobtrusively support their users’ objectives and tasks in a context-aware manner.” Birnbaum (1997) was among the first who put technology in the rear and pointed out that future information systems must be capable of hiding their own complexity and providing invisible interfaces. He termed those systems “Pervasive Information Systems”, which are distinct from traditional information systems in certain aspects, i.e. the notion of user interaction and connectedness within a smart space become important. Hence, services built on an information systems platform are the key at which customers experience pervasiveness. Kourouthanassis et al. (2007) describe the differences between traditional desktop information systems and PIS in that they define the latter as systems which deal with non-traditional computing devices that seamlessly bind the digital with the physical environment and become one unit in the user’s perspective. As a result, emerging pervasive IT artifacts forming part of PIS induce a new user experience and are thus of particular interest for research of technology acceptance.

3.3 Research model

Based on the integration of the extended “Unified Theory of Acceptance and Use of Technology” (UTAUT2) proposed by Venkatesh et al. (2012) and three pervasiveness factors proposed by Karaiskos (2009), we developed and empirically tested a structural model for the explanation and prediction of users’ intention to use a pervasive technology such as Google Glass.

This section describes the underlying research model for the study. We focused on the integration of pervasiveness factors into the UTAUT2 framework to examine to what extent these factors influence the technology acceptance for pervasive technologies. One important reason why UTAUT2 was chosen for this study is its focus on the consumer use context (Venkatesh et al., 2012). Its predecessor, UTAUT, defines the critical factors with reference to the prediction of *Behavioral Intention* to use a technology and *Use Behavior* against the background of an organizational context (Venkatesh et al., 2003). This circumstance makes the extended UTAUT2 more suitable in comparison to UTAUT.

In principle, UTAUT2 adopted the constructs from the original UTAUT model and adapted the definitions to the consumer context (Venkatesh et al., 2012). Consequently, *Performance Expectancy* is defined as the degree to which a consumer benefits in performing a certain activity when using the technology in question; *Effort Expectancy* refers to the degree of ease associated with consumers' use of technology; *Social Influence* describes to what extent a consumer believes using the technology is appreciated by his or her social environment (e.g. family and friends); *Facilitating Conditions* is defined as to the notion of the resources and support available to perform a behavior. The aforementioned constructs are theorized to influence behavioral intention to use a technology. In accordance with UTAUT, three of the original four moderator variables were adopted in UTAUT2, namely *Age*, *Gender* and *Experience*. The latter refers to the passage of time from the initial use of a target technology by an individual. They are theorized to moderate certain relationships as indicated in the research model in Figure 30.

The basic UTAUT model was then extended by three new constructs in UTAUT2, these are *Hedonic Motivation*, *Price Value*, and *Habit* (Venkatesh et al., 2012). *Hedonic Motivation*, is defined as the fun or pleasure arising from the use of a technology. In IS research and specifically in the consumer context, it has been shown to be a predictor of users' behavioral intention to use a technology (Brown and Venkatesh, 2005). The second construct, *Price Value*, is defined as the users' cognitive tradeoff between the perceived benefits of using a technology and its associated monetary cost. In this context, *Price Value* has a positive influence on *Behavioral Intention* when the perceived benefits outweigh the monetary costs. The third construct, *Habit*, is defined as the extent to which an individual thinks of the behavior as automatic (Limayem et al., 2007). These additional three constructs constitute UTAUT2 and facilitate research on technology acceptance from a consumer perspective.

Following the clarification of the individual constructs to be considered in our research model, the question remains of where the pervasiveness constructs might be placed in the model. They can either be direct or indirect determinants of the dependent variable (*Behavioral Intention*). Karaiskos (2009) argues that a direct effect would mean that a technology characteristic by itself predicts an individual's intention to use a system, which has never been validated in past research. Rather, the pervasiveness constructs act as indirect determinants and must be placed as antecedents of the independent variables of the UTAUT2. In this case they have a mediating effect, that is, they directly influence the independent variables in UTAUT2, which, in turn, have a stronger direct effect on *Behavioral Intention* to use a system due to the additional effect of their antecedents.

In line with UTAUT2, we link the independent variables *Performance Expectancy*, *Effort Expectancy*, *Social Influence*, *Hedonic Motivation*, and *Price Value* to the dependent variable *Behavioral Intention*. We hypothesize the relationships between the pervasiveness constructs and the UTAUT2 constructs since the relationships on the part of UTAUT2 have been tested in several other studies. Besides, we do not test for all potential relationships between the pervasiveness constructs and the UTAUT2 constructs. Most of the relationships were taken from the results of the regression analysis from Karaiskos (2009) with only a few deviations.

To adjust the UTAUT2 model to our research setting, we made the following modifications to the original model:

- First, we removed the construct use behavior. At the time of the survey, the technological device in the study, Google Glass, was only available as a prototype to a community of Google Glass developers, which made it impossible for all survey participants to test or use it. Nevertheless, we retained *Behavioral Intention* as a good predictor of actual behavior (Ajzen, 1991; Sheppard et al., 1988). This approach is employed in many other studies (e.g. Thong et al. 2011).
- Second, we removed the construct *Habit.* Having this construct in our research model would require the survey participants to use Google Glass for a reasonable timeframe.
- Third, we removed the construct *Facilitating Conditions* as it lead to issues in the measurement model so that validity was violated. A further explanation is provided when the measurement model is discussed.

- Fourth, we added the pervasiveness constructs *Ubiquity*, *Unobtrusiveness*, and *Context Awareness* as antecedents to the independent variables of UTAUT2. This is also supported by Davis (1993), who states that system design features have an indirect effect on attitude towards using a technology.
- Fifth, we added two moderators, *Experience* and *Age* that influence the relationships between pervasiveness constructs on the one hand and *Performance Expectancy* and *Effort Expectancy* on the other hand. The moderator experience needs to be regarded in a broader sense, that is to say, there exists a number of devices for which we consider the moderator as a general experience with pervasive technologies.

Figure 31 shows the research model with the relationships between the pervasiveness and the UTAUT2 constructs together with the corresponding hypotheses. The hypotheses are explained in more detail in the next section 3.4.

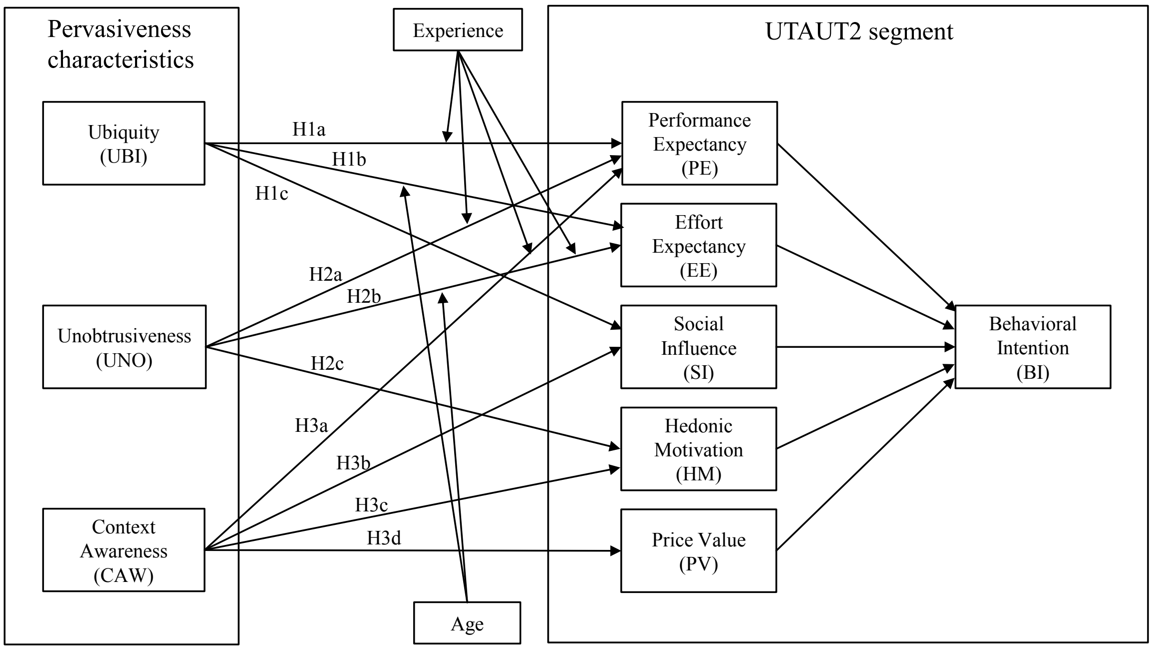

Figure 31. Research model

3.4 Hypotheses development

Our objective of examining PIS and their influence on technology acceptance motivated us to modify the UTAUT2 model in that we integrated new constructs measuring pervasiveness of a technology. Karaiskos (2009) proposes three constructs to measure PIS, namely, *Ubiquity*, *Unobtrusiveness*, and *Context Awareness*. These constructs are supposed to unearth the inherent pervasive characteristics of a technology affecting an individual in his intention to use a system.

3.4.1 Ubiquity

Ubiquity is the first pervasiveness construct we consider in our study. It is defined as "the system's capability to provide users with continuous access to information resources irrespective of their location within the system's boundaries" (Karaiskos, 2009). We expect *Ubiquity* to positively influence *Performance Expectancy* and *Effort Expectancy*. This can be explained by a user's evaluation of task-technology-fit, which is defined as the degree to which a technology assists an individual in performing a task (Goodhue and Thompson, 1995). If a user has nearly always access to a technology, he or she is potentially always able to perform a task. For example, in case a user needs to reach a location without knowing the way, he or she may use a pervasive technology (e.g. smartphone) to provide him or her the directions to this location. However, the accessibility of a technology alone is not sufficient for performing a task effectively. Rather, the user needs to have some experience in using the services provided by a pervasive technology.

The continuous access to a pervasive technology might also positively impact *Effort Expectancy*. We assume that the user of a pervasive technology will find it easier to learn how to use the technology when he or she carries it with oneself the whole day. Especially in certain contexts, in which people experience "dead time" (e.g. waiting or commuting) they might play with or test the technology's features. Further, this might depend on the age of the user. Younger people tend to deal with technologies in a different way as older people, i.e. they learn and use it in fluent and sophisticated ways (Vodanovich et al., 2010). It means that younger people will appreciate to have virtually always access to the technology, while older people usually devote their time to learning how to use a technology.

Finally, we expect *Ubiquity* to positively impact social influence. This stands in contrast to Karaiskos (2009), who argues that technology factors only have a direct effect on those constructs that consider the system as object of evaluation. However, Thong et al. (2011) state that information and communication technologies and services are typically used to interact with a social environment in the consumer context. Google Glass features this kind of services and enables an individual to constantly stay in contact with his or her social environment. As a consequence, an individual might have a stronger effect on potential consumers suggesting an impact on *Social Influence*. Thus, we hypothesize:

H1a: The influence of Ubiquity on Performance Expectancy will be moderated by experience, such that the positive effect is stronger among people with high experience.

H1b: The influence of Ubiquity on Effort Expectancy will be moderated by age, such that the positive effect is stronger among younger people.

H1c: Ubiquity has a positive effect on Social Influence.

3.4.2 Unobtrusiveness

Unobtrusiveness is the second pervasiveness construct considered in our study. It is defined as the extent to which a system becomes both cognitively and physically invisible when using it (Karaiskos, 2009). We expect *Unobtrusiveness* to positively influence *Performance Expectancy*, *Effort Expectancy*, and *Hedonic Motivation*. When performing a task with the support of a pervasive technology, the task performance will increase the less a user is distracted (Lyytinen and Yoo, 2002a). This has also been demonstrated by (Coursaris et al., 2012), who studied the negative impact of distraction on perceived efficiency and perceived effectiveness. An unobtrusive technology might be of particular importance when a distraction can lead to safety issues as might be the case while a user is driving a car (Nelson et al., 2009). Technology over-fit, which negatively impacts task performance as a consequence of users being overwhelmed by features and functionalities (Junglas and Watson, 2003), might be an issue of why experienced users cherish an unobtrusive pervasive technology.

Also, services provided by a pervasive technology contribute to *Effort Expectancy* if they are presented in an unobtrusive way to avoid overloading a user (Gil et al., 2011). Particularly, this holds for older people with low experience, since they tend to have more difficulties in learning new technologies (Morris et al., 2005). What’s more, it becomes an aggravating circumstance if they are distracted or overwhelmed by the way services are presented. A reinforcing effect might also be a lack of experience with the type of technology.

The technology should also minimize the distraction when invoking specific services, e.g. hedonic services. As Deng et al. (2010) show in their study, the perceived hedonic performance depends on the cognitive absorption. It might be positively influenced by an unobtrusive technology for which we assume *Unobtrusiveness* to have a positive effect on *Hedonic Motivation*. This is also in line with the results from Karaiskos (2009) who found a weak but significant effect of *Unobtrusiveness* on perceived enjoyment. Thus, we hypothesize:

H2a: The influence of Unobtrusiveness on Performance Expectancy will be moderated by experience, such that the positive effect is stronger among people with high experience.

H2b: The influence of Unobtrusiveness on Effort Expectancy will be moderated by age and experience, such that the positive effect is stronger among older people with low experience.

H2c: Unobtrusiveness has a positive effect on Hedonic Motivation.

3.4.3 Context awareness

Context Awareness is the last pervasiveness construct in our study. It is defined as the degree to which a system is capable of processing contextual information to dynamically and proactively adapt its functionality and to provide relevant information/services to its user depending on the user's task (Dey and Abowd, 1999; Karaiskos, 2009). We expect *Context Awareness* to positively influence *Performance Expectancy*, *Social Influence*, *Hedonic Motivation*, and *Price Value*. Following the definition of *Context Awareness*, task performance will increase in case a user is supported by relevant information or services to perform a task effectively. In this context, we assume that the more experience a user has with context-aware systems, the more efficiently he or she will perform a task.

The assumption of *Context Awareness* impacting *Social Influence* contradicts again the assertion made by Karaiskos (2009) that technology factors only have a direct effect on those constructs that consider the system as object of evaluation. Despite that, his results show a significant positive effect of *Context Awareness* on *Social Influence*. In line with this result, we assume that services such as location-based services (LBS) as part of *Context Awareness* may have a positive impact on *Social Influence*. This can be explained by the dissemination of pervasive technologies supporting LBS and fostering the integration of social networking and pervasive computing (Rosi et al., 2011). For instance, Facebook and Twitter support the function of posting the user's geo-location (e.g. while traveling) to share impressions or emotional state with his or her social environment. Furthermore, in a voluntary context social influence affects the perception about a technology with the mechanisms of internalization and identification (Venkatesh et al., 2003). Users of pervasive technologies providing functions that positively impact their social status gains might have a stronger impact on others who might believe they should use a pervasive technology in order to comply with their social environment.

At the same time, users experience enjoyment when using such functions that not only add utility, but also become part of the social communication (Barkhuus et al., 2008). Furthermore, *Context Awareness* is different from the other pervasiveness constructs in that it is a more tangible technology characteristic due to its functional nature. Thus, users might perceive *Context Awareness* as an enabling function for other services that provides an added value (e.g. through LBS) for which users might be willing to spend more money because of the high value for money of the technology. Thus, we hypothesize:

H3a: The influence of Context Awareness on Performance Expectancy will be moderated by experience, such that the positive effect is stronger among people with high experience.

H3b: Context awareness has a positive effect on Social Influence.

H3c: Context awareness has a positive effect on Hedonic Motivation.

H3d: Context awareness has a positive effect on Price Value.

3.4.4 Indirect effects

Lastly, we expect the pervasiveness constructs to have an indirect effect through the predictors of *Behavioral Intention*. All pervasiveness constructs as such characterize technology attributes that are desirable for consumers. However, as explained above, these attributes may only have an indirect effect on user intention to use a pervasive technology. Thus, we hypothesize:

H4a: Performance Expectancy, Effort Expectancy, and Social Influence mediate the positive effect between Ubiquity and Behavioral Intention.

H4b: Performance Expectancy, Effort Expectancy, and Hedonic Motivation mediate the positive effect between Unobtrusiveness and Behavioral Intention.

H4c: Performance Expectancy, Social Influence, Hedonic Motivation, and Price Value mediate the positive effect between Context Awareness and Behavioral Intention.

3.5 Data collection

Participant recruiting for the present study was conducted using the crowdsourcing platform Amazon Mechanical Turk (AMT). This platform acts as an online labor market enabling employers (called requesters) to publish tasks, so-called Human Intelligence Tasks (HITs), which are performed by employees (called workers). The completion of a HIT by a worker usually follows a monetary incentive (called a reward) depending on the complexity and duration of a HIT. Workers are practically anonymous to requesters due to their unique worker ID, which preserves worker anonymity. Furthermore the worker ID does not allow individual workers to participate more than once in the survey. Another benefit of using AMT is the requester's ability to define certain criteria (e.g. country of residence or approval rate of past HITs) which the workers must meet in order to access the HIT. Particularly for surveys, this option allows for higher data quality since it permits researchers to make a participant preselection. Hence, the participants of our study were recruited with the requirements that they (i) were U.S. residents, (ii) had at least 100 HITs completed, and (iii) had a 95% task approval rate for their previous HITs. The first criterion stems from the fact that Google Glass is primarily promoted in the U.S. and thus more likely known among U.S. citizens than in other countries. As of spring 2014, Google Glass was only available as a prototype to a community of Google Glass developers. The second and third criterion guaranteed to engage only experienced workers rather than any novices who might not worry about their approval rate and potentially degrade the result. A further means to increase the probability of high data quality is to offer a comparatively high payment. For this reason, the participants in our study were paid $0.65 for a survey completion duration of approximately 10 minutes which corresponds to a rate of pay of $3.90 per hour. The median hourly wage for HITs on AMT is $1.38 (Horton and Chilton, 2010). It should also be mentioned that our decision to use AMT based on the fact that the obtained data quality via AMT does not suffer in comparison to a laboratory experiment (Sprouse, 2011).

The open source survey application Limesurvey[2] was used for data collection. Useful functions such as parameterizing surveys in detail or data export to the Statistical Package for the Social Sciences (SPSS) were decisive criteria to choose this survey tool. We implemented the survey in such a way that potential participants from AMT were informed about the content of the survey before they were redirected to Limesurvey in order to involve only interested participants. Prior to survey completion, the participants were instructed to read a short text about Google Glass. This text included information about the device's characteristics, its possible areas of application, and information about the price range for the end-user version. Below the written information, we also included visual material in the form of a figure and two short promotional videos. The figure showed the technical specifications describing all the important elements of the device, while the videos mainly focused on the device application. This introductory information about Google Glass was deemed to be sufficient to get acceptable responses from the participants.

The next step was the rating of the individual measurement items of the survey on a 7-point Likert scale ranging from "strongly disagree" to "strongly agree" (Table 5). The measurement scales for the UTAUT2 constructs *Performance Expectancy* (PE), *Effort Expectancy* (EE), *Social Influence* (SI), *Facilitating Conditions* (FC), *Hedonic Motivation* (HM), *Price Value* (PV), and *Behavioral Intention* (BI) were drawn and adapted from Venkatesh et al. (2012), while those for the pervasiveness constructs — *Ubiquity* (UBI), *Unobtrusiveness* (UNO), and *Context Awareness* (CAW) — were drawn and adapted from Karaiskos (2009). During survey completion it was not possible to skip any of the survey items, otherwise the respective participant was made aware of unrated items still to be completed. In so doing, we ensured that missing data will not be an issue in later stages.

[2] Limesurvey is a survey service-platform to prepare, run and evaluate online surveys. (www.limesurvey.org)

Table 5. Measurement items

Construct	Item	Statement
Performance Expectancy (PE)	PE1	I would find Google Glass useful in my daily life.
	PE2	Using Google Glass would help me to achieve things more quickly.
	PE3	Using Google Glass would increase my productivity.
Effort Expectancy (EE)	EE1	Learning how to use Google Glass would be easy for me.
	EE2	My interaction with Google Glass would be clear and understandable.
	EE3	I would find Google Glass easy to use.
	EE4	It would be easy for me to become skillful at using Google Glass.
Social Influence (SI)	SI1	People who are important to me would think that I should use Google Glass.
	SI2	People who influence my behavior would think that I should use Google Glass.
	SI3	People whose opinions that I value would prefer that I use Google Glass.
Facilitating Conditions (FC)	FC1	I have the resources necessary to use Google Glass.
	FC2	I have the knowledge necessary to use Google Glass.
	FC3	Google Glass is compatible with other technologies I use.
	FC4	I can get help from others when I would have difficulties using Google Glass.
Hedonic Motivation (HM)	HM1	Using Google Glass would be fun.
	HM2	Using Google Glass would be enjoyable.
	HM3	Using Google Glass would be very entertaining.
Price Value (PV)	PV1	Google Glass is reasonably priced.
	PV2	Google Glass will be a good value for the money.
	PV3	At the future price, Google Glass provides a good value.
Unobtrusive-ness (UNO)	UNO1	My attention would not need to be focused on Google Glass the whole time.
	UNO2	I would not have to concentrate fully on Google Glass when using it.
	UNO3	I would not need to be intensely absorbed when using Google Glass.
	UNO4	The usage of Google Glass would not disrupt me from other activities.
	UNO5	Google Glass would not distract me too often.
	UNO6	Google Glass would not require continuous attention.
Ubiquity (UBI)	UBI1	Google Glass would be available to use wherever I need it.
	UBI2	Google Glass would be available to use whenever I need it.
	UBI3	I would be able to use Google Glass anytime.
	UBI4	Google Glass would be accessible everywhere in my daily life.
	UBI5	Google Glass would be always available to me.
Context Awareness (CAW)	CAW1	Google Glass is able to adapt to changing conditions.
	CAW2	Google Glass can act according to the current circumstances.
	CAW3	The actions of Google Glass are in line with the situation.
	CAW4	Google Glass automatically adapts to the situation at hand.
	CAW5	Google Glass can automatically trigger actions relevant to the situation.
Behavioral Intention (BI)	BI1	I intend to use Google Glass in the future.
	BI2	I will always try to use Google Glass in my daily life.
	BI3	I plan to use Google Glass frequently.

Concluding the survey, the participants were requested to answer three questions about social demographics, which included their gender, age, and experience with smartphones (Table 6). The latter was measured by asking the participants about their experience with smartphones (in years) because Google Glass was not available to the general public at the time of the study. Hence, we substituted it with a common device that each participant was assumed to possess. Although it is not the stated Google Glass as in the context of our study, both share many aspects (e.g. smart device, similar applications) so that it can be assumed they can be used interchangeably in order to obtain data for experience with a general pervasive technology.

At the end of data collection, we had a total of 353 responses, exceeding by far our target sample size of 250 responses. The additional responses were desirable since it is recommended to increase target sample size due to a higher likelihood of outliers when recruiting participants via crowdsourcing platforms (Sprouse, 2011).

Table 6 summarizes the social demographic information about our sample of 346 valid responses after data screening (see section 3.6.1). The gender distribution shows a more than twice as high value for male than for female (68% vs. 32%). While the absolute amount for female (110) is still high enough for statistical inferences, this observation might trace back to the technological context of the survey for which males typically are more interested than females. The age distribution indicates an inconsiderable bias towards younger people (≤ 30 years) with a cumulative value of 52%. One reason might be that younger people tend to be more tech-savvy than older people. A reinforcing effect might also be the circumstance that Google Glass is thought of as a novel mobile device generation and younger people, often called digital natives, usually adopt technologies more rapidly than older people (Vodanovich et al., 2010). The experience with smartphones among our participants shows that 13% do not possess a smartphone, while the groups of 1-3 years and 4-6 years have the highest frequency with 32% and 45%, respectively. These numbers are easily comprehensible if one starts from the premise that the first real smartphone was the first generation Apple iPhone released in 2007. Despite this interpretation, some of the participants have a longer experience with the possible reason that they considered an enhanced feature phone to be a smartphone.

Table 6. Social demographics of the sample

Moderator	Category	Frequency	in %	Mean	SD	Median
Gender	Female	110	31.8	-	-	-
	Male	236	68.2			
Age [years]	18-25	90	26.0	33.1	10.8	30
	26-30	90	26.0			
	31-35	65	18.8			
	36-40	31	9.0			
	41-45	20	5.8			
	46-50	14	4.0			
	Above 50	36	10.4			
Experience [years]	0	46	13.3	3.8	2.6	4
	1-3	110	31.8			
	4-6	154	44.5			
	7-9	24	6.9			
	Above 9	12	3.5			

3.6 Data analysis

This section is about the data analysis process and presents the results obtained from the study. Figure 32 outlines the sequence of steps of the data analysis process. First, we screened the data to obtain an appropriate data set for conducting structural equation modeling (SEM).

Next, we used a two-step approach as analysis procedure of SEM, which estimates the measurement model and the structural model separately (Anderson and Gerbing, 1988). Typically, an exploratory factor analysis (EFA) precedes a confirmatory factor analysis (CFA) in which a measurement model serves to confirm the factor structure of the dataset. Since we build on established scales, we skipped EFA and started directly with the CFA (Byrne, 2010). A researcher might start with a CFA in the case some knowledge of the underlying latent variable structure is available (Byrne, 2010). On the basis of theoretical knowledge or empirical research, a researcher is able to theorize a priori about the relationships of the observed measures and the inherent constructs. Hence, the objective of CFA is to examine if the obtained data fits the hypothesized measurement model. This result serves as a basis for testing hypotheses statistically in a structural model. However, as discussed in the CFA, we included modification indices in the measurement model to achieve acceptable model fit. For this reason we conducted a follow-up EFA due to insufficient model fit for the initial model as suggested by Schmitt (2011).

After the measurement model evaluation, the structural model is analyzed. Rather than inspecting the individual constructs and their items, the structural model focuses on the relationships between the constructs. Similarly as in the CFA, model fit is tested again with the additional estimation and analysis of path coefficients.

Additionally, we examined potential moderator effects and performed a mediation analysis to test for indirect effects of the pervasiveness constructs on *Behavioral Intention*. Instead of applying multiple regression analysis as was done by Karaiskos (2009), we make use of covariance-based SEM (CB-SEM) in our study. This allows us to estimate a series of multiple regression equations simultaneously while integrating more than a single dependent variable in the research model (Hair et al., 2009). Furthermore, for the analysis of categorical moderators CB-SEM is recommended (Lowry and Gaskin, 2014). The tools we used for data analysis are SPSS version 21 and Analysis of Moment Structures (AMOS) version 22.

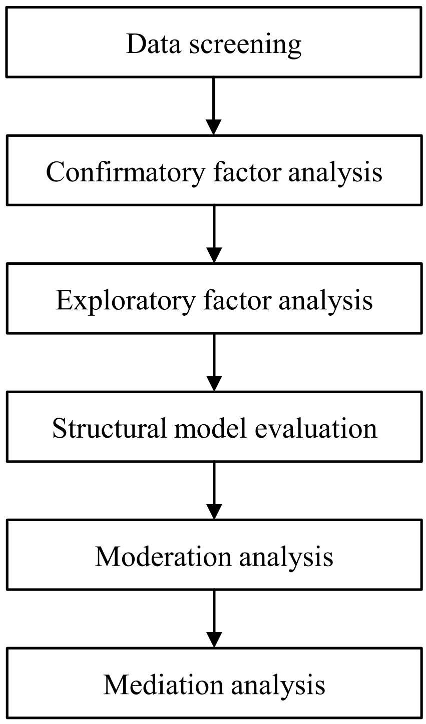

Figure 32. Data analysis process

3.6.1 Data screening

Prior to estimating parameters and testing hypotheses in SEM, researchers should perform data screening as a preliminary step (Bagozzi and Yi, 2011). As a first basic step, researchers need to check the completeness of the data set, i.e. whether it contains missing values. They must be addressed because they can seriously bias conclusions drawn from an empirical study (Byrne, 2010). Missing values might occur for a variety of reasons, e.g. it may happen that a subject was not able or willing to answer all of the questions in a survey. Even though AMOS is able to compute data sets with missing values (Arbuckle, 2005), we set it as mandatory for the participants to rate all items in the survey. The survey tool pointed out missing input to the participant and made it impossible for him/her to proceed with or submit the survey. Hence, the check for completeness could be skipped for our study.

In a next step, the data set was tested for outliers. An outlier is characterized as a case that is conspicuously different from the rest (Hodge and Austin, 2004). Our focus was on keeping as many cases as possible in the data set, which is why we performed a single test for unengaged participants. They are marked by using a consistent rating value throughout all their responses, leading to the assumption that they are not interested in the survey. To detect these cases, we calculated the standard deviation across all item ratings of each case. The threshold value for keeping a case in the data set was set to a standard deviation of 0.3 or higher, which all cases fulfilled except for four. A visual inspection of these outliers and their ratings showed that the pertinent participants rated each item with either a single value or a maximum of two different values. These cases were removed from the data set. However, this method only revealed outliers which had values close together (e.g. 4 and 5). For this reason, we conducted a visual inspection and discovered three more outliers. In total, we detected seven outliers according to which the final data set considered for data analysis had 346 cases.

A critically important assumption when conducting SEM analyses is, that the data is multivariate normal (Byrne, 2010). Thus, before any data analyses are undertaken, it is always important to check that this criterion has been met. It was addressed by assessing the univariate skewness and kurtosis of each of the items. Particularly with regard to kurtosis, researchers need to be attentive as it causes problems in SEM analyses and detrimentally affects tests of variances and covariances (DeCarlo, 1997). Curran et al. (1996) recommend that the value for skewness should be within the range of ±2 and for kurtosis within the range of ±7 to be indicative of normality. Sposito et al. (1983) propose an even narrower range for kurtosis of ±2.2, which we took as threshold for our analysis.

Table 7. Skewness and kurtosis

Construct	Item	Skewness	Kurtosis
Performance Expectancy	PE1	-.387	-.880
	PE2	-.567	-.428
	PE3	-.366	-.851
Effort Expectancy	EE1	-.963	.532
	EE2	-.879	.467
	EE3	-.829	.254
	EE4	-1.041	.776
Social Influence	SI1	.207	-.833
	SI2	.167	-.882
	SI3	.191	-.798
Facilitating Conditions	FC1	-.652	-.526
	FC2	-.964	.270
	FC3	-.954	.447
	FC4	-.629	-.311
Hedonic Motivation	HM1	-1.449	1.924
	HM2	-1.373	1.501
	HM3	-1.359	1.416
Price Value	PV1	-.024	-.787
	PV2	-.199	-.644
	PV3	-.449	-.375
Ubiquity	UBI1	-.579	-.046
	UBI2	-.693	.223
	UBI3	-.589	-.384
	UBI4	-.587	-.368
	UBI5	-.625	-.134
Unobtrusiveness	UNO1	-.480	-.457
	UNO2	-.464	-.584
	UNO3	-.530	-.391
	UNO4	-.098	-.941
	UNO5	.002	-.980
	UNO6	-.397	-.660
Context Awareness	CAW1	-.401	-.129
	CAW2	-.705	.609
	CAW3	-.482	-.051
	CAW4	-.385	-.258
	CAW5	-.618	-.043
Behavioral Intention	BI1	-.190	-1.144
	BI2	.079	-1.123
	BI3	-.064	-1.215

The values for skewness and kurtosis for each item were computed in SPSS. All values for skewness were in the range of ±1 except for the items EE4 and HM1-3, yet still in the acceptable range. The values for kurtosis were in the range of ±1 except those for *Hedonic Motivation* and *Behavioral Intention*, but also meeting the conditions to be indicative of normality. The results of the data screening tests indicate that the data set with the final sample of 346 cases is appropriate for application with SEM. Consequently, the next step is to build the measurement model.

Table 7 above depicts the skewness and kurtosis values for all items, with none of them exhibiting problematic values. The results of the data screening tests indicate that the data set with the final sample of 346 cases is appropriate for application with SEM. Consequently, the next step is to build the measurement model.

3.6.2 Confirmatory factor analysis

In this section, we first tested the measurement model for model fit in order to verify to what extent our proposed model accounts for the variables in the dataset. Second, we conducted tests for reliability and construct validity, while the latter is divided into two subtypes of validity, namely, convergent and discriminant validity.

3.6.2.1 Model fit

Prior to testing for reliability and validity, the overall fit measures were computed to assess the fit of our structural model to the data. The so-called goodness-of-fit indices can be classified into two categories — absolute and incremental (Hu and Bentler, 1995). An absolute fit index assesses to what extent an a priori model fits the sample data. In contrast, an incremental fit index indicates the relative improvement in fit of the researcher's model over a statistical baseline model (Kline, 2011). The baseline model usually equals the independence model, which assumes zero covariances among the observed variables. The investigated absolute fit indices include the relative chi-square (χ^2/df), the standardized root mean square residual (SRMR; Bentler, 1995), and the root mean square error of approximation (RMSEA; Steiger and Lind, 1980).

In contrast to the traditional chi-square (χ^2) test, the relative chi-square fit index overcomes the issue of nearly always rejecting the proposed model when large sample sizes are used (Bentler and Bonett, 1980; Wheaton et al., 1977). Therefore the ratio of χ^2

to degrees of freedom is considered. Even though there is no general consensus that suggests an acceptable ratio for this statistic, recommendations range between three or less and five to be indicative of good fit (Carmines and McIver, 1981; Wheaton et al., 1977).

The root mean square residual (RMR) is the extent to which the residuals of the sample covariance matrix deviate from the hypothesized covariance model (Hooper et al., 2008). However, as this measure is calculated with unstandardized variables, it is sensitive to the scales of the observed variables (Gefen et al., 2011; Kline, 2011). For this reason, the standardized RMR (SRMR) is typically interpreted as it overcomes this problem (Hooper et al., 2008). Its value ranges from zero to one, with lower values indicating better fit. A high value of SRMR is indicative of residuals that are large on average. Acceptable values should be less or equal to 0.08 (Hu and Bentler, 1999). Before this threshold was published a value of 0.10 or less was deemed as acceptable (Medsker et al., 1994). We consider a value of 0.08 or less as good fit, with an upper limit of 0.10 for still acceptable fit.

The RMSEA estimates the lack of fit in the proposed model compared to a perfect model and is scaled as a badness-of-fit index (Kline, 2011). It refers to the question: "How well would the model, with unknown but optimally chosen parameter values, fit the population covariance matrix if it were available?" (Browne and Cudeck, 1992) Its value ranges from zero to one, with a value close to zero indicating good model fit. Browne and Cudeck (1992) suggested a RMSEA value of 0.05 or less to be indicative of good fit, while a value between 0.05 and 0.08 suggests mediocre fit, and a value above 0.10 indicates room for improvement. MacKenzie et al. (2011) argue that a generally good fitting model should have a RMSEA value of 0.06 or less, while Arbuckle (2005) states that a model with a RMSEA value above 0.10 should not be employed. In addition, MacCallum et al. (1996) suggest to report the confidence interval (CI) around the RMSEA point estimate. Some SEM programs (e.g. AMOS) calculate the lower and upper bounds of the 90% CI for the RMSEA to indicate the precision of the point estimate (Byrne, 2010). The width of the CI increases with smaller sample size, which implies less precision. In a well-fitting model, the lower bound is close to zero, while the upper bound should be less than 0.08 (Hooper et al., 2008).

In addition to the absolute fit indices, two incremental fit indices were considered. First, we examined the Tucker-Lewis Index (TLI) followed by the Comparative-Fit Index (CFI). The TLI, also known as Non-normed Fit Index (NNFI), is a reliability coefficient which represents the proportion of covariation to be explained that is accounted for by a specified model (Tucker and Lewis, 1973). TLI values will typically be between 0 and 1, however, for confirmatory models the value can fall outside this range (Burt, 1973). A recommended target value for good fit is 0.95 or greater (Hu and Bentler, 1998). The CFI measures the relative noncentrality between a hypothesized model and the independence model (Bentler, 1990). CFI values range between 0 and 1, with values approaching 1 indicating acceptable fit. Hu and Bentler (1999) suggest a cut-off value for CFI of 0.95.

A rigorously confirmatory approach happens only on rare occasions because most researchers are unwilling to reject a proposed model and seek for retaining their achievements by proposing alternative models (Schumacker, 2006). Consequently, they consider a post hoc analysis in which they modify the initial model in order to improve model fit. This kind of modification process is also termed specification search (MacCallum, 1986). Given the statistical evidence of insufficient model fit for our initial model, we considered a respecification of the measurement model based on modification indices. This strategy involves inspecting the suggested modification indices calculated by AMOS. They show to what extent certain parts of the model can be improved by increasing the number of parameters so that the chi-square drops faster than the degrees of freedom (Arbuckle, 2005). However, such a data-driven procedure should be considered with caution as it is not supported by theory and should only be employed when a rationale can be given.

We obtained the following model fit indices for the initial model, which were close to being acceptable: Relative Chi-square (2.577), RMSEA (0.068), SRMR (0.046), TLI (0.927), CFI (0.935). To account for this minor misfit, we activated the function to calculate the modification indices in AMOS. A review of the modification indices revealed substantial evidence of misspecification as a consequence of error covariances among items of each of the pervasiveness constructs. We aimed for integrating as few as possible modification indices in order to achieve acceptable model fit while still addressing model parsimony. At this stage, it is important to note that correlating error terms of items within a construct must be well justified (Hooper et al., 2008). We proceeded cautiously when implementing the modification indices, i.e. only one at a time with a subsequent assessment of model fit improvement (Schumacker, 2006). Hence, we limited the number of covaried error terms to the following items:

- UBI1 ↔ UBI2
- UNO5 ↔ UNO6
- UNO4 ↔ UNO5
- CAW4 ↔ CAW5

It becomes obvious that only the items of the pervasiveness constructs are involved. The expected change statistics for these modification indices were the highest among the suggested error covariances, thus we acted upon this basis. One reason might be the higher number of items for those constructs in comparison to the other constructs, which might have caused confusion of a survey respondent when reading similar statements. For example, in case of UBI1 and UBI2 the wording of the statements differs in only one word so that a respondent might have read the same content for both and consequently rated both statements with the same value. Another potential reason is the item placement. In each of the remaining cases, the problematic items are among the last of a construct, which might have led to ratings with equal values due to similar statements. Moreover, these constructs were placed towards the end of the survey which means that respondent fatigue might have contributed to a quicker and thus uniform rating pattern.

Table 8. Summary of fit indices and results for the measurement model

Fit index	Initial model	Revised model	Threshold (Source)
Relative Chi-square (χ^2/df)	2.577	1.911	≤ 3 (Carmines and McIver, 1981)
RMSEA (CI)	0.068 (0.063; 0.072)	0.051 (0.047; 0.056)	≤ 0.06 (MacKenzie et al., 2011)
SRMR	0.046	0.053	≤ 0.08 (Hu and Bentler, 1999)
TLI	0.927	0.958	≥ 0.95 (Hu and Bentler, 1998)
CFI	0.935	0.963	≥ 0.95 (Hu and Bentler, 1999)

Table 8 summarizes the fit indices for the initial model and the revised model after the consideration of modification indices. Further, the targeted thresholds are specified. It can be observed that the fit indices for the revised measurement model exceed the commonly accepted standards, suggesting that the revised measurement model provides an acceptable fit to the data.

3.6.2.2 Reliability and validity

After establishing model fit, a researcher needs to check for (i) reliability, (ii) convergent validity, and (iii) discriminant validity (MacKenzie et al., 2011). To demonstrate reliability, we examined the composite reliability (CR) for each construct for which we set a cut-off value of 0.7 (Bagozzi and Yi, 2011). Constructs with an equal or higher value than the cut-off value can be considered as reliable. All constructs satisfied this condition, in that they showed a value of 0.89 or higher (see Table 9). Convergent validity is the extent to which different items that are designed to measure the same construct correlate with each other (Campbell and Fiske, 1959). It was established by examining the item reliability and the average variance extracted (AVE).

Table 9. Composite reliability, average variance extracted, maximum shared variance, and correlation matrix

	CR	AVE	MSV	PE	EE	SI	HM	PV	UBI	UNO	CAW	BI
PE	0.94	0.84	0.53	**0.91**								
EE	0.95	0.82	0.20	0.41	**0.90**							
SI	0.96	0.88	0.54	0.70	0.35	**0.94**						
HM	0.97	0.90	0.50	0.70	0.45	0.52	**0.95**					
PV	0.90	0.75	0.32	0.55	0.28	0.46	0.50	**0.87**				
UBI	0.95	0.84	0.53	0.52	0.38	0.40	0.38	0.38	**0.88**			
UNO	0.89	0.57	0.32	0.55	0.44	0.36	0.52	0.41	0.41	**0.76**		
CAW	0.92	0.69	0.50	0.53	0.39	0.46	0.49	0.43	0.50	0.71	**0.83**	
BI	0.95	0.88	0.54	0.73	0.44	0.73	0.67	0.56	0.57	0.52	0.52	**0.94**

Notes:
1. *PE — Performance Expectancy, EE — Effort Expectancy, SI — Social Influence, HM — Hedonic Motivation, PV — Price Value, UNO — Unobtrusiveness, UBI — Ubiquity, CAW — Context Awareness, BI — Behavioral Intention.*
2. *CR — Composite Reliability, AVE — Average Variance Extracted, MSV — Maximum Shared Variance.*
3. *Diagonal elements are the square roots of the AVE (in bold) and off-diagonal elements are correlations.*
4. *All correlations were significant at the $p < 0.001$ level.*

Table 10. Item loadings and descriptive statistics

Construct	Item	Loading	Mean	SD	Cronbach α
Performance Expectancy	PE1	0.902	4.57	1.81	0.94
	PE2	0.930	4.69	1.69	
	PE3	0.910	4.44	1.81	
Effort Expectancy	EE1	0.899	5.40	1.51	0.95
	EE2	0.882	5.22	1.44	
	EE3	0.940	5.29	1.47	
	EE4	0.893	5.43	1.46	
Social Influence	SI1	0.931	3.47	1.74	0.96
	SI2	0.935	3.52	1.78	
	SI3	0.947	3.48	1.74	
Hedonic Motivation	HM1	0.946	5.76	1.47	0.97
	HM2	0.962	5.66	1.55	
	HM3	0.941	5.67	1.57	
Facilitating Conditions *DROPPED*	FC1	0.560	4.77	1.81	0.74
	FC2	0.812	5.55	1.48	
	FC3	0.726	5.38	1.49	
	FC4	0.487	4.98	1.60	
Price Value	PV1	0.807	3.97	1.71	0.90
	PV2	0.973	4.25	1.68	
	PV3	0.810	4.59	1.60	
Unobtrusiveness	UNO1	0.758	4.79	1.61	0.90
	UNO2	0.820	4.63	1.64	
	UNO3	0.870	4.64	1.62	
	UNO4	0.699	4.04	1.78	
	UNO5	0.672	3.91	1.78	
	UNO6	0.710	4.42	1.69	
Ubiquity	UBI1	0.840	5.22	1.35	0.95
	UBI2	0.823	5.27	1.35	
	UBI3	0.916	5.06	1.56	
	UBI4	0.929	5.01	1.55	
	UBI5	0.910	5.09	1.48	
Context Awareness	CAW1	0.803	5.10	1.28	0.92
	CAW2	0.901	5.24	1.26	
	CAW3	0.900	5.12	1.28	
	CAW4	0.798	4.96	1.33	
	CAW5	0.751	5.03	1.36	
Behavioral Intention	BI1	0.903	4.25	1.97	0.95
	BI2	0.936	3.78	1.91	
	BI3	0.966	3.97	1.99	

First, we tested for item reliability by checking all squared standardized regression weights to be above 0.707. This threshold ensures that over a half of the variance is captured by the latent construct (Chin, 1998). Table 10 above summarizes all item loadings and descriptive statistics for each construct. As can be seen, all items had higher values than 0.707 except for FC1, FC4, UNO4, and UNO5, with the latter UNO items being very close to the threshold.

Second, we calculated the AVE values for each construct (see Table 9). The AVE includes the variance of the items captured by their assigned construct relative to the total amount of variance. Constructs showing an AVE of less than 0.5 are subject to insufficient convergent validity. All constructs except FC exceeded the threshold value. Since FC revealed issues for convergent as well as item reliability we eventually decided to drop this construct, which led to a purification of our scales.

Discriminant validity is the extent to which a construct discriminates from other constructs (Campbell and Fiske, 1959). This implies that a construct is able to account for more variance in the associated items than (i) measurement error or similar external, unmeasured influences; or (ii) other constructs within the conceptual framework. If this is not the case, then the validity of the individual items and of the construct is questionable (Fornell and Larcker, 1981). Discriminant validity is supported if the AVE for each construct is greater than its shared variance with any other construct. Shared variance is the amount of variance that a construct is able to explain in another construct and is represented by the square of the correlation between any two constructs. Therefore, we calculated the maximum shared variance (MSV) representing the highest value for all shared variances that needs to be less than the AVE to suggest discriminant validity.

Table 11 summarizes the criterions and thresholds for each of the reliability and validity types used in our study. Furthermore it shows the sources of which we applied the thresholds.

Table 11. Evaluation criteria for measurement model

Validity type	**Criterion**	**Threshold**	**Source**
Construct reliability	Composite Reliability (CR)	≥ 0.7	(Bagozzi and Yi, 2011)
Convergent validity	Item loadings	> 0.707	(Gefen et al., 2000)
	Average Variance Extracted (AVE)	≥ 0.5	(Fornell and Larcker, 1981)
Discriminant validity	Fornell/Larcker	MSV < AVE	(Fornell and Larcker, 1981)

The second step in the CFA was a measurement model invariance analysis. It is suggested when conducting a multi-group analysis (Steinmetz et al., 2008) otherwise the conclusions of this kind of analysis might be meaningless (Schmitt and Kuljanin, 2008). The invariance analysis tests if the factor structure is equivalent across different values of a multi-group moderator. Therefore, both continuous moderator variables *Age* and *Experience* were transformed into categorical variables. The two groups for *Age* are "30 or younger" and "above 30." The two groups for *Experience* are "1-4 years" and "5 years or more," while we excluded the group with no experience.

In the next step, we tested for configural and metric invariance during the CFA to validate construct compatibility across groups (Vandenberg and Lance, 2000). Configural invariance is a crucial condition to be fulfilled for a model to be invariant across groups. It tests whether the construct structure represented in the CFA achieves adequate fit when both groups are tested simultaneously together and freely (Hair et al., 2009). We checked model fit for both moderator variables, *Age* and *Experience*, considering their respective groups. In both cases configural invariance could be obtained. Further, we tested for metric invariance for both moderator variables. A chi-square test revealed evidence of differences between both groups for each moderator variable, although we could only obtain partial rather than full metric invariance. According to MacKenzie et al. (2011), partial metric invariance is sufficient as long as at least one item is metrically invariant, which applied to our result. Thus, the groups of the moderator variables *Age* and *Experience* could be considered as invariant.

To test for common method variance, we performed a Harman's single-factor test (Podsakoff and Organ, 1986). Factor analyses in SPSS produced neither a single factor nor one general factor that accounted for the majorinity of the variance, indicating a low risk of common method bias.

3.6.3 Exploratory factor analysis

The follow-up EFA was conducted as a consequence of the consideration of modification indices to achieve an acceptable model fit for the measurement model in section 3.6.2.1. Although this kind of model improvement is common in contemporary research (Whittaker, 2012), it is purely data-driven and not supported by theory (MacCallum et al., 1992). In fact, "most uses of 'confirmatory' factor analyses are, in actuality, partly exploratory and partly confirmatory." (Gerbing and Hamilton, 1996) Consequently, we conducted a follow-up EFA prior to analyzing the structural model. This approach is advocated by Schmitt (2011) when a researcher obtains an adequate-fitting model by model respecification based on modification indices.

We used SPSS to conduct the EFA and started with defining the extraction and rotation method. As recommended by Costello and Osborne (2005), we used maximum likelihood as extraction method in combination with direct oblimin rotation to identify the factorial structure of our data. Further, we fixed the number of factors to be identified to the expected number.

Table 12 shows the individual factor loadings sorted by size together with descriptive statistics. A clean factor structure could be obtained attributable to high item loadings onto their intended constructs without cross-loadings higher than ±0.3. All items of the intended constructs reveal higher loadings than 0.6 except for CAW1 which can still be considered as acceptable due to the high sample size.

Prior to achieving this result, we needed to account for FC. The items of FC had low loadings and in addition to that they were highly correlated with EE, so that the FC construct and its corresponding items were dropped. All remaining constructs reached a Cronbach's alpha value of 0.90 or above, thus exceeding the cutoff value of 0.7 recommended by Nunally (1978). The Kaiser-Meyer-Olkin measure of sampling adequacy (Kaiser, 1974) showed a value of 0.93 as for which we can assume to have yielded a suitable dataset for factor analysis.

Table 12. Pattern matrix and descriptive statistics

	Factor								
	1	2	3	4	5	6	7	8	9
Mean	3.99	5.13	5.34	4.27	5.70	4.56	4.42	5.09	3.47
SD	1.86	1.32	1.34	1.50	1.46	1.66	1.36	1.12	1.67
Cronbach	0.95	0.95	0.95	0.90	0.97	0.94	0.90	0.92	0.96
BI3	**0.89**	0.04	-0.06	0.01	-0.06	0.01	0.01	0.01	0.01
BI2	**0.84**	0.02	-0.02	0.03	0.00	-0.02	0.03	0.06	0.01
BI1	**0.68**	-0.06	-0.01	0.09	-0.09	-0.11	0.02	0.05	0.06
UBI5	-0.03	**0.89**	-0.03	0.04	-0.04	0.07	-0.01	0.03	0.05
UBI4	-0.04	**0.87**	-0.04	0.03	0.05	-0.05	0.07	0.00	0.05
UBI3	0.05	**0.84**	-0.01	-0.02	0.06	-0.12	0.01	0.04	-0.04
UBI1	0.04	**0.79**	-0.03	0.03	-0.09	0.01	-0.01	0.06	-0.04
UBI2	0.06	**0.76**	0.00	0.02	-0.08	-0.01	-0.02	0.08	-0.03
EE1	0.04	-0.03	**-0.94**	-0.01	0.06	0.04	0.01	-0.03	0.04
EE3	-0.01	0.04	**-0.92**	0.00	-0.01	-0.02	0.02	-0.01	-0.02
EE4	-0.02	0.05	**-0.87**	0.01	-0.08	0.01	-0.04	0.00	-0.03
EE2	0.01	-0.01	**-0.83**	0.00	0.02	-0.08	0.03	0.02	0.04
PV2	0.01	0.06	0.04	**0.93**	0.04	-0.11	-0.02	-0.02	0.04
PV1	0.03	-0.02	-0.03	**0.86**	0.01	0.07	0.00	-0.04	0.00
PV3	0.03	0.04	0.00	**0.66**	-0.09	-0.06	0.05	0.03	0.06
HM2	0.03	0.01	-0.03	-0.03	**-0.92**	0.01	0.02	-0.02	0.07
HM1	0.03	0.03	0.01	0.01	**-0.90**	-0.03	0.02	0.00	0.01
HM3	0.02	0.00	0.01	0.03	**-0.88**	-0.06	0.01	0.00	-0.02
PE2	-0.06	0.02	-0.03	0.03	-0.05	**-0.89**	0.03	0.06	0.00
PE3	0.06	0.04	0.02	0.05	-0.02	**-0.74**	0.03	-0.02	0.11
PE1	0.14	0.01	-0.07	0.01	-0.07	**-0.70**	-0.01	0.01	0.03
UNO3	0.01	-0.06	-0.02	0.02	-0.02	-0.09	**0.73**	0.15	-0.05
UNO6	-0.02	0.03	-0.05	-0.03	-0.07	-0.06	**0.72**	-0.09	0.02
UNO5	0.13	0.12	0.03	-0.02	-0.01	-0.03	**0.70**	-0.14	0.13
UNO4	0.16	0.17	0.03	-0.05	0.07	-0.04	**0.69**	-0.09	0.14
UNO2	0.00	0.00	-0.06	0.07	-0.05	0.06	**0.67**	0.14	-0.01
UNO1	-0.03	-0.11	-0.07	0.13	-0.07	-0.01	**0.61**	0.16	-0.11
CAW4	0.09	0.01	0.01	0.01	0.03	-0.02	0.02	**0.81**	0.01
CAW5	0.07	-0.01	0.01	-0.03	-0.01	-0.07	-0.01	**0.77**	0.02
CAW2	-0.04	0.11	-0.04	-0.01	-0.06	0.02	0.04	**0.75**	0.09
CAW3	0.02	0.09	-0.07	0.03	-0.04	-0.03	0.02	**0.72**	0.07
CAW1	-0.02	0.26	0.01	0.08	0.00	-0.01	0.07	**0.54**	0.05
SI3	0.02	-0.01	-0.01	0.01	-0.04	0.00	0.03	0.01	**0.90**
SI2	0.00	-0.04	-0.02	0.03	-0.04	-0.03	-0.01	0.05	**0.88**
SI1	0.03	0.00	-0.03	0.03	0.00	-0.04	-0.02	0.06	**0.85**

Extraction Method: Maximum-Likelihood.

Rotation Method: Oblimin with Kaiser Normalization.

As a conclusion, the result of the EFA confirms the issues of the CFA regarding the FC construct. Moreover it confirms the structure of the three pervasiveness constructs and their associated items, for which we used modification indices during CFA.

3.6.4 Structural model

With the analysis of the measurement model completed, we continue with the structural model. Prior to the evaluation, we again considered the usage of modification indices to achieve acceptable model fit. The error term of *Performance Expectancy* was covaried with the error terms of *Hedonic Motivation* and *Social Influence*. This step can be justified by the relationship between *Performance Expectancy* on the one hand and *Hedonic Motivation* and *Social Influence* on the other hand. First, an increase of *Performance Expectancy* likely induces an increase of *Hedonic Motivation* since the usage of a pervasive technology in an effective manner might cause a positive feeling when using the technology. Second, an increase of *Social Influence* might induce an increase in *Performance Expectancy*. This can be argued by the positive feedback of a user's social environment when it has good experiences with a technology in terms of effectiveness.

Table 13 summarizes the model fit indices considered in our study and shows the corresponding values obtained from the structural model. Further, the targeted thresholds are specified. It can be observed that the results for our structural model are close to or exceed the commonly accepted standards, suggesting that the model provides an acceptable fit to the data.

Table 13. Summary of fit indices and results for the structural model

Fit index	**Initial model**	**Revised model**	**Threshold**
Relative Chi-square (χ^2/df)	2.469	2.165	≤ 3
RMSEA (CI)	0.065 (0.061; 0.070)	0.058 (0.054; 0.063)	≤ 0.06
SRMR	0.108	0.967	≤ 0.08
TLI	0.932	0.946	≥ 0.95
CFI	0.938	0.951	≥ 0.95

The structural model in Figure 33 presents the result for the path coefficients and variance explained for each endogenous construct. The complete summary of the results including moderating effects is provided in section 3.6.4.3.

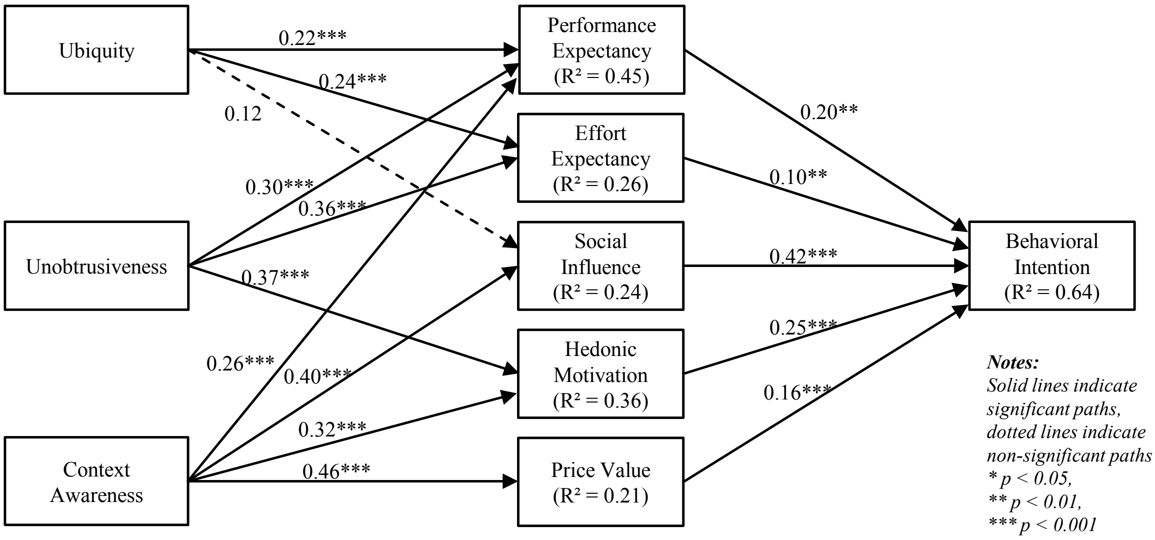

Figure 33. Structural model

3.6.4.1 Moderation analysis

An analysis of moderating effects requires the consideration of moderating variables in the research model. Essentially, moderation signifies that the strength of a relationship between two variables varies as a function of a third variable, known as a moderator variable (Baron and Kenny, 1986). Figure 34 illustrates this phenomenon in that the relationship between a predictor (X) and the outcome (Y) is moderated by a third variable (Z).

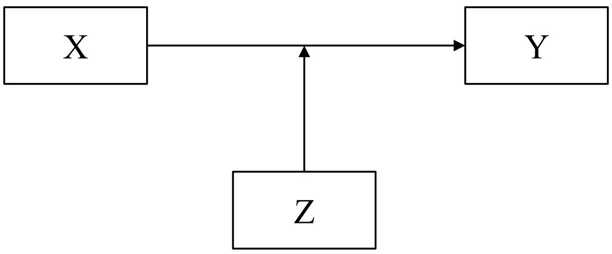

Figure 34. Moderation

The effect of a moderator is exemplified in Figure 35. It reveals the difference of the strength of a relationship depending on the moderator's value (e.g. men or women). The more the circles overlap, the more the predictor accounts for the variance in the outcome. In this example, the relationship for men is significantly weaker than it is for women, as for which a significant moderator effect can be concluded. Moderation can contribute to the understanding of relationships, in that the moderator variable places constraints on how or when a process can function (Hayes, 2009). For example, a relationship that is insignificant without considering a moderator, might be further examined by including a meaningful moderator. By this means, a researcher might be able to understand under which conditions a relationship might be significant.

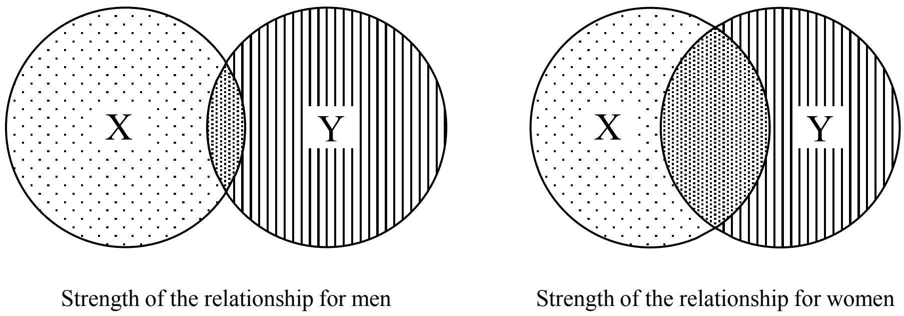

Figure 35. Example of difference in effects for a moderating variable

It is important to note that a moderator variable can be a categorical (e.g., gender) or continuous (e.g., ratings on a survey scale). In the first case of a categorical variable, the analysis method is referred to multi-group moderation. In doing so, a dataset is split along values of a categorical variable (e.g. gender or age), and a given model is tested with each set of values. In case of a continuous variable, a moderated effect is typically modeled as an interaction between the independent variable and the moderator variable. The interaction is frequently represented as the product of the independent variable and the moderator variable (Hayes, 2009).

The moderating effects in our study were captured by using the categorical variables *Age* and *Experience*. In section 3.6.2.2, we conducted an invariance analysis to provide evidence for both moderators to be invariant across their groups. The moderators were examined by analyzing the differences of their respective groups. To test for the influence of *Age*, we divided the data set into two groups: equal or less than 30 years (N=180) and more than 30 years (N=166). The two groups for *Experience* were 1-4 years (N=154) and more than 4 years (N=140), while we excluded the group without experience. Table 14 shows the results of the moderating effects of both variables. The results of the z-tests indicate if there are significant differences between the respective groups. The critical value for the z-test is +/- 1.645 at the 90% confidence level.

Table 14. Moderating effects of the variables Age and Experience

Moderator	Group	UBI→PE	UBI→EE	UNO→PE	UNO→EE	CAW→PE
None		0.22***	0.24***	0.30***	0.36***	0.26***
Age (years)	≤ 30	0.29***	0.35***	0.25***	0.26***	0.33***
	> 30	0.14 (ns)	0.10 (ns)	0.39***	0.51***	0.23*
	z-test	-1.192 (ns)	**-1.883***	1.062 (ns)	**2.259****	-0.564 (ns)
Experience (years)	1-4	0.06 (ns)	0.17*	0.25**	0.40***	0.38***
	> 4	0.40***	0.34***	0.41***	0.28**	0.09 (ns)
	z-test	**2.519****	0.717 (ns)	**2.145****	-1.328 (ns)	**-1.836***

Notes: **** p < 0.001; ** p < 0.01; * p < 0.05; (ns): not significant*

Notes for z-test: **** p-value < 0.01; ** p-value < 0.05; * p-value < 0.10; (ns): not significant*

3.6.4.2 Mediation analysis

A mediation analysis is conducted when indirect effects are expected to be inherent in certain relationships. Mediation, or an indirect effect, is characterized by an independent variable impacting a dependent variable through a mediator (Preacher et al., 2007). Figure 36 illustrates the effect and mediation types. So far, we only examined direct effects in our study. A direct effect is the impact of the independent variable (X) on the dependent variable (Y) and is represented by path *c* in Figure 36a. The two types of mediation are known as partial and full mediation (Baron and Kenny, 1986). Partial mediation means that both direct (*c'*) and indirect (*a* and *b*) effects significantly impact the dependent variable. In this context, *c'* stands for the direct effect between X and Y after controlling for the mediator M (Figure 36b). The indirect effect between X and Y through M is the product $a \times b$ (Hayes, 2009), and can be interpreted as a chain of effects (MacKinnon et al., 2004). The effect of the independent variable on the mediator is represented by path *a*, while the effect of the mediator on the dependent variable is represented by path *b*. Full mediation means that *c'* drops out of significance in the presence of M, and that the indirect effect is significant (Figure 36c).

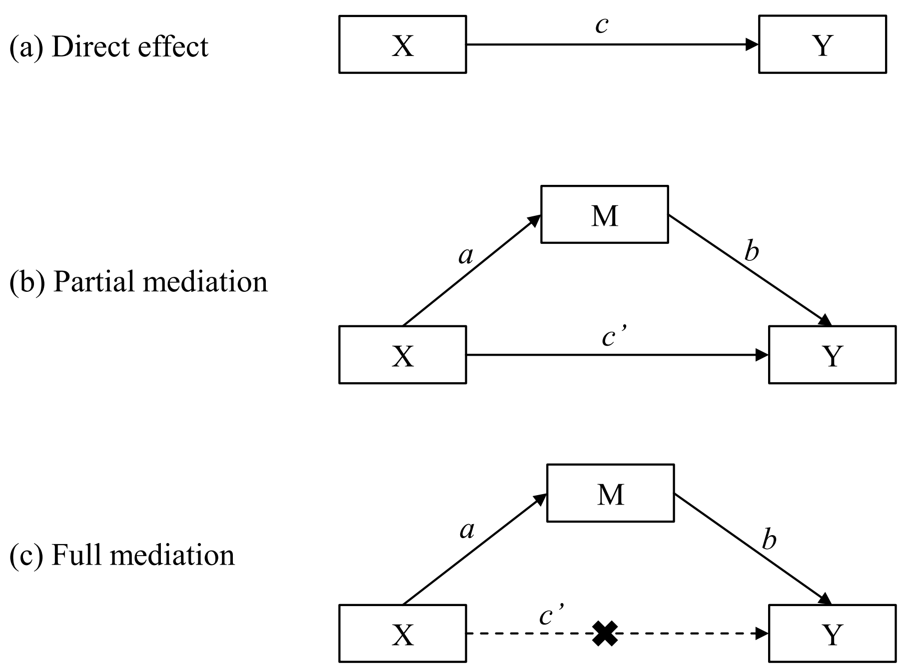

Figure 36. Direct effect and mediation types

A mediation analysis can be conducted through a variety of methods. The so-called Baron and Kenny approach is the most widely used method (Baron and Kenny, 1986; Hayes, 2009; Iacobucci et al., 2007). This approach consists of the following steps:

1. The independent variable X must be correlated with the dependent variable Y. This step forms the basis for an effect that may be mediated and corresponds with Figure 36a.
2. The independent variable X must be correlated with the mediator M. In this step, the first part of the indirect effect (path *a* in Figure 36) is estimated and tested for significance.
3. The mediator M must be correlated with the dependent variable Y. In this step, the second part of the indirect effect (path *b* in Figure 36) is estimated and tested for significance.
4. To establish that M mediates the X-Y relationship, the effect of X on Y controlling for M (path *c'*) must be either significant (partial mediation) or insignificant (full mediation).

Following this guideline, we conducted a mediation analysis based on a mediation model depicted in Figure 37. It is based on the structural model, however, we removed the insignificant path UBI→SI as it violated point 2 in the list above.

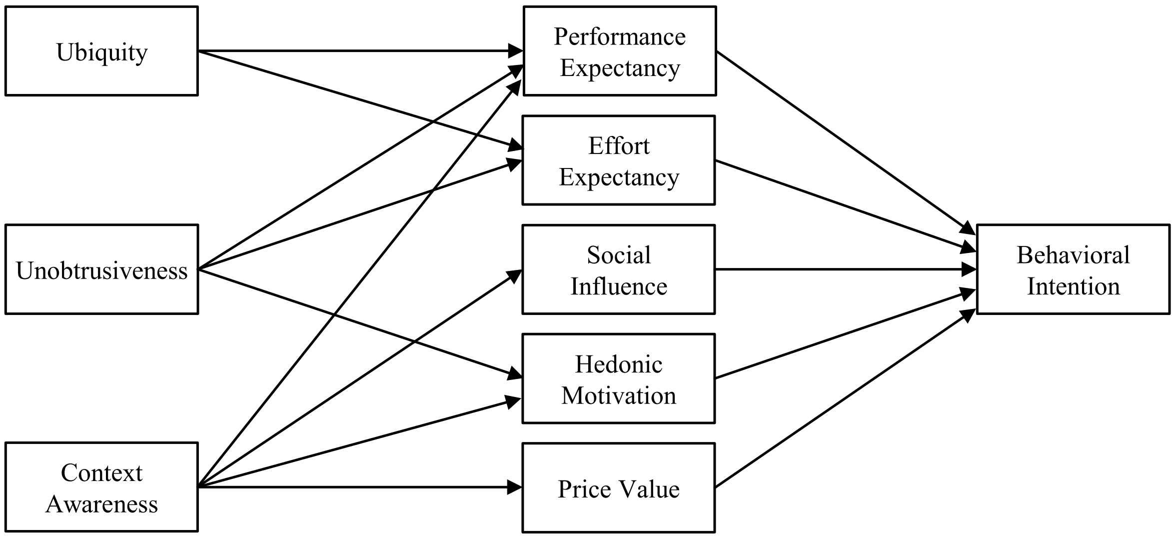

Figure 37. Mediation model

For analyzing mediation effects in our study, we again chose CB-SEM over multiple regression as SEM outperforms regression for mediation analysis (Iacobucci et al., 2007). Thus, we ran the analysis in AMOS, but this time using bootstrapping as advocated by (Bollen and Stine, 1990). Bootstrapping is a non-parametric technique based on resampling with replacement, i.e. a new sample of size *n* is constructed by sampling cases from the original (smaller) sample, which acts as a pseudo-population that represents the resulting broader population (Preacher et al., 2007). The sampling distribution of an indirect effect can be empirically computed through each of these newly generated samples. Because a bias in the central tendency of the bootstrapped sample distribution will not exactly equal the indirect effect, a bias-corrected bootstrap is employed to address bias correction (MacKinnon et al., 2004). Cheung and Lau (2007) propose practical recommendations for using bootstrapping in AMOS, in that they specify a number of bootstrap samples (e.g. 1000) and activate bias-corrected confidence intervals (e.g. 95%). One drawback of a higher number of bootstrap samples is the increasing computation time, however, this is not a major issue today (Preacher et al., 2007). Thus, we set a number of 2000 bootstrap samples with a 95% bias-corrected confidence interval.

The hypotheses testing for H4a-c involves a mediation analysis. In this case, a researcher has mainly two options to conduct a mediation analysis in AMOS. First, the total indirect effect can be computed for analysis purpose. However, this means the individual indirect effects through each of the mediators would remain hidden. Second, an iterative process of computing a set of simple mediation models (such as in Figure 36b and Figure 36c) for each mediator can be considered to obtain all individual mediation effects. We opted for the second approach since the objective was not only to know if the effects of the pervasiveness constructs on *Behavioral Intention* are mediated by the predictors of *Behavioral Intention*, but also to identify the specific mediators.

The first step included the estimation of the direct effects between the pervasiveness constructs and *Behavioral Intention*. The direct effects from *Ubiquity* and *Unobtrusiveness* on *Behavioral Intention* were significantly higher than from *Context Awareness* on *Behavioral Intention*, though all direct effects were significant. This result provided the basis for further analysis according to point 1 in the guideline. In the next step, we added the mediators and estimated the indirect effects between the pervasiveness constructs and *Behavioral Intention* through the mediators. This step combines point 2 and 3 of the guideline because if both relationships (X→M and M→Y) are significant, the indirect effect will be significant as well. Only four out of nine indirect effects were significant. Those paths having *Performance Expectancy* or *Effort Expectancy* as mediators had no indirect effects. In other words, only those paths having *Hedonic Motivation*, *Social Influence*, or *Price Value* were qualified for mediation effects. In the last step, we tested the direct effect for significance in the presence of the mediator. Particularly with regard to the relevant paths for mediating effects, we obtained only a significant direct effect between *Unobtrusiveness* and *Behavioral Intention*. This implies that the effect between *Unobtrusiveness* and *Behavioral Intention* is partially mediated through *Hedonic Motivation*. The effect between *Context Awareness* and *Behavioral Intention* is fully mediated through *Social Influence*, *Hedonic Motivation*, and *Price Value*, whereas the effect between *Ubiquity* and *Behavioral Intention* is not mediated. The results of the mediation analysis are summarized in Table 15.

Table 15. Mediation effects

Relationship	Direct effect without mediator	Indirect effect	Direct effect with mediator	Mediation type
UBI→PE→BI	0.205**	0.179**	0.013 (ns)	No mediation
UBI→EE→BI	0.205**	0.184**	0.007 (ns)	No mediation
UNO→PE→BI	0.223**	0.208***	0.011 (ns)	No mediation
UNO→EE→BI	0.223**	0.207***	0.011 (ns)	No mediation
UNO→HM→BI	0.223**	0.238***	0.049***	**Partial mediation**
CAW→PE→BI	-0.084 (ns)	-0.079 (ns)	-0.079 (ns)	No mediation
CAW→SI→BI	-0.084 (ns)	-0.094 (ns)	0.171**	No mediation
CAW→HM→BI	-0.084 (ns)	-0.083 (ns)	0.052**	No mediation
CAW→PV→BI	-0.084 (ns)	-0.085 (ns)	0.065**	No mediation

*Notes: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; (ns): not significant*

Figure 38 shows that the direct path between *Ubiquity* and *Behavioral Intention* stays significant in the presence of the mediators *Performance Expectancy* and *Effort Expectancy*. The first parts of the indirect effects from *Ubiquity* to the mediators are significant. However, both mediators have insignificant effects on *Behavioral Intention*, for which the indirect effect is not significant and no mediation can be concluded.

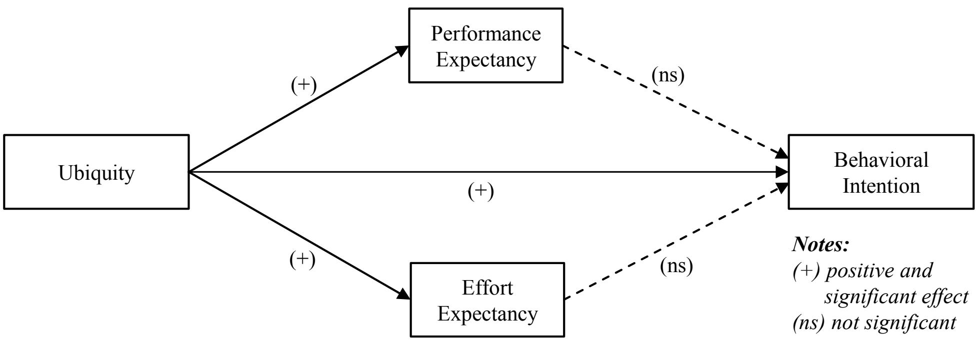

Figure 38. Mediation effects for Ubiquity

Figure 39 shows that the direct path between *Unobtrusiveness* and *Behavioral Intention* stays significant in the presence of the mediators *Performance Expectancy*, *Effort Expectancy*, and *Hedonic Motivation*. All relationships between *Unobtrusiveness* and the mediators are significant, however, *Performance Expectancy* and *Effort Expectancy* have insignificant effects on *Behavioral Intention* once again. Only *Hedonic Motivation* has a significant effect on *Behavioral Intention*, for which the relationship UNO→HM→BI is partially mediated.

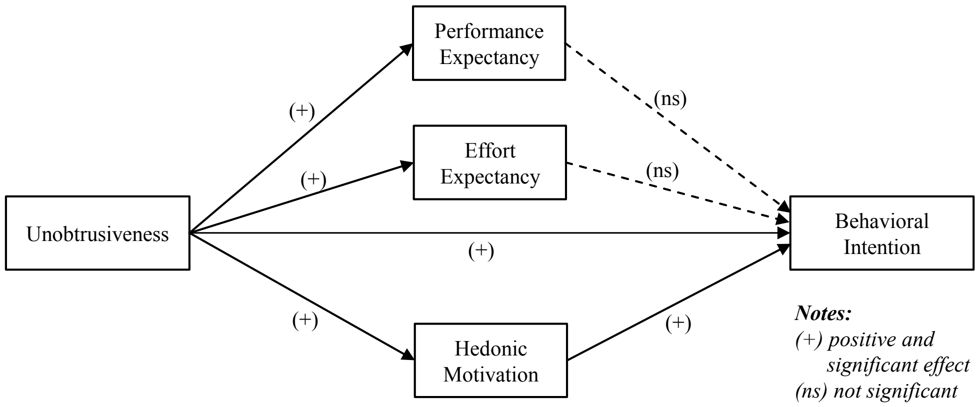

Figure 39. Mediation effects for Unobtrusiveness

Figure 40 shows that the direct path between *Context Awareness* and *Behavioral Intention* is insignificant, which is why point one of the list of the Baron and Kenny approach is violated. At this point, no mediation can occur since no direct effect exists between the independent and the dependent variable. As a result, no further examination has been conducted.

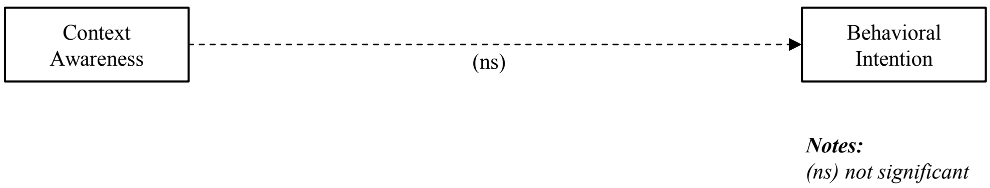

Figure 40. Mediation effects for Context Awareness

3.6.4.3 Results

In this section we summarize the final results of the structural model including the moderating and mediation effects and examine to what extent the hypotheses are supported. Regarding the structural model, *Ubiquity* showed weaker effects as compared to *Unobtrusiveness* and *Context Awareness*. The path coefficient of the relationship UBI→PE was significant and also the moderating variable *Experience* highlights significant differences between its groups. The result shows that the hypothesized relationship UBI→PE is stronger for people with higher experience, thus providing support for H1a. Further, we obtained a significant effect in the relationship UBI→EE moderated by *Age*. This result is according to H1b, which hypothesized a stronger effect in the relationship UBI→EE for younger people. H1c hypothesized a positive effect for the relationship UBI→SI, which could not be supported.

The relationships between *Unobtrusiveness* and the predictors of *Behavioral Intention* reveal only significant effects. Hence, H2a was supported because the moderating effect of *Experience* was significant. The result showed a stronger effect for people with higher experience in the relationship UNO→PE. The path coefficient for the relationship UNO→EE was significant, however, the hypothesized moderation was only significant for *Age* but not for *Experience*, i.e. it revealed only for older people a significant effect. Thus, H2b was only partially supported. The relationship UNO→HM was also significant, which is why H2c could be supported.

Context Awareness shows only significant and strong effects on *Social Influence*, *Hedonic Motivation*, and *Price Value*. The first relationship CAW→PE included the moderator *Experience*. Both the relationship and the moderator were significant, i.e. the effect was stronger for people with lower experience. Thus, H3a could be supported. The relationships CAW→SI, CAW→HM, and CAW→PV showed significant effects, for which we conclude H3b, H3c, and H3d as being supported.

Table 16. Final result for structural model and moderator effects

Hypothesis	Relationship	Path coefficient	Moderator(s)	Result
H1a	UBI→PE	0.22***	Experience	Supported
H1b	UBI→EE	0.24***	Age	Supported
H1c	UBI→SI	0.11 (ns)	None	Not supported
H2a	UNO→PE	0.24***	Experience	Supported
H2b	UNO→EE	0.35***	Experience, Age	Partially supported
H2c	UNO→HM	0.29***	None	Supported
H3a	CAW→PE	0.28***	Experience	Supported
H3b	CAW→SI	0.39***	None	Supported
H3c	CAW→HM	0.35***	None	Supported
H3d	CAW→PV	0.44***	None	Supported

*Notes: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; (ns): not significant*

Our model accounts for 64% of the variance in *Behavioral Intention*. In addition, the pervasiveness constructs were able to explain a medium to high percentage of variance in each independent variable of the UTAUT2. Table 16 above shows the results for the structural model including the moderator effects. Nine out of the ten hypotheses are either partially or fully supported.

The mediation analysis revealed no indirect effects for the relationship UBI→PE/EE→BI and CAW→PE/SI/HM/PV→BI but one indirect effect for the relationship UNO→PE/EE/HM→BI. We hypothesized for the first relationship that the effect of *Ubiquity* on *Behavioral Intention* will be mediated through *Performance Expectancy* and *Effort Expectancy*. However, even though there was a direct effect between *Ubiquity* and *Behavioral Intention* we could not identify any indirect effect; H4a could not be supported. The underlying hypothesis for the second relationship was that the effect of *Unobtrusiveness* on *Behavioral Intention* will be mediated through *Performance Expectancy*, *Effort Expectancy*, and *Hedonic Motivation*. Again, *Performance Expectancy* and *Effort Expectancy* did not mediate the hypothesized effect, but *Hedonic Motivation* did, even though the indirect effect was very weak. Thus, the corresponding hypothesis H4b could only be partially supported. The third relationship CAW→PE/SI/HM/PV→BI included indirect effects. As a result of no direct effect from CAW to BI without a mediator, the relationship CAW→PE→BI could not have any indirect effects with mediators. This is why H4c could not be supported. Table 17 summarizes the results for the mediation model.

Table 17. Final results for mediation analysis

Hypothesis	**Relationship**	**Moderator(s)**	**Result**
H4a	UBI→PE/EE→BI	None	Not supported
H4b	UNO→PE/EE/HM→BI	None	Partially supported
H4c	CAW→PE/SI/HM/PV→BI	None	Not supported

3.7 Discussion

3.7.1 Theoretical implications

The wearable Google Glass and its potential users as subjects in this study were used to identify the reasons for people's intention to use a pervasive technology. First, the measurement model could confirm that the pervasiveness constructs developed by no issues in terms of reliability and construct validity. This validation might encourage other researchers in considering these constructs in their research. Second, the pervasiveness constructs and the results of the multiple regression analysis by Karaiskos (2009) have supported our research in deriving the hypotheses. His results are in line with most of our results, except for the relationships UNO→PE and CAW→PV, for which he could not identify any significant effects but the corresponding hypotheses could be supported in our study. Third, our results of the moderator effects show that the relationships have consistent tendencies. That is, the moderator variable *Age* significantly and consistently moderates the relationships involving EE, while *Experience* moderates the relationships involving PE.

Regarding the three pervasiveness constructs, it can be stated that *Context Awareness* seems to be the most important characteristic for potential consumers of a pervasive technology. It defines a feature for which we could identify strong effects on the considered independent constructs of UTAUT2. In contrast, *Ubiquity* and *Unobtrusiveness* can be considered as important for *Performance Expectancy* and *Effort Expectancy*, while *Unobtrusiveness* shows also a positive effect on *Hedonic Motivation*. It means a potential consumer cherishes *Ubiquity* and *Unobtrusiveness* of a pervasive technology as a driver of improved effectiveness and efficiency in accomplishing tasks without becoming distracted.

Although it was not our primary focus, we discuss the direct effects on *Behavioral Intention*. In comparison with the results from UTAUT2, we can see that all predictors of *Behavioral Intention* reveal only minor deviations with the exception of SI, which has the strongest direct effect among all predictors of *Behavioral Intention* in our study. A probable reason is a considerable mediating effect from *Context Awareness* to *Behavioral Intention* through social influence which was not part of our mediation analysis.

3.7.2 Practical implications

Besides the theoretical implications mentioned above, our study allows for drawing conclusions relevant to pervasive technology developers. First, we can argue that for the design and development of a pervasive technology all pervasiveness constructs should be considered since they all showed medium to high significant effects on the predictors of UTAUT2. Second, we can observe that consumers cherish visible over invisible pervasiveness characteristics, more explicitly, functional capabilities (*Context Awareness*) over system design characteristics (*Ubiquity* and *Unobtrusiveness*). Thus, we can conclude that it seems important to consumers that a pervasive technology incorporates context-aware services such as LBS. Third, *Ubiquity* and *Unobtrusiveness* remain important characteristics relevant to the utilitarian perspective, i.e. *Performance Expectancy* and *Effort Expectancy*. *Ubiquity* seems to be essential to potential users in that they wish an omnipresent internet access, while *Unobtrusiveness* is considered as being important in terms of avoiding distraction when performing a task. This implies that there is a trade-off between proactive applications that are intended to support the user and the way these applications notify a user.

3.8 Conclusions

Our research examined the factors that influence the adoption of pervasive technologies by using a modified UTAUT2 as a base model and extending it by three pervasiveness constructs, namely *Ubiquity*, *Unobtrusiveness*, and *Context Awareness*. This integrated model was used to measure pervasiveness in the context of the pervasive technology Google Glass.

By means of an online survey, we obtained an adequate dataset with 346 cases for our data analysis. This analysis was conducted by applying covariance-based structural equation modeling and provided empirical support for the applicability of the integrated model. Further analyses encompassed the testing of moderating and mediation effects. The hypothesized moderating effects could be corroborated for our dataset with only one exception. Regarding mediation effects, we could identify only one weak indirect effect between *Unobtrusiveness* and *Behavioral Intention*. In summary, *Context Awareness* had the strongest effects on all predictors of the UTAUT2 model considered in our study, while the other two showed significant but weaker effects. Our model accounts for 64%

of the variance in *Behavioral Intention*, in addition the pervasiveness constructs were able to explain a high percentage of variance for each of the independent variables in UTAUT2.

The present study comes with limitations that point to opportunities for further research. First of all, even though the size of our sample is large enough for testing our structural model, larger samples would be beneficial to additionally investigate the differences in adoption behavior between geographic regions and additional demographic factors such as income or education. Second, while having obtained sufficient explanatory power, our results nevertheless leave room for additional factors not included in our research model that might influence adoption behavior. In particular, the inclusion of the factors *Facilitating Conditions* and *Habit* would allow for a full integration of the pervasiveness constructs into UTAUT2. Finally, we propose to discuss and empirically test the relevance of privacy factors since those gain increasing importance among potential users of pervasive technologies.

4. Towards a Future Internet of Things in Retail

4.1 Introduction

The retail industry underwent a number of disruptions and challenges during the last 50 years. In the 1960s and 1970s, as discount stores were opened by retail companies such as Walmart, it caused a profound impact on their retail competitors and changed the retail sector fundamentally. Their strategy of cost leadership due to size, scale of operation, and efficient supply chain management (SCM) enabled them to operate at lower costs and to offer their products at lower prices than their competitors. The 1970s and 1980s saw a technological disruption with the adoption of the barcode which found its way into the retail industry. First barcode scanning systems were installed in the United States and shortly afterwards in Europe and their inherent advantages made a success story up to date. Barcode systems proved to be a cost-effective and easy to implement solution, and beyond that it provided increased accuracy compared to keyboard entries. Without any doubt, a radical change was the emergence of e-commerce in the 1990s, which became quickly a key challenge for traditional retailers. The benefits were clearly noticeable for both online retailers and customers in terms of lower transaction costs due to internet-based transactions, a better market understanding as customer behavior could be better tracked with data analysis, and unlimited geographical coverage as e-commerce can be accessed from any place, at any time. Today, e-commerce is no longer an alternative, it is an imperative. In similar fashion, the Internet of Things (IoT) will most likely be responsible for radical changes in retailing when looking ahead to the next ten to twenty years.

Today, the concept of IoT remains a future vision, however, it seems to gain a particular importance to specific industries and other key players with the result that serious efforts are taken to make it become a reality. In 2002, three years after the term “Internet of Things” was coined by Ashton (2009), the IoT was predicted to become visible for the upcoming ten years in “most every consumer item, from jeans to dish soap, will probably bear a tiny chip that continually broadcasts its existence to radio-frequency readers at loading docks, store shelves, entrances and parking lots-just about everywhere.” (Schoenberger, 2002) We know today that the evolution of the IoT takes more time than expected, not least because of the reluctance of industry to drive its evolution further.

Issues such as return on investment or security and privacy are obstacles that need still to be overcome. Despite the fact that many future IoT scenarios have not come true yet, further development and integration of key technologies continued which serve as a basis for many of these scenarios. For example, near-field communication (NFC) is incorporated in many smartphones today in order to enable mobile payment.

Apart from individual businesses and people, success or failure of the IoT also depends on macroeconomic conditions. In this respect, the governance of the IoT and the legal framework play a crucial role (Weber and Weber, 2010). It was the conventional wisdom that the Internet is uncontrollable and cannot be governed; however, continuous increases in government regulation have proven otherwise (Bowie and Jamal, 2006). This raises the question as to what extent the IoT is a controllable medium to comply with the often-mentioned privacy policy, which remains a key public issue for the IoT. It is not a matter if, but how basic features of privacy (secrecy, anonymity, and solitude) will be addressed in a trustful manner to avoid people fearing the IoT (Weber and Weber, 2010). This is of particular importance in view of IoT applications in healthcare where sensitive and confidential personal data is stored on and retrieved from (cloud) servers.

At the beginning of the emergence of the IoT, SCM was considered as one of the first profiting domains of being able to read things electronically based on the RFID technology (Asif and Mandviwalla, 2005). Closely connected with SCM, the retail industry began exploring the opportunities of employing RFID technology. Companies such as Gillette Company or Gap, Inc. started early to explore the potentials and benefits of RFID-tagged products in order to prevent stock-outs or to cut costs (Bose and Pal, 2005). In 2003, the world's largest retailer, Walmart, took the lead in RFID for retail by announcing that it requires its major suppliers to adopt this technology and tag all cases and pallets by 2005 (Boyle, 2003). At that time, many experts were convinced that this strategy would contribute to the technology's breakthrough in retail. However, a number of technological as well as organizational challenges, the issue of cost distribution among all supply chain parties, and security and privacy issues prevented the worldwide implementation of RFID in retail to date.

In this study, we follow the objective of estimating the probable future development of the IoT within the retail industry. We addressed major economic and societal issues encountered in the development of future scenarios for the IoT in general and the retail sector in particular. For this purpose, a Delphi study was conducted to predict how certain projections in the context of the IoT will apply to future scenarios and in what way they will be influenced by the macroeconomic and microeconomic developments.

The remainder of this chapter is organized as follows. Section 4.2 gives an overview of related work, while section 4.3 explains the underlying research methodology. Section 4.4 outlines the Delphi study and its results, which provided the input for the scenario development presented in section 4.5. Finally, section 4.6 summarizes the study and draws implications from the results.

4.2 Related work

As much as e-commerce signified a radical change in retailing, the IoT might impact it to a similar extent. A plethora of studies have focused on the employment of RFID technology in retail in the last ten years, mainly because it has been considered as the key technology and driver for the IoT (Ngai et al., 2008). Besides, a number of academic and non-academic foresight studies in the context of retail have been published in the last ten to fifteen years.

An early work stems from Clough (2002) who investigated UK food retailing from post-1950 to 2010. In a multi-stage approach, he conducted a comprehensive qualitative analysis to identify the elements of the theories of retail change which explain the UK food retailing change between 1950 and 2000. A further objective was to uncover the driving forces which are summarized in a history of main events. Major factors identified comprise government policy, socio-economic change, changes in technology, and retailer change. These results served as input for the forecasting study. Those elements of the theories of retail change which are relevant were taken as input to forecast likely developments in the UK food retail industry to the year 2010. Finally, a Delphi study complemented the research to obtain a projection of socio-economic trends at the time of the study. The results show that likely developments for retail affect the cost base due to improved services and sophisticated systems or competition will increase because of international retailers entering the market, among others.

A further early study addressed the impacts of emerging e-commerce technologies on overall business processes (Ewton, 2003). By means of an analytic Delphi study, twelve e-commerce experts assessed the adoption of e-commerce technologies and their impacts on business processes. With the initial e-commerce technologies identified, an analytic hierarchy process was used to quantify the judgments. The results of the study reveal that e-mail and electronic customer relationship management were considered as having the most impact on creating business change agents. The main challenges were seen in the lack of bandwidth and missing portable-computing platforms.

Goodman et al. (2007) designed future retail scenarios against the background of sustainable development for the year 2022. The objective was to deliver scenarios which challenge the retail sector while taking into account continuous and radical change and thus to develop robust and future-proof strategies for a sustainable retailing. Based on the opinions of more than 60 experts, four scenarios were compiled of which three deal with consumers that are less willing to trust that business follows societal interests, while in the fourth, consumers want business to take a greater social role.

Bhattacharya et al. (2011) examined the key business processes and value chain activities that are improved by RFID. They conducted a Delphi study with 74 experts in which the three dimensions of RFID adoption status, RFID applicable business processes, and RFID applicable value chain activities have been considered. Each of these dimensions consists of a number of items which were evaluated individually to obtain a rating average. In a further step, a factor analysis revealed to what extent each item loads onto its corresponding dimension. Receiving, tracking and tracing, and replenishing were identified as the most significant RFID applicable business processes, while in-store operations, warehouse management, and replenishment are the most significant RFID applicable value chain activities. A related study by Bhattacharya (2012) analyzed RFID adoption drivers, benefits, and implementation challenges. A mixed method approach was undertaken which consisted of a content analysis and a subsequent Delphi study. In the content analysis, academic and trade articles were analyzed to identify the key issues and concepts. This served as input for the Delphi study which was based on the same expert panel as in the study described above. The results show that the main driver for RFID adoption are technology costs, while the main benefits were seen in the inventory and visibility aspects of RFID technology. In summary, the major challenge for RFID adoption could be attributed to the importance of costs and the associated return on investment rather than privacy concerns.

PriceWaterhouseCoopers and TNS Retail Formward (2007) carried out a study in which they identified 15 growth drivers and predicted 15 trends that were assumed to redefine the retail environment by 2015. Among shifting demographics, household downsizing and new marketing channels, the report draws the conclusion that the retail industry will need to adopt a more targeted consumer approach to reach an increasingly diverse and tech-savvy population. It projects that retailers in conjunction with their customers will be more demanding, more global as well as diverse and will operate across more channels than ever before. A follow-up study identified and examined the key change drivers that might impact the US retail landscape as well as its customers (PriceWaterhouseCoopers and Kantar, 2012). Among others, the discovered key change drivers are speed of technological changes and demographic changes, while the identified key trends encompass globalization, omnichannel and consumer-centric retailing.

The potential of RFID item-level tagging in the retail sector was investigated by Kasiri et al. (2012). Their objective was to detect the tangible as well as intangible benefits of RFID item-level tagging for retail store operations such as marketing, merchandising, and SCM. Therefore, they adapted the balanced scorecard framework to create an item-level RFID balanced scorecard model and derived performance measures for each of the regarded operations. These performance measures were confirmed in a Delphi study with ten participating consultants and senior managers from leading US retailers. Subsequently, a cause-and-effect diagram could be generated as a result of the Delphi study. The study's results clearly suggest that SCM benefits the most from RFID item-level tagging, while there are less effects on merchandising and marketing but both should not be underestimated.

The "Global E-Tailing 2025" study considers four exploratory future scenarios that have been developed on the basis of a global and medium-term perspective (Deutsche Post DHL, 2014). The scenarios provide for all contingencies, that is, they deliberately take into account upheavals and discontinuities in order to foresee both opportunities and risks which might impact the strategies and possible courses of action. In a multi-step process, influencing factors were elaborated and provided the basis for the key factors and their future development. These developments were evaluated by experts to distill projections which, in turn, were integrated into raw scenarios after a consistency analysis. The final steps included the transformation of raw scenarios into detailed scenarios and to develop strategic implications for each individual scenario. The final result highlights for each scenario probable developments in the retail sector and the implications for the logistics industry.

The impact of ICT on the future of retail was investigated by Mulligan and Gurguc (2015). In their study, they focus on two areas within retail, these are, fast moving consumer goods and order fulfillment, for which they examine the impact of ICT on productivity improvements and industrial transformation. Based on systems analysis, they elaborate the operating boundaries of each industrial structure and highlight the role of data within those boundaries and the resulting information value chains.

The retail sector depends on logistics and the manner in which goods and services are delivered to consumers, which plays a crucial role in retail SCM. We found three relevant foresight studies related to SCM. The first study deals with the change of consumer behavior between 2009 and 2020 (Deutsche Post, 2009). Further, the impact of macroeconomic conditions (e.g. technological developments) and their probable influence on the behavior of companies and individuals were investigated. On the basis of extensive discussions with a group of 38 specialists, 81 theses on the future were consolidated and presented to a group of 900 industry experts for evaluation. The main results consist of ten trends for the next ten years clustered in three different dimensions, these are, global developments, the "new" customer, and altered logistics.

The second study undertaken by Deutsche Post describes five raw future scenarios for the world in 2050 (Deutsche Post, 2012). These scenarios were developed on the basis of survey inputs of internal logistics experts from Deutsche Post DHL and interviews with external experts from diverse fields. In a first step, the influencing factors that determine trends in the logistics environment were identified and classified to obtain 14 key factors. In a second step, three to four projections were developed for each key factor based on expert interviews. The projections were mapped onto the final five raw scenarios and discussed with the internal as well as external experts to verify the consistency and underlying logic of the scenarios. Finally, implications for the logistics industry and strategic options were elaborated.

The third study examined the future of the logistics services industry (von der Gracht and Darkow, 2010). It describes potential long-term developments of the logistics environment by creating future scenarios. The study not only focuses on the micro-environment, but also on the macro-environment in that projections are formulated according to a PEST-analysis (political, economic, social, and technological). The projections are evaluated by a panel of 30 experts in a Delphi study with a time horizon to the year 2025. In the subsequent scenario development process, they conclude five dominant themes that are likely to influence the macro-environment as well as the industry structure. Finally, they included analyses of discontinuities and surprising occurrences to account for possible but improbable changes in the macro-environment and in the industry structure for the logistics service industry.

Only a few of the studies presented take the perspective from a macro- and micro-environment. None of the studies combine these perspectives with a Delphi study and scenario development process to evaluate certain projections quantitatively as well as qualitatively, except for von der Gracht and Darkow (2010). Even though their study is in a related field to retail, namely logistics, it does not cover retail specific areas. Thus, we adopt the approach taken by von der Gracht and Darkow (2010) and apply it to the field of retail.

An overview of the related work is provided in Table 18 which summarizes the studies in chronological order and briefly presents the author, industry context, methodology employed, time horizon, and main results.

Table 18. Overview of related works

Title (Author(s))	Industry context	Methodology	Horizon	Main results
Retail change: a consideration of the UK food retail industry, 1950-2010 (Clough, 2002)	Retail	Delphi study based on a panel of 11 experts	2010	Evaluation of the UK food retail change post-1950 and extension of retail change theory. Forecast of likely key developments until 2010 and a projection of socio-economic trends.
Assessment of the impacts of e-commerce technologies on overall business processes: an analytic Delphi process (Ewton, 2003)	Retail	Delphi study based on a panel of 12 experts	-	Identification of key e-commerce technologies and business change agents. E-mail and electronic customer relationship management were considered as having the most impact on creating business change agents. Main challenges are the lack of bandwidth and missing portable computing platforms.
Retail Futures - Scenarios for the Future of UK Retail and Sustainable Development (Goodman et al., 2007)	Retail	Scenario analysis based on more than 60 expert views	2022	Four scenarios for the future of UK retail with emphasis on sustainable development: 1) My way; 2) Sell it to me; 3) From me to you; 4) I'm in your hands.
Retailing 2015: New Frontiers (PriceWaterhouseCoopers and TNS Retail Formward, 2007)	Retail	Trend forecasting	2015	Identification of change drivers and critical success factors for retailers and suppliers to manage the complexity and diversity of retailing in 2015.
Delivering Tomorrow - Customer Needs in 2020 and Beyond - A Global Delphi Study (Deutsche Post, 2009)	Logistics	Delphi study based on a panel of 38 specialists and 900 industry experts	2020	81 theses on possible future trends and events were assessed by experts for their likelihood of occurrence and a possible time when they would occur from 2015-2020. Ten most important trends are derived from the results.
Scenarios for the logistics services industry: A Delphi-based analysis for 2025 (von der Gracht and Darkow, 2010)	Logistics	Scenario development and Delphi study based on a panel of 30 experts	2025	First, 41 projections were generated which were then assessed by experts to estimate the development of probable and unforeseen scenarios. Recommendations for strategy development are provided.

Table 18. Overview of related works (continued)

Title (Author(s))	**Industry context**	**Methodology**	**Horizon**	**Main results**
A Delphi study of RFID applicable business processes and value chain activities in retail (Bhattacharya et al., 2011)	Retail	Delphi study based on a panel of 74 experts	-	Key business processes and value chain activities improved by RFID are evaluated by experts. Receiving, tracking and tracing, and replenishing are the business processes which are impacted the most by RFID. In-store operations, warehouse management, and replenishment are the most important RFID applicable value chain activities.
Retailing 2020: Winning in a polarized world (PriceWaterhouseCoopers and Kantar, 2012)	Retail	Expert interviews	2020	Six key drivers: 1) Speed of technological changes; 2) Shifts in US demographics and shopper behavior; 3) Ripple effects of the changing global shopper; 4) Global economics of procurement; 5) Transparency and knowledge-centric shopping; 6) Challenges to retailer economic models. Six key trends: 1) Consumer-driven supply chain; 2) Growth fragmentation of retail channels; 3) Retail growth from unfamiliar markets; 4) Omnichannel retailing; 5) Consumer-driven transparency; 6) Consumer-centric retailing.
A balanced scorecard for item-level RFID in the retail sector: a Delphi study (Kasiri et al., 2012)	Retail	Delphi study based on a panel of 10 expert interviews	-	Development of a holistic model of RFID-enabled changes and adoption of the balanced scorecard model as a decision-making framework. Highest impact of RFID on supply chain opposed to merchandising and marketing. The proposed balanced scorecard model also indicates potential opportunities for item-level RFID use in retailing.

Table 18. Overview of related works (continued)

Title (Author(s))	**Industry context**	**Methodology**	**Horizon**	**Main results**
Delivering Tomorrow - Logistics 2050 - A Scenario Study (Deutsche Post, 2012)	Logistics	Scenario analysis based on 22 expert interviews	2050	Five of the identified clusters were chosen as raw future scenarios: 1) Untamed economy, impending collapse; 2) Mega-efficiency in mega cities; 3) Customized lifestyles; 4) Paralyzing protectionism; 5) Global resilience, local adaptation. Analysis of implications on 1) Infrastructure development; 2) Carbon efficiency in transport; 3) Supply chain visibility and security; 4) Customs regulations; and 5) International trade agreements and the reduction of red tapes.
Impact of RFID on the Retail Value Chain: An Exploratory Study Using a Mixed Method Approach (Bhattacharya, 2012)	Retail	Content analysis and Delphi study based on a panel of 74 experts	-	A content analysis of articles revealed key issues and concepts of RFID adoption drivers. This served as input for the Delphi study. Firm-centric inventory and visibility aspects outweigh anticipated customer service benefits. The main challenge is technology cost as driving adoption decisions rather than privacy concerns.
Global E-Tailing 2025 (Deutsche Post DHL, 2014)	Retail	Scenario analysis based on ethnographic trend scouting in 12 cities and expert interviews	2025	Four future scenarios: 1) Hybrid consumer behavior in convergent worlds of retailing; 2) Self-presentation in virtual communities; 3) Artificial intelligence in the digital retail sphere; 4) Collaborative consumption in a regionalized retailing landscape
ICT & the Future of Retail (Mulligan and Gurguc, 2015)	Retail	Systems analysis	-	The impact of ICT on retail is measured in the two dimensions productivity improvements and industrial transformation. Big data and information value chains are predicted to be critical for the effective and efficient functioning of the retail industry. ICT will also reshape the nature of the retail industry in that the coordination improves between consumers, manufacturers, and retailers due to new innovative means.

4.3 Methodology

The Delphi method is mainly used as a forecasting method and was first used in technology forecasting studies initiated by the RAND (Research and Development) Corporation for the American military during the 1950s. At this time, it was applied to "obtain the most reliable consensus of opinion of a group of experts … by a series of intensive questionnaires interspersed with controlled opinion feedback." (Dalkey and Helmer, 1963) The Delphi method is supposed to enhance creative thinking, thus it is "one of the best known methods for dealing with open-ended and creative aspects of a problem because it motivates independent thought and gradual formation of group solutions." (Gupta and Clarke, 1996) Further, it is a socio-scientific method that aggregates expert knowledge of selected panelists in a structured and systematic process. This method is considered particularly useful in cases where long-range estimations of 20 to 30 years are made, as expert opinions are the only source of information available for well-founded estimations (van Zolingen and Klaassen, 2003). It starts from the premise that group judgment is more valid than individual judgments. In a multi-staged survey, the objective is to reach consensus on a specific issue or topic among a set of experts, the expert panel, who have a broad knowledge in their field of expertise. As a widely used research instrument, it aims to close the gap of incomplete knowledge or to develop forecasts. A commonly accepted definition, on which most of the researchers draw, stems from Linstone and Turoff (2002) who define the Delphi method as "a method for structuring a group communication process so that the process is effective in allowing a group of individuals, as a whole, to deal with a complex problem."

Even though the Delphi method offers degrees of flexibility in its application (Kendall, 1977), it depends on four key features that may be regarded as necessary to meet the requirements of a "Delphi" procedure (Rowe and Wright, 1999). The four features are (i) anonymity, (ii) iteration, (iii) controlled feedback, and (iv) statistical aggregation of group response. The use of questionnaires ensures that anonymity is achieved. The rationale behind this aspect is that anonymity restricts possible bias that could arise from peer pressure or dominant individuals within the expert group. Iteration of the questionnaire over a number of rounds enables the individuals to alter their opinions and judgments without justifying themselves to the other experts in the group. Controlled feedback is provided after each questionnaire iteration in order to inform each individual about the opinions of the other expert group members. In most cases, the feedback is given as a simple statistical summary of the group response such as the mean value. At the end of the last iteration, a statistical aggregation (mean or median) of the group response is calculated.

Panel size and the expert aptitude for the research context in question are two issues in a Delphi study (Linstone and Turoff, 2002). Skulmoski and Hartman (2007) reviewed a number of Delphi studies and the sizes of the panels varied from 3 to 171 which clearly demonstrates that there is no definite rule for a specific sample size. There are different opinions on the size of an expert panel. Turoff (1970) and Johnson (1976) suggest a number of 10 to 15 experts, while Cavalli-Sforza and Ortolano (1984) state that "a typical Delphi panel has about 8 to 12 members." As a general guideline, the number of experts in a panel will vary depending on the scope of the problem and the available resources (Fink et al., 1984; Hasson et al., 2000). However, Murphy et al. (1998) show that the higher the number of experts, the more reliable are the judgments of the panel. At the same time, they also claim that there is no evidence about the relationship between the size of the panel and the reliability and validity of the final consensus.

In relation to panel size is the issue of high dropout rates during a Delphi study (van Zolingen and Klaassen, 2003). This issue can be traced back to different reasons, for example, experts realize that the participation is more burdensome and time-consuming than anticipated or they suffer from respondent fatigue after two or three rounds (Fink et al., 1984; Mitchell, 1991). If high dropout rates occur, it may mean that the final results are based upon a non-representative sample subgroup and the conclusions drawn are questionable (van Zolingen and Klaassen, 2003).

The estimated time duration for questionnaire completion in each round is a decisive argument for expert participation. According to Mitchell (1991), the maximum time commitment required per round should not be longer than 30 minutes. Regardless of the final decision on estimated time duration by the researcher, the experts should know about the time-related aspects of the study (e.g. number of rounds or estimated time duration of each round) from the beginning.

Pretesting questionnaires is an essential step to ensure reliability in Delphi studies (Okoli and Pawlowski, 2004). It avoids later misunderstandings among survey participants beforehand and gives the researcher the opportunity to improve the questionnaire prior to the actual survey. Subjects who test the questionnaire should give feedback on criteria such as clarity and comprehensibility of questions, problems with the tasks, technical problems, and time duration (Häder, 2009). Ideally, a pretest should be performed by coworkers who were not involved in the questionnaire design in order to minimize bias (Turoff, 2002).

In our study, we incorporate expert knowledge based on the Delphi method into scenario planning as a promising option. A number of authors advocate the development of Delphi-based scenarios for the explorative and long-term oriented derivation of future scenarios (von der Gracht and Darkow, 2010; Kameoka et al., 2004; Nowack et al., 2011), hence we used this modified approach of a Delphi study. In this context, scenarios support the research in identifying and elucidating strategic objectives and to develop knowledge-based estimations for decision-makers. The scenarios used in our study are self-contained and embody possible visions that present alternative views of the future indicating potential trends and challenges.

4.4 Delphi study

The Delphi study presented in this section was undertaken within the EU project "Internet of Things Architecture" (IoT-A) as part of the socio-economic analysis of the IoT. It delivered results for the impact of the IoT on the retail industry using future retail scenarios. The study was conducted between May and July 2013.

The process by which this study has been conducted is depicted in Figure 41. It can be divided into five main process steps each consisting of a number of tasks. The first process step was the preparation of the study in which the research framework with the corresponding research question were defined. Following this, we made a comprehensive expert selection which is explained in more detail in section 4.4.1. The next process step was a pre-study in which we collected qualitative input from our expert panel to support the development of projections (see section 4.4.2). This set of projections, in turn, was subject to evaluation by the experts in the subsequent two survey rounds. The two Delphi rounds conducted, round 1 and 2, are described in section 4.4.3 and 4.4.4, respectively. We provide a summary of all results in section 4.4.4, which were the basis on which the scenarios of the probable future were developed in section 4.5.

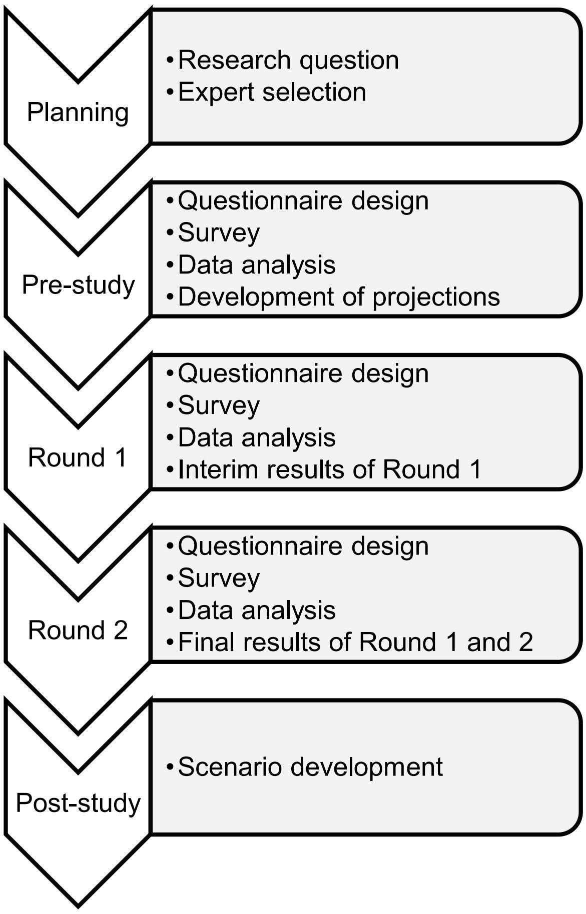

Figure 41. Delphi study process

4.4.1 Planning

The initial step of our study was the formulation of the research question. As explained in section 4.2, we adapted the research framework of Delphi-based scenarios applied by von der Gracht and Darkow (2010). This framework allowed us to consider the macro- and micro-environment of the retail industry and to conduct a quantitative as well as qualitative evaluation of expert opinions based on a Delphi study to estimate certain future retail scenarios. We formulated two underlying research questions for our study:

1. How will the macro-environment (political, economic, social, and technological structure) change in general for the retail industry in the context of the Internet of Things by the year 2030?
2. How will the micro-environment change specifically for the retail industry in the context of the Internet of Things by the year 2030?

The appropriate selection of experts is a critical requirement in each Delphi study since the results depend on the right input. Therefore, qualified experts with a deep understanding of the problem context are necessary to ensure the group decision mechanism to work correctly (Okoli and Pawlowski, 2004). To meet this quality requirement, we employed multi-perspective criteria to establish our expert panel (Nowack et al., 2011). We compiled a list with potential candidates who either were academics or practitioners. The requirement for an academic to appear in the list was a scientific publication in an IoT-related field, while a practitioner had to either work in an IoT-related company or do research on this topic. We considered it necessary to primarily approach IoT experts rather than retail experts as a technological knowledge base was deemed critical and IoT experts usually have a broad understanding of IoT applications. The final list contained 57 candidates of which 28 were academics and 29 practitioners. In a next step, we contacted each of the candidates in that we sent them an invitation email with an overview of the study (see Appendix B) and the request to give notification whether or not they agree to participate in the study. For the sake of simplicity among the expert panel, we referred to the pre-study as round 1 in the invitation mail but internally round 1 and 2 were the two survey iterations for obtaining the quantiative evaluations.

Our final expert panel consisted of 15 participants. This number met our targeted expert group size of 12-15 experts and complies with recommendations presented in section 4.3. Thus, we achieved a response rate to our invitation of 26%. Those experts who participated were also asked to give a self-assessment about their retail knowledge. Figure 42 shows the self-assessments of the participating IoT experts. The figures reconfirm that our selection of experts regarding the topic IoT was reasonable. Thirteen experts indicated to have at least a high knowledge in IoT, while two of them even had a very high knowledge (see Figure 42a). For the retail industry, the self-assessments of the experts' knowledge are slightly lower but still entirely sufficient to evaluate topics related to retail in order to achieve acceptable results (see Figure 42b). Our target was to have at least half of the group with a retail knowledge of medium or higher which could be achieved since only two participants had a lower knowledge.

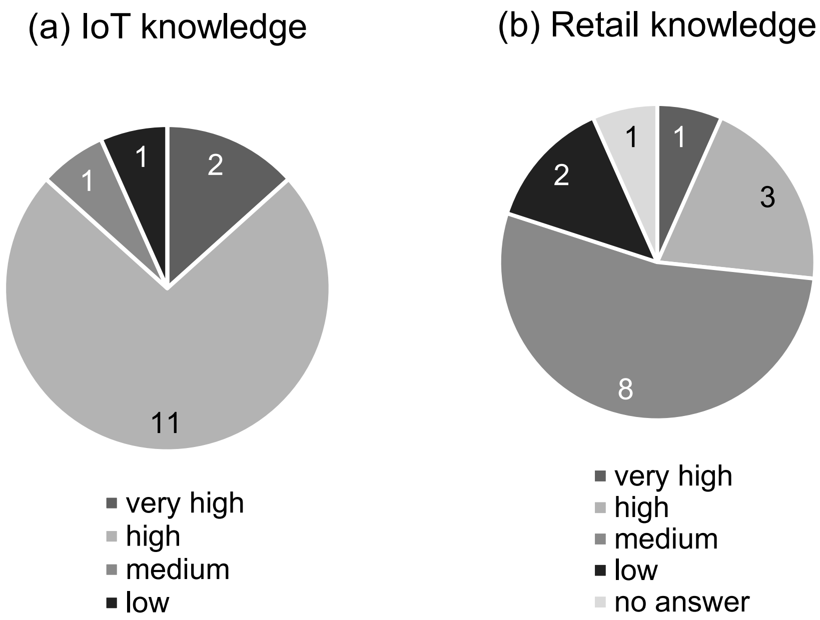

Figure 42. Expert knowledge

The international experts stemmed from eleven different countries, most of them from Europe (see Table 19). The gender distribution of the expert panel was 14 male and 1 female. The majority were either researchers or consultants and the average experience in their positions was 12.5 years.

Table 19. Expert origin

Country	Participants
Austria	1
Belgium	1
France	1
Germany	2
Greece	1
Italy	2
Luxembourg	1
Netherlands	3
Slovenia	1
UK	1
USA	1

4.4.2 Pre-study

The pre-study's objective was to identify potential factors that will influence the future in terms of social and economic development, given the increasing proliferation of IoT. The pre-study questionnaire was designed with open-ended questions in the fashion of a brainstorming enabling the experts to give their professional opinions on different IoT-related topics in a semi- or unstructured open response. This allowed them to elaborate freely with a broad scope on the topic under investigation. A qualitative analysis of the results was undertaken to provide a foundation on which we designed the first round questionnaire. Particularly, the factors identified were analyzed and generated input for the development of the projections for future scenarios. This procedure of input generation by experts in a pre-study round was adopted from De Vet et al. (2005).

The pre-study questionnaire was designed in a semi-structured format according to the perspectives of the PEST framework and the retail industry. The survey was implemented and conducted with the help of the online survey tool Limesurvey. All experts were asked to complete the questionnaire with five sets of questions according to the perspectives of the PEST framework and the retail industry. First, we wanted to know which impact, challenge or issue for each perspective might play an important role in the future. As this sole information was not considered as sufficient, we also asked for the cause(s) and effect(s) of the corresponding impact, challenge or issue to get a clearer understanding of the context.

The qualitative answers served as input for the subsequent quantitative rounds in which the projections for the perspectives of the PEST framework and the retail industry were first formulated and then given to the experts to estimate their impact as well as probability of occurence. The input from the pre-study was carefully scanned for potential influencing factors that could be considered in the development of the projections. In total, we identified 57 factors within the submitted survey answers. Furthermore, a thorough desk research was conducted in order to combine the expert input with data from literature with the result of additional 42 factors identified. Out of these factors we developed the projections for the target year 2030. We chose this target year based on the assumption that everyday objects will communicate by 2025 (Atzori et al., 2010), and extended this assumption by five years in order to project a time horizon of nearly 20 years in the future.

Table 20. Final list of projections

No.	Projection for the year 2030
	Political
1	The Internet of Things (IoT) adoption process is slowed down due to the domination of influential standardization organizations and missing real open standards.
2	Unregulated data generation and distribution has led to a consumer demand for more restrictions and laws to ensure better data protection and ownership.
3	The full potential of IoT cannot be exploited in consequence of too strict rules and regulations in data privacy.
4	The harmonization of European data protection legislation has led to a coherent application of this legislation and a high level of enforcement.
	Economic
5	The growth of e-commerce and m-commerce, and changes in consumer behavior, have increased the benefits for retailers. Multiple channels enable retailers to constantly stay in touch with consumers.
6	The market leaders for IoT solutions are located in the US and in China due to their leading roles in hardware and software development.
7	Big Data generated by IoT closes the information gap. This enables retailers to exploit real-time data and new data analysis methodologies to forecast consumer trends. This information is used to increase profits.
8	The issue of cost distribution of information and communication technology (ICT) in open loop systems is solved by payment models. Parties which benefit the most pay the most. Thus, supply chain information sharing works because each party acquires a financial interest.
9	Required ICT demands large capital investments, which can hardly be raised by small and medium-sized retailers.
	Social
10	People mistrust the IoT because they are not aware of personal data becoming “public domain.”
11	Transformation of work affects the retail sector. Manual work has become less important due to an increasing degree of automation (e.g. self-checkout).
12	Retailers provide new concepts (e.g. remote order with home delivery) to cope with the continuous challenge of demographic change.
13	Consumers increasingly demand sustainable retailing, i.e. waste reduction of perishables, fair trade products.
14	Information security is perceived as a basic requirement in the provision of IoT services, not only in view of ensuring information security for an organization, but also for the benefit of the citizens.
	Technological
15	Mobile payment acceptance, utilization, and confidence is well established. Cash will no longer be accepted which will have mutual benefit to the retailer and the shopper.
16	New technologies in retail obtain faster consumer acceptance as compared to 2013.
17	Barcode systems are almost completely substituted by smart label systems (e.g. RFID).
18	RFID is the leading technology grounding the success of IoT as it is the most mature IoT technology. As a result of the declining unit prices, RFID remains the most prevalent enabling technology for IoT.
	Retail industry
19	Retailers blend the online and offline shopping - the digital and the physical – into one seamless, omnichannel shopping experience.
20	Shoppers are willing to share personal information and shopper preference data. Retailers use this sensitive information appropriately to enhance the shopping experience.
21	Customers get advice at the point of sale through mobile shopping assistants or their own mobile device according to their preferences, presence of allergic components, or the actual product quality of food.
22	Service and in-store experiences continue to break out of the one-size-fits-all offerings. These experiences have become more individualized and specialized for specific target groups.

The draft versions of the projections were subjected to a number of internal revisions in order to obtain a high quality. After their initial formulation, a project-internal assessment of the draft projections was performed to check for completeness and plausibility of the content. After the project-internal assessment, a pretest was conducted by two project-external experts, who have not been involved in the questionnaire design, to get feedback about the content and the time needed for completion. The feedback was processed and suggestions for improvements were considered where necessary.

As a result, 22 projections made it into the final list of projections for evaluation (see Table 20). From a structural point of view, we maintained the structure of the perspectives of the PEST framework in conjunction with the retail industry.

4.4.3 Round 1

The final list of projections was the main outcome of the pre-study. After the pretest, all experts of the panel received an invitation mail to participate in the first round and to evaluate the projections (see Appendix C). In the first round, the projections were evaluated to measure the degree of consensus among the experts based on statistical analyses. The timeframe of this round was from end of May until mid-June 2013.

All projections were evaluated for their probability of occurrence, their impact on the retail industry, and their desirability in order to obtain measures for statistical analyses. As in the pre-study, we implemented the questionnaire into the survey tool Limesurvey. First, we asked the experts for the probability of occurrence which was measured using a 9-point Likert-scale ranging from 10% to 90%. The reason why we left out values below 10% and above 90% was because none of the projections were absolutely unlikely or likely, respectively. Additionally, we asked the experts to provide a brief reason in a text field to better understand their estimate and to offer feedback in case of misunderstandings. Second, the impact on the economy was measured on a 5-point Likert-scale ranging from very high to very low. Third, the desirability of occurrence was evaluated by using a binary value, i.e. “desirable” or “not desirable.” This three-step structure was applied for each of the 22 projections.

After all 15 surveys have been completed, the results were processed in order to perform a first interim analysis based on descriptive statistics, these are, the interquartile range (IQR), mean, and standard deviation (SD). In most Delphi studies, consensus among participants is assumed when a certain percentage of evaluations fall within a predefined range. Regarding the consensus criterion for our study, we followed suggestions from literature indicating that an IQR of 2 or less suffices to claim consensus, taking into account the wide range of the Likert-scale for the probability of occurrence (von der Gracht and Darkow, 2010). The IQR is the absolute value of the difference between the upper and lower quartile, with smaller values meaning higher degrees of consensus (Rayens and Hahn, 2000). Further, we calculated the mean and SD for the probability of occurrence, the mean of the impact on the economy, and the desirability of occurrence.

The interim results of the first round show that 6 of the 22 evaluated projections (27%) reached consensus among the experts (see Table 21). Eight projections had an IQR of 3 for which they were close to consensus. It becomes obvious that a very strong agreement among the experts could be achieved for the perspective of the retail industry. Three of the four projections reached consensus, with two projections showing an IQR of 1. In general, all projections which reached consensus showed a relatively high mean value for their probability of occurrence; that is, a value of 6 or higher. Regarding the impact on the economy, the mean values vary between 3.2 and 4.3 and do not have any consistent pattern. However, the average to high values show the relevance of the developed projections and justify their inclusion. The results for desirability depend on the formulation of the projection, which is why for instance the first projection has a rather low desirability because of its negative connotation. Interestingly, all projections with a low desirability (<40%) were seen as having a relatively low impact on the economy except for projection number 6. Further, we found a correlation between desirability and the probability of occurrence; that is, projections with a low desirability were rated with a relatively low probability of occurrence.

The results of the interim analysis were integrated in a feedback document for the experts. This document had to be generated for each expert individually as it included the results of each expert and the group opinion showing to which degree each expert deviated from the general opinion. Furthermore, we aggregated all comments for each projection to give all experts an insight of opinions about the projections provided from each expert.

Table 21. Delphi statistics for round 1

	Round 1 (n=15)				
Projection no. and short title	**IQR**	**Mean**	**SD**	**Impact**	**Desirability**
Political					
1. IoT adoption	3	3.4	1.6	3.3	33.3
2. IoT potential	4	5.4	2.5	3.5	46.7
3. Privacy issues in consumer data	4	4.7	2.6	3.2	26.7
4. Legislation harmonization	4	4.9	2.2	3.5	86.7
Economic					
5. Consumer-retailer interaction	3	7.3	2.0	4.3	86.7
6. Global market share	3	5.4	2.4	4.1	20.0
7. Data analysis	6	6.7	2.8	3.9	80.0
8. ICT cost sharing	3	5.3	2.0	3.6	73.3
9. ICT investments	3	3.3	1.5	3.4	13.3
Social					
10. Societal distrust	6	3.9	2.7	3.3	20.0
11. Work transformation	4	4.7	2.2	3.4	33.3
12. Demographic changes	2*	7.3	1.8	4.0	93.3
13. Sustainable retailing	3	6.7	1.8	4.1	100.0
14. Information security	2*	7.6	1.7	3.4	93.3
Technological					
15. Cashless payments	2*	6.3	1.7	3.4	66.7
16. Technology acceptance	4	6.3	2.5	3.5	73.3
17. Substitution of barcode	3	7.1	2.1	3.3	86.7
18. Technology maturity	3	5.5	2.2	3.7	60.0
Retail industry					
19. Omnichannel retail strategy	4	7.1	1.9	3.7	73.3
20. Savvier shopper	1*	6.4	1.5	3.6	80.0
21. Intelligent shopping applications	2*	6.9	1.8	3.5	80.0
22. Individualized services	1*	7.2	1.8	4.0	86.7

Note: An asterisk marks projections where final consensus was reached, i.e. an IQR of 2 or less
IQR = Interquartile Range
SD = Standard deviation

4.4.4 Round 2

After compiling the feedback document for each expert subsequent to the first round, the second round was prepared. The purpose of the second round was to give the experts the opportunity to reconsider their assessments on the basis of the group's opinion indicated in the feedback document of round 1. Based on the results of round 1, the second questionnaire for round 2 was developed. The dropout rate after round 1 was 7%, i.e. we could get 14 completed questionnaires in round 2 in contrast to 15 in round 1. According to Nowack et al. (2011), this dropout rate is close to the average dropout rates of other Delphi studies and can thus be regarded as uncritical for the validity of the results. The timeframe of the second round was from end of June until mid-July 2013.

The experts were only asked to reassess the probability of occurrence for the remaining 16 projections, i.e. for those projections for which no consensus could be reached in the first round. We expected the experts not to change their initial opinion about the impact and desirability so that we limited the reassessment to the probability of occurrence for the projections. As in many past Delphi studies, the number of rounds was limited to two rounds. The reason for this decision was that the highest consensus typically appears in the first round, while with each subsequent round the level of consensus gains stability. After a second round, at latest third round, one can assume that the results will not increase the statistical accuracy (Erffmeyer et al., 1986). Following this rationale, round 2 was the last round in the Delphi study. The results of the second round were processed in order to obtain the same statistical measures for the probability of occurrence as in round 1 for those projections which had no consensus in the first round.

Table 22 summarizes the descriptive statistics from round 1 and 2 in order to draw a comparison. The experts reached consensus for 11 of the 22 projections in total after round 1 and 2 which equals a percentage of 50%. In round 2, the experts reached consensus for five projections. The results show that for both the economic and social perspective the experts could reach consensus for two further projections in round 2, while one projection belongs to the political perspective. Overall, the experts reached strong consensus for projections of the social and the retail industry perspective with percentages of 80% and 75%, respectively. A possible reason for the high degree of consensus in the social perspective might be that social concerns and challenges potentially caused by the IoT provoke a lot of controversy in society. In contrast, it seems that the retail industry perspectives targeting the micro-environment were more concrete and comprehensible and thus expert opinions converged easier, which can be seen from the fact that each of these projections has a very low value for their IQR and SD.

Another important insight is the trend between the first and second round. Regarding the IQR as consensus criterion, all corresponding values converged or stayed the same between round 1 and 2, with the exception of projection number 18. This means the experts generally converged in their opinions of the probability of occurrence for the remaining projections in the second round. The results show that those projections with an IQR of 3 in the first round reached consensus in round 2 more likely, with the exception of projection number 11. It means that if the experts initially disagreed significantly, then it was unlikely to reach consensus in the subsequent round.

Table 22: Delphi statistics for round 1 and 2

	Round 1 (n=15)			Round 2 (n=14)				
Projection no. and short title	**IQR**	**Mean**	**SD**	**IQR**	**Mean**	**SD**	**Impact**	**Desirability**
Political								
1. IoT adoption	3	3.4	1.6	2*	3.1	1.2	3.3	33.3
2. IoT potential	4	5.4	2.5	4	4.6	2.2	3.5	46.7
3. Privacy issues in consumer data	4	4.7	2.6	4	4.3	2.2	3.2	26.7
4. Legislation harmonization	4	4.9	2.2	3	5.4	1.6	3.5	86.7
Economic								
5. Consumer-retailer interaction	3	7.3	2.0	2*	6.8	2.2	4.3	86.7
6. Global market share	3	5.4	2.4	3	5.6	1.5	4.1	20.0
7. Data analysis	6	6.7	2.8	4	6.9	2.2	3.9	80.0
8. ICT cost sharing	3	5.3	2.0	1*	5.5	1.3	3.6	73.3
9. ICT investments	3	3.3	1.5	3	4.2	2.2	3.4	13.3
Social								
10. Societal distrust	6	3.9	2.7	4	3.9	2.1	3.3	20.0
11. Work transformation	4	4.7	2.2	2*	5.6	1.5	3.4	33.3
12. Demographic changes	2*	7.3	1.8				4.0	93.3
13. Sustainable retailing	3	6.7	1.8	2*	6.1	1.5	4.1	100.0
14. Information security	2*	7.6	1.7				3.4	93.3
Technological								
15. Cashless payments	2*	6.3	1.7				3.4	66.7
16. Technology acceptance	4	6.3	2.5	3	6.4	2.3	3.5	73.3
17. Substitution of barcode	3	7.1	2.1	3	6.2	2.2	3.3	86.7
18. Technology maturity	3	5.5	2.2	4	6.1	1.9	3.7	60.0
Retail industry								
19. Omnichannel retail strategy	4	7.1	1.9	3	7.0	1.9	3.7	73.3
20. Savvier shopper	1*	6.4	1.5				3.6	80.0
21. Intelligent shopping applications	2*	6.9	1.8				3.5	80.0
22. Individualized services	1*	7.2	1.8				4.0	86.7

Note: An asterisk marks projections where final consensus was reached, i.e. an IQR of 2 or less
IQR = Interquartile Range
SD = Standard deviation

A further analysis of the survey data draws the results in a new perspective taking into account the dimensions "probability of occurrence" and "impact." Figure 43 depicts the results for all of the 22 projections along the two dimensions in a scatterplot. The mean values for the probability of occurrence were converted and appear as percentage values; for instance, a value of 4.7 was converted into 47%. Each combination of a symbol and number represents the corresponding projection listed in Table 20. A white square illustrates a projection where consensus among the experts was achieved, while a black triangle illustrates a projection where consensus among the experts was not achieved.

The distribution of projections in Figure 43 provides valuable insights along the two dimensions "probability of occurrence" and "impact." It can be observed that all projections have an average impact above 3 and most of the projections have a probability of occurrence of 50% or more. Furthermore, it shows that a considerable proportion of the projections have a high concentration in the frame of a probability of occurrence between 54% and 64% and an impact between 3.3 and 4.1. The results clearly demonstrate that projections, where consensus was not achieved, have an average probability of occurrence significantly lower than where consensus could be reached. Furthermore, the projections without consensus are more scattered along the horizontal axis in comparison to the projections with consensus.

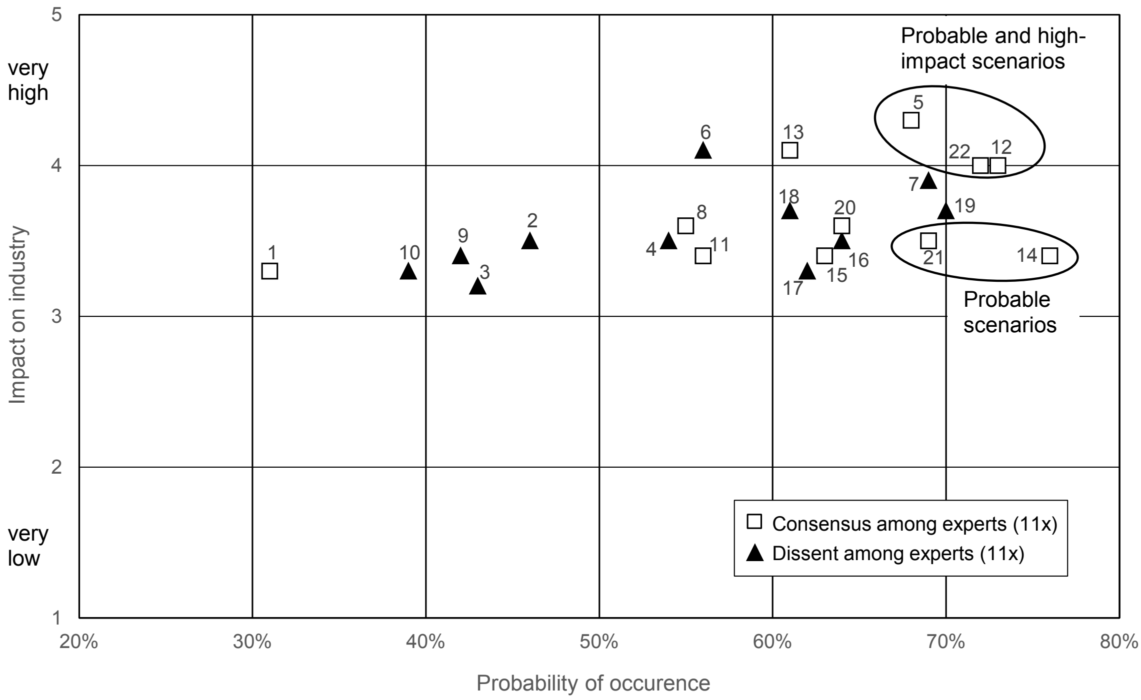

Figure 43. Overall evaluation of projections by probability and impact

Figure 43 also shows two important clusters. The first cluster contains two probable projections which have a probability of more than 65% but only an average impact. The second cluster contains three probable and high-impact projections; i.e. an impact of 4 or higher. In section 4.5, these two clusters are further elaborated to develop relevant and probable future retail scenarios.

4.5 Scenario development

In this section, we develop probable future retail scenarios based on the final results presented in the previous section. We draw on Figure 43 which shows the two clusters for probable scenarios. The corresponding five projections were analyzed on the basis of the experts' comments provided in the first Delphi round. The five projections were part of the economic, social, and retail industry perspective which shows the importance of these particular topics in the context of the IoT.

Table 23 summarizes the five projections in a structure in which first short statements of the experts' justifications for a low and high probability are outlined and second the number of related entries for each corresponding statement. Low probability statements originated from evaluations of the probability of occurrence of 50% or lower, while high probability statements are based on evaluations of the probability of occurrence of higher than 50%. Furthermore, we draw a conclusion of all statements given, to create a probable scenario for each projection.

Table 23. Probable scenarios of the future

No.	Projection for the year 2030	Number of entries
5	**The growth of e-commerce and m-commerce, and changes in consumer behavior, have increased the benefits for retailers. Multiple channels enable retailers to constantly stay in touch with consumers.**	
	Low probability:	
	The future will bring novel concepts of retailing in 2030 one cannot imagine today.	3
	High probability:	
	Social commerce based on social media will emerge and be a new hype.	2
	Real-time location-based systems will be integrated in m-commerce to engage customer attention and to generate new retail channels.	2
	Current situation indicates future development in that direction.	4
	Customer analytics bring science to the art of retail.	2
	Conclusion:	
	Traditional stores will certainly exist 15-20 years from now, but they will not look the same as today. Retailers need to adapt or change their business model to a multichannel reality in which boundaries between the online and physical worlds disappear. Social media and customer analytics will increasingly be part in these retail channels. The technological means for location-based services need a better integration in m-commerce. New forms of retailing one cannot imagine today will be likely in the future.	

Table 23. Probable scenarios (continued)

No.	Projection for the year 2030	Number of entries
12	**Retailers provide new concepts (e.g. remote order with home delivery) to cope with the continuous challenge of demographic change.**	
	Low probability:	
	Reduced mobility of elderly people must be addressed in all its facets.	1
	High probability:	
	That trend can already be seen today.	4
	Generation Y will grow and will soon take over as principal consumers, while older, less tech-savvy elderly people are slowly disappearing.	2
	Demographic change is just one reason for new concepts but retailers have to adapt their services according to the audience.	2
	Conclusion:	
	The demographic change will play an important role in retailing. Unlike today, retailers will be faced with the "Generation Y" or so-called digital natives who will experience a different aging process in the future. They grew up with all kinds of technology and will thus cope easier with future retailing concepts as compared to elderly people today. In particular, the reduced mobility needs to be taken into account to shape retail concepts for elderly people.	
14	**Data security is perceived as a basic requirement for the provision of Internet of Things services, not only in view of ensuring data security for an organization, but also for the benefit of the citizens.**	
	Low probability:	
	Consumer confidence will decrease and people look to government for security and solutions.	1
	People need awareness of the processing of their data.	1
	High probability:	
	The IoT will deal with huge amounts of personal data, especially when coupled with Big Data. In this context, the information security is already being perceived as a basic requirement, due to growing awareness of negative impacts of numerous data breaches.	2
	The vast amount of today's security issues makes society aware of data security.	3 3
	Data security and privacy are a fundamental right for people.	1
	People need to accept that particular services can only be provided if personal data is processed	
	Conclusion:	
	Data security is absolutely critical for IoT applications. People want to know how their personal data is processed and used. However, people are also aware of providing their personal data to receive certain services. If data security and privacy cannot be provided, consumer confidence will decrease and threaten the success of the IoT.	

Table 23. Probable scenarios (continued)

No.	Projection for the year 2030	Number of entries
21	**Customers get advice at the point of sale through mobile shopping assistants or their own mobile device according to their preferences, presence of allergic components, or the actual product quality of food.**	
	Low probability:	
	Privacy issues might prevent this scenario.	2
	High probability:	
	Processes such as buying, pick-up, or return items should be doable using any retail channel without constraints across those channels.	1
	Usability of mobile shopping assistants is critical for consumer adoption.	2
	Apart from smartphones, wearables will play an important role as mobile shopping assistants.	2
	Mobile device integration into retailer networks must be seamless for which suitable interfaces must be available.	3
	Conclusion:	
	Retailers will interact with their customers via mobile shopping assistants at the point of sale in one way or another. They need to blur the boundaries between digital and physical by leveraging technologies such as smart wearables. Regardless of the device type, integration and usability are two main adoption drivers of mobile shopping assistants. Furthermore, customer privacy must be ensured at all times.	
22	**Service and in-store experiences continue to break out of the one-size-fits-all offerings. These experiences have become more individualized and specialized for specific target groups.**	
	Low probability:	
	People will not demand individualized products at the expense of their privacy.	1
	High probability:	
	Augmented reality enabled by smart wearables will be common in the future.	1
	Personal data is being used to customize all products and services.	3
	With digital platforms and manufacturing technology evolving, retailers are able to offer their products to a wider audience and at a larger scale leading to mass customization.	1
	Customer analytics enabled by smart shelves or path-to-purchase data for optimizing store layouts will be usual practice.	2
	Conclusion:	
	In-store shopping experiences will change significantly in the future. Retailers will offer a combination of individualized and standardized products in such a way that they are able to employ mass customization. Personal data will be vitally important to shape individualized products and services for customers. In this context, customer analytics will also provide benefits to the retailer in terms of store optimizations.	

4.6 Conclusion and implications

Our research aimed at developing probable future scenarios in the retail industry in the context of the Internet of Things. Two research questions related to the macro- and micro-environment guided our research. We followed the structure of the PEST (political, economic, social, and technological) framework for the macro-environment perspective, while the micro-environment was investigated from an industrial structure perspective.

We used empirical research by conducting a two-round Delphi study with an expert panel of 15 participants. In a first step, a pre-study delivered the input for developing 22 future projections for the retail industry containing IoT aspects. These projections were fed back to the expert panel for evaluation of their probability of occurrence, impact, and desirability. After the first round we could observe that 6 out of the 22 projections reached consensus. The second round yielded 5 more projections for which consensus among the experts could be achieved, resulting in a total number of 11 agreed projections.

We identified five projections with consensus which had a high probability and a medium to high impact. These projections from the economic, social, and retail industry perspective were taken for scenario development of a probable future. Based on experts' comments, we aggregated the information in statements and concluded specific future scenarios. Among these scenarios, the topics demographic change, data security, multi-channel retailing, mobile shopping assistants, and individualized services and products were seen as most promising topics for the future of retailing.

Based on the results of our study, we can derive the following implications for the retail industry. Retailing executives will be forced to redesign retail business models to cope with the convergence of physical and digital channels enabled by a digital transformation due to the IoT. They need to acknowledge that new technologies will be faster, cheaper, and more versatile in the future. In this respect, retailers need to leverage technologies and their applications such as location-based services which can help find customers and target them with individualized offers. To design these offers, customer analytics and profiling will increasingly applied by retailers, however, this will also raise concerns about data security and privacy issues among customers which was frequently mentioned in the expert comments. Regarding the demographic change, traditional retailers will face the challenge of satisfying today's "Generation Y" which is a more diverse group in how they shop, where they shop and how they spend their money. Even though they will be more tech-savvy as elderly people today, they require novel shopping concepts in which a reduced mobility is taken into account. Finally, we could observe that augmented reality has the potential to become a driver of revolutionary shopping experiences.

Our research comes with some limitations mainly related to the methodology. First, scenario development builds on qualitative research, which is often regarded as not meeting all traditional scientific research criteria. By supporting our qualitative research with statistical measures, we integrated a quantitative approach to reconcile the opposing perspectives of objectivism and relativism. The number of experts in our panel was considered as sufficient, however, a larger expert panel would have provided more expert opinions on the evaluated projections for scenario development. Second, our results show that half of the projections could not reach consensus among the experts. Even though additional rounds are scarcely to be expected changing the results significantly, future research might consider a Delphi study in which the projections are evaluated over three rounds. A different composition of the expert panel, in which not only IoT experts participate, might also give opportunity for new insights into the retail industry and its complexity.

5. Summary

This dissertation examines the Internet of Things from three different perspectives. The first perspective addresses a business application of the Internet of Things in that the potential of sensor-based issuing policies in the supply chain was investigated. The second perspective covers the field of technology acceptance according to which we examined to what extent potential users of a pervasive technology intend to use such a technology. The third perspective provides a future prospect of probable retail scenarios related to the Internet of Things. For each of these perspectives, we have conducted a separate study.

In the first study, we tackled the issue of product quality of perishable goods and how it can be taken into consideration for the issuing of goods in a perishables supply chain. We examined the performance of eleven different issuing policies at the distribution center based on three different issuing criterions, namely, "arrival date," "product age," and "product quality". Using computer simulation, we showed how sensor-driven issuing decisions may prove useful and provide benefits under specific conditions for both retailers and customers as compared to conventional issuing policies. To obtain these benefits, the employment of novel technologies such as smart sensors will be key to the transition from conventional to sensor-based issuing policies. By processing the data gathered by these technologies, detailed traceability and visibility of an in-transit or stored item is provided all the way from the manufacturer to the retail store. It allows a retailer to respond quickly and flexibly to changes in item's conditions to not only optimize the good's flow but also the product quality offered to the customer. Despite our focus on a specific area within logistics, the potential of employing sensor technology in an industrial setting could be proved in economic as well as ecological terms. This potential will probably induce entirely new business models or radical changes of parts thereof, improve business processes, and reduce costs and risks.

The second study deals with pervasive technologies and user acceptance. We developed an integrated research model composed of already existing and validated research results, namely the extended "Unified Theory of Acceptance and Use of Technology" and three pervasiveness constructs, these are: ubiquity, unobtrusiveness, and context awareness. This integrated model was used to measure user acceptance in the context of the pervasive technology Google Glass. Using covariance-based structural equation modeling, we provided empirical support for the applicability of the integrated model. In a further step we analyzed moderating and moderation effects. The results of the moderation analysis shows that nine out of ten hypotheses could be either partially or fully supported while one could not be supported. Three hypotheses were related to mediation analysis of which one could be partially supported while two could not be supported. Overall, the results indicate an acceptable model fit and good explanatory power as the proposed research model accounts for 64% of the variance in the dependent variable Behavioral Intention. This study highlights important characteristics of pervasive technologies and how they are regarded by potential users since technological capabilities is only a basic driver of pervasive technologies but people's behavior is the determining factor for the technology's utilization. The results provide relevant information for developers of pervasive technologies and of the characteristics the potential users cherish in relation to other technology acceptance factors.

The third study aimed at developing probable future scenarios in the retail industry in the context of the Internet of Things. Our approach considers the macro- and micro-environment each of which is reflected in a research questions. To examine the macro-environment perspective, we used the PEST (political, economic, social, and technological) framework, while the micro-environment was investigated from an industrial structure perspective. These two perspectives provided the basis for the survey of the two-round Delphi study. In a pre-study, we collected input for developing projections according to the structure of the two perspectives. These projections were subject to an evaluation by the expert panel in a two-round Delphi study. After the second round, we identified five projections with consensus among the experts which had a high probability and a medium to high impact on the economy. We took these projections into account for scenario development of a probable future in the retail industry. Among these scenarios, the topics demographic change, data security, multi-channel retailing, mobile shopping assistants, and individualized services and products were seen as most promising topics for the future of retailing.

The Internet of Things includes a broad range of different topics which points to a limitation of this research work. We take into account the fact that the enormous number of topics cannot be covered by only one dissertation and focus on a selection of topics which examine the Internet of Things from three different perspectives. The first perspective covers a business- and application-oriented research, while the second perspective pertains to the behavioral-science paradigm. The last study takes a more holistic approach and long-term perspective to derive future-oriented strategies in the retail sector. The limitations within each of the studies has been discussed in the respective chapters.

The studies that have been conducted in this dissertation leave ample room for future research, as has been indicated in the individual chapters. We highlight the most important research directions related to the Internet of Things. As has been pointed out in the chapters before, security and privacy remain as a major challenge for consumer acceptance. The ubiquity and interactions enabled by the Internet of Things will provide many conveniences and useful services for individuals, but also create many opportunities to violate privacy. Particularly, the recent global surveillance disclosures about the United States National Security Agency (NSA) created a new public awareness of data security and privacy. Despite that the majority believes the benefits of the Internet of Things will outweigh their concerns about privacy and security (Ponemon Institute, 2015). Data analytics is another research field crucial to the Internet of Things. A vast amount of raw data being continuously collected by all kinds of devices needs to be analyzed to create full and accurate information and knowledge. Data mining techniques are expected to provide the creation of important knowledge from big data. The usefulness of big data is also closely connected with trust. System-level capabilities such as in-field sensor calibration techniques and advances in multisensor data fusion are necessary to guarantee data accuracy and correctness. Otherwise further inference might be operating based on wrong or missing data with the result of wrong conclusions. This is also fundamental for decision-making using the created knowledge. For example, the number of false negatives and false positives guarantee safety in healthcare applications (Tu et al., 2009) or optimizations in supply chain processes (Keller et al., 2010). These are only few challenges of many to overcome since new research directions arise due to the large scale of devices, changing society in terms of demographics, and continuing issues of privacy and security.

6. References

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Appendix

A Simulation source code

A.1 Simulation parameter setting

```
static void Main(string[] args)
{
       Console.WriteLine(System.DateTime.Now.ToString());

       new Model1Container().Database.ExecuteSqlCommand("DELETE FROM
SimOutputSet");

       foreach (Behavior b in Enum.GetValues(typeof(Behavior)))
          foreach (DemandRate d in Enum.GetValues(typeof(DemandRate)))
             foreach (LifeTime l in Enum.GetValues(typeof(LifeTime)))
                foreach (Policy p in Enum.GetValues(typeof(Policy)))
                {
                     Model1Container db = new Model1Container();
                     db.Configuration.AutoDetectChangesEnabled = false;

                     for (int rdc = StepSizeQDC; rdc <= SimInput.QDC; rdc +=
                     StepSizeQDC)
                     {
                            for (int rstore = StepSizeRDC; rstore <=
                            SimInput.QStore; rstore += StepSizeRDC)
                            {
                                   Task<SimOutput>[] t = new
                                          Task<SimOutput>[MaxReplications];

                                   for (int i = 1; i <= MaxReplications; i++)
                                   {
                                          SimInput input = new SimInput()
                                          {
                                             Replication = i,
                                             Behavior = b,
                                             DemandRate = d,
                                             LifeTime = l,
                                             Policy = p,
                                             RDC = rdc,
                                             RStore = rstore,
                                             Horizon = 500,
                                             WarmUpTime = 50
                                          };
                                   }
                            }
                     }
              }
}
```

A.2 Shipment arrival at DC

```
if ((input.Policy == Policy.FEFO_TTI) || (input.Policy == Policy.LEFO_TTI) ||
    (input.Policy == Policy.FIFO_TTI) || (input.Policy == Policy.LIFO_TTI) ||
    (input.Policy == Policy.HQFO) || (input.Policy == Policy.LQFO))
{
       int spoiled = vars.QueueManDC.RemoveAll(i => i.Quality
<SimInput.MinQuality);
       vars.RecDC -= spoiled;
        if (vars.Time >= input.WarmUpTime) vars.SpoilageDC += spoiled;
}
else ((input.Policy == Policy.FEFO) || (input.Policy == Policy.LEFO))
{
       int spoiled = vars.QueueManDC.RemoveAll(i => i.Age >
(double)input.LifeTime);
       vars.RecDC -= spoiled;
       if (vars.Time >= input.WarmUpTime) vars.SpoilageDC += spoiled;
}
vars.InvDC.AddItems(vars.Time, vars.QueueManDC.Where(i => i.Arrival ==
vars.Time));
vars.QueueManDC.RemoveAll(i => i.Arrival == vars.Time);
```

A.3 Shipment arrival at RS

```
if ((input.Policy == Policy.FEFO_TTI) || (input.Policy == Policy.LEFO_TTI) ||
    (input.Policy == Policy.FIFO_TTI) || (input.Policy == Policy.LIFO_TTI) ||
    (input.Policy == Policy.HQFO) || (input.Policy == Policy.LQFO))
{
    int spoiled = vars. QueueDCStore.RemoveAll(i => i.Quality
<SimInput.MinQuality);
    vars.RecDC -= spoiled;
    if (vars.Time >= input.WarmUpTime) vars.SpoilageDC += spoiled;
}
else ((input.Policy == Policy.FEFO) || (input.Policy == Policy.LEFO))
{
    int spoiled = vars.QueueDCStore.RemoveAll(i => i.Age >
(double)input.LifeTime);
    vars.RecDC -= spoiled;
    if (vars.Time >= input.WarmUpTime) vars.SpoilageDC += spoiled;
}
vars.InvStore.AddItems(vars.Time,vars.QueueDCStore.Where(i => i.Arrival ==
vars.Time));
vars. DCStore.RemoveAll(i => i.Arrival == vars.Time);
```

A.4 Customer demand at RS

```
int demand = 0;
int served = 0;
Random rnd = new Random();

switch (input.DemandRate)
{
    case DemandRate.Low:
       demand = (int)Math.Round(MathNet.Numerics.Distributions.Normal.Sample(rnd,
                (double)input.DemandRate, SimInput.StDevDemand_Low));
       if (demand < 0) demand = 0;
       served = Math.Min(demand, vars.InvStore.Count);
       break;
    case DemandRate.BaseCase:
       demand = (int)Math.Round(MathNet.Numerics.Distributions.Normal.Sample(rnd,
                (double)input.DemandRate, SimInput.StDevDemand_Medium));
       if (demand < 0) demand = 0;
       served = Math.Min(demand, vars.InvStore.Count);
       break;
    case DemandRate.High:
       demand = (int)Math.Round(MathNet.Numerics.Distributions.Normal.Sample(rnd,
                (double)input.DemandRate, SimInput.StDevDemand_High));
       if (demand < 0) demand = 0;
       served = Math.Min(demand, vars.InvStore.Count);
       break;
}

switch (input.Behavior)
{
       case Behavior.Random:
              for (int customer = 0; customer < served; customer++)
              {
                     int p = MathNet.Numerics.Distributions.DiscreteUniform.Sample
                             (rnd, 0, vars.InvStore.Count - 1);
                     if (vars.Time >= input.WarmUpTime)
                     {
                            vars.QualitySold +=
vars.InvStore.ElementAt(p).Quality;
                            int i = (int)(vars.InvStore.ElementAt(p).Quality /
10);

                            if (i < 0) i = 0;
                            if (i >= 10) i = 9;
                            QualityCat[i]++;
                     }
                     vars.InvStore.RemoveAt(p);
                     vars.RecStore--;
              }
              break;

       case Behavior.ExpiryBased:
              var newest = vars.InvStore.OrderBy(i => i.Age).Take(served);
              foreach (Inventory.StoredItem p in newest)
              {
                     if (vars.Time >= input.WarmUpTime)
                     {
                            vars.QualitySold += p.Quality;
                            int i = (int)(p.Quality / 10);
                                          if (i < 0) i = 0;
                            if (i >= 10) i = 9;
                            QualityCat[i]++;
```

```
                    }
                    vars.InvStore.Remove(p);
                    vars.RecStore--;
                }
                break;

        case Behavior.QualityBased:
                var best = vars.InvStore.OrderByDescending(i =>
                        i.Quality).Take(served);
                foreach (Inventory.StoredItem p in best)
                {
                    if (vars.Time >= input.WarmUpTime)
                    {
                        vars.QualitySold += p.Quality;
                        int i = (int)(p.Quality / 10);
                        if (i < 0) i = 0;
                        if (i >= 10) i = 9;
                        QualityCat[i]++;
                    }
                    vars.InvStore.Remove(p);
                    vars.RecStore--;
                }
                break;
}
if (vars.Time >= input.WarmUpTime) vars.Customers += demand;
if (vars.Time >= input.WarmUpTime) vars.Stockouts += (demand - served);
```

A.5 Periodic review at RS

```
if ((input.Policy == Policy.FEFO_TTI) || (input.Policy == Policy.LEFO_TTI) ||
    (input.Policy == Policy.FIFO_TTI) || (input.Policy == Policy.LIFO_TTI) ||
    (input.Policy == Policy.HQFO) || (input.Policy == Policy.LQFO))
{
       int spoiled = vars.InvStore.RemoveAll(i => i.Quality <
SimInput.MinQuality);
       vars.RecStore -= spoiled;
       if (vars.Time >= input.WarmUpTime) vars.SpoilageStore += spoiled;
}
else ((input.Policy == Policy.FEFO) || (input.Policy == Policy.LEFO))
{
       int spoiled = vars.InvStore.RemoveAll(i => i.Age >
(double)input.LifeTime);
       vars.RecStore -= spoiled;
       if (vars.Time >= input.WarmUpTime) vars.SpoilageStore += spoiled;
}
```

A.6 Order placement at RS

```
if (vars.RecStore < input.RStore)
{
       vars.Outstanding += SimInput.QStore;
       vars.RecStore += SimInput.QStore;
       if (vars.Time >= input.WarmUpTime) vars.OrdersStore++;
}
```

A.7 Periodic review at DC

```
if ((input.Policy == Policy.FEFO_TTI) || (input.Policy == Policy.LEFO_TTI) ||
    (input.Policy == Policy.FIFO_TTI) || (input.Policy == Policy.LIFO_TTI) ||
    (input.Policy == Policy.HQFO) || (input.Policy == Policy.LQFO))
{
       int spoiled = vars.InvDC.RemoveAll(i => i.Quality < SimInput.MinQuality);
       vars.RecDC -= spoiled;
       if (vars.Time >= input.WarmUpTime) vars.SpoilageDC += spoiled;
}
else ((input.Policy == Policy.FEFO) || (input.Policy == Policy.LEFO))
{
       int spoiled = vars.InvDC.RemoveAll(i => i.Age > (double)input.LifeTime);
       vars.RecDC -= spoiled;
       if (vars.Time >= input.WarmUpTime) vars.SpoilageDC += spoiled;
}
```

A.8 Order placement at DC

```
if (vars.RecDC < input.RDC)
{
       for (int i = 0; i < SimInput.QDC; i++)
       {
              int lead =
MathNet.Numerics.Distributions.DiscreteUniform.Sample(rnd,
                         (int)SimInput.MinLeadTimeDC,
(int)SimInput.MaxLeadTimeDC);
              double quality = MathNet.Numerics.Distributions.Normal.Sample(rnd,
                                SimInput.MeanQuality, SimInput.StDevQuality);
              if (quality < 0)
              {
                     quality = 0;
              }
              else if (quality > 100.0)
              {
                     quality = 100.0;
              }
              double age = MathNet.Numerics.Distributions.Normal.Sample(rnd,
                            SimInput.MeanAge, SimInput.StDevAge);
              if (age < 0) age = 0;
              vars.QueueManDC.AddItem(vars.Time + lead + 1,
              new Item() { Age = (int)Math.Round(age), Quality = quality });
       }
       if (vars.Time >= input.WarmUpTime) vars.OrdersDC++;
       vars.RecDC += SimInput.QDC;
}
```

A.9 Calculation of daily deterioration and holding costs

```
foreach (Queue.TransportedItem item in vars.QueueManDC)
{
       double loss = MathNet.Numerics.Distributions.Normal.Sample(rnd,
                     vars.MeanDeterioration, vars.StDevDeterioration);
       if (loss < 0) loss = 0;
       item.Quality -= loss;
       item.Age++;
}
foreach (Queue.TransportedItem item in vars.QueueDCStore)
{
       double loss = MathNet.Numerics.Distributions.Normal.Sample(rnd,
                     vars.MeanDeterioration, vars.StDevDeterioration);
       if (loss < 0) loss = 0;
       item.Quality -= loss;
       item.Age++;
}
foreach (Inventory.StoredItem item in vars.InvDC)
{
       double loss = MathNet.Numerics.Distributions.Normal.Sample(rnd,
                     vars.MeanDeterioration, vars.StDevDeterioration);
       if (loss < 0) loss = 0;
       item.Quality -= loss;
       item.Age++;
}
foreach (Inventory.StoredItem item in vars.InvStore)
{
       double loss = MathNet.Numerics.Distributions.Normal.Sample(rnd,
                     vars.MeanDeterioration, vars.StDevDeterioration);
       if (loss < 0) loss = 0;
       item.Quality -= loss;
       item.Age++;
}

if (vars.Time >= input.WarmUpTime)
    vars.HoldingCost += vars.InvDC.Count * SimInput.CostHoldingDC +
    vars.InvStore.Count * SimInput.CostHoldingStore;
```

B Invitation mail to Delphi study

A EUROPEAN DELPHI STUDY ON THE INTERNET OF THINGS IN THE RETAIL INDUSTRY

SUMMARY

- European research project "Internet of Things Architecture (IoT-A)" (http://www.iot-a.eu)
- Delphi study to estimate the socio-economic impacts caused by the Internet of Things in the retail industry

OVERVIEW

The IoT-A research project aims at developing an architectural reference model for the Internet of Things based on the definition of an initial set of key building blocks. Together they are envisioned as crucial foundation for enabling any kind of interaction with and between everyday objects, i.e. the future Internet of Things (IoT). This concept will not only drive the technological progress within the IoT but also have varying degrees of socio-economic effectiveness. In this study we are interested in how the macro-environment will change in the future and what impacts the IoT will have on the retail industry.

RESEARCH QUESTION AND OBJECTIVES

How will the macro-environment (political/legal, economic, social, and technological structure) of the retail industry change in the future with simultaneous consideration of a pervasive Internet of Things?

The specific objectives of this study comprise:

- Identification of socio-economic challenges and issues and their consequences for the introduction of the IoT in the retail industry.
- Identification of future socio-economic developments which will influence the adoption of Internet of Things technologies and applications.

DELPHI METHOD

Specifically, the structure for each round of the Delphi study is as follows:

- Round 1 aims at collecting first input from participants to build the following questionnaires upon their existing knowledge (expected time exposure = 30 min)
- In round 2 the participants will be asked to give quantitative feedback on the summarized and structured content obtained from the initial round. After feedback analysis the degree of consensus will be delivered to each participant. (expected time exposure = 20 min)
- Round 3 aims at increasing consensus by reassessing those items for which consensus was not reached. (expected time exposure = 20 min)

Conditions:

- All participants are anonymous among each other and communication between monitoring team and participant is treated confidentially.
- All results will be made available for participants including potential publications.

If you have any further questions, please do not hesitate to contact us. We thank you in advance for your willingness to contribute to our research project.

C Invitation mail to round 1 of the Delphi study

THE IMPACT OF THE INTERNET OF THINGS ON SOCIO-ECONOMIC CHANGE – A DELPHI STUDY

SUMMARY

- European research project "Internet of Things Architecture (IoT-A)" (http://www.iot-a.eu)
- Delphi study to estimate the socio-economic impacts caused by the Internet of Things in the retail industry

OVERVIEW

The EU project 'Internet of Things Architecture' (IoT-A) conducts a Delphi study and invites experts in the fields of Internet of Things and the Retail domain to participate. We would like to analyze the future development of the Internet of Things (IoT) in general as well as specifically for the retail industry.

RESEARCH OBJECTIVES

How will the macro-environment (political/legal, economic, social, and technological structure) of the retail industry change in the future with simultaneous consideration of a pervasive Internet of Things?

The objective of the study is to obtain empirical findings to answer:

- What social and economic development will take place in Europe, given the increasing proliferation of the IoT?
- What challenges and issues related to the IoT must be overcome in Europe?
- How will the IoT affect the retail industry in Europe regarding retailer business activities and consumer behavior?

DELPHI METHOD

Specifically, the structure for each round of the Delphi study is as follows:

- Round 1: The participants will be asked to give quantitative feedback on different projections for the year 2030. After feedback analysis the degree of consensus will be delivered to each participant.
- Round 2: The objective is to increase consensus by reassessing those items for which consensus could not be reached.

Basic notes on participation:

- The questionnaire is in **English**.
- As it is about a Delphi study the willingness to participate in **both rounds** is needed.
- Round 1 requires about **30 minutes** to fill in the questionnaire.
- Round 2 will most likely be shorter as each item for which consensus could be reached will not be reassessed.
- Your answers will be treated **completely confidential** and you remain always **anonymous** to the other participants.
- The final results will be made available for each participant in the form of a report at the end of the study.