Managing RFID Implementations

Implications for Managerial Decision Making

Dissertation
of the Julius Maximilian University of Würzburg
to obtain the title of
Doctor rerum politicarum

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Kurzfassung

Die vorliegende Arbeit beschäftigt sich mit dem Management von RFID Implementierungen im Einzelhandel. Dabei leistet die Arbeit einen Beitrag, indem wichtige aber bisher in der wissenschaftlichen Fachliteratur nur wenig beachtete Aspekte beleuchtet werden. Hierfür werden drei Studien zu drei relevanten Managementaspekten durchgeführt. Zunächst wird die Kundenakzeptanz im Bezug auf pervasive Retail Applikationen betrachtet und mithilfe der Privacy Calculus Theorie ermittelt, welche Aspekte für die Kundenakzeptanz pervasiver Systeme besonders relevant sind. In Studie zwei wird eine RFID-gestützte Roboterinvnetur anhand einer Simulationsstudie evaluiert. Die Studie zeigt, dass eine durch Roboter durchgeführte Inventur für einen Einzelhändler zu empfehlen ist, falls die Roboter tatsächlich mit den von den Herstellern beworbenen Erkennungsraten arbeiten. In der dritten und letzten Studie werden die Potenziale von RFID-Daten zur Entscheidungsunterstützung des Managements evaluiert. Es werden drei Methoden vorgestellt um aus RFID-Daten nützliche Informationen zu gewinnen. Abschließend wird ein generisches Vorgehensmodell zur Informationsextraktion entwickelt. Die Arbeit ist sowohl an Praktiker gerichtet, die ihre RFID-basierten Prozesse verbessern möchten, als auch an Wissenschaftler die RFID-basierte Forschung betreiben.

Schlagwörter: RFID, Management, Akzeptanz, Privatsphäre, Bestandsmanagement, Roboter, Inventur, Simulation, Data Analytics

Abstract

The present dissertation investigates the management of RFID implementations in retail trade. Our work contributes to this by investigating important aspects that have so far received little attention in scientific literature. We therefore perform three studies about three important aspects of managing RFID implementations. We evaluate in our first study customer acceptance of pervasive retail systems using privacy calculus theory. The results of our study reveal the most important aspects a retailer has to consider when implementing pervasive retail systems. In our second study we analyze RFID-enabled robotic inventory taking with the help of a simulation model. The results show that retailers should implement robotic inventory taking if the accuracy rates of the robots are as high as the robots' manufacturers claim. In our third and last study we evaluate the potentials of RFID data for supporting managerial decision making. We propose three novel methods in order to extract useful information from RFID data and propose a generic information extraction process. Our work is geared towards practitioners who want to improve their RFID-enabled processes and towards scientists conducting RFID-based research.

Key words: RFID, management, acceptance, privacy, inventory management, robot, inventory, simulation, data analytics

Erklärung

Ich erkläre, dass ich die Arbeit selbständig verfasst, keine anderen als die angegebenen Quellen und Hilfsmittel benutzt und die diesen Quellen und Hilfsmitteln wörtlich oder sinngemäß entnommenen Ausführungen als solche kenntlich gemacht habe. Weiterhin habe ich die vorliegende Arbeit bisher keiner anderen Prüfungsbehörde vorgelegt.

Würzburg, den 28.02.2018 Alexander Weinhard

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CHAPTER 1

Introduction

Automatic identification (Auto-ID) systems have been supposed to revolutionize the identification of products and objects in several industries (Bose et al., 2005). Radio Frequency Identification (RFID), one of the Auto-ID approaches, recently started to slowly replace its predecessor the barcode. More and more retailers, foremost in the fashion industry, have started to implement RFID into their supply chains. One example is the fashion company Zara, a subsidiary of Inditex. Zara uses RFID technology in more than 1400 of its 2000 stores in over 64 countries and plans to equip the remaining stores as well (Bach, 2016). Another example is the German fashion retailer Adler Modemärkte AG which is also pushing forward RFID technology and already implemented RFID hardware in 170 stores (RFID im Blick, 2014).

Although RFID is on the rise, there seems to be little research on how managers and companies can leverage the potentials of novel RFID applications such as RFID-enabled robotic inventory taking or RFID-enabled smart fitting rooms. Consequently, the only way for companies to gain experience with such applications seems to be through trial and error. Managers are therefore faced with the decision to implement novel RFID-based applications without actually knowing whether they will really benefit their business and how they can actually use the data generated by these applications. Our goal is therefore to provide managers, particularly in the retail industry, with contemporary scientific advice on how to leverage RFID implementations. Concretely, we show how to assess customer acceptance, how to evaluate novel applications with the help of simulations and how to use the data generated by an RFID infrastructure to support managerial decision making.

1.1 Auto-ID systems

Auto-ID has the purpose of supplying information about goods, persons and objects in general. Most well known is the barcode, a binary code encoded in parallel bars, a system that has revolutionized the retail industry. Even though the barcode is very cheap to implement, it has many drawbacks like the dependability on a direct line of sight. Most well known examples for the barcode are the European Article Number (EAN) and the Universal Product Code (UPC) (Finkenzeller, 2015).

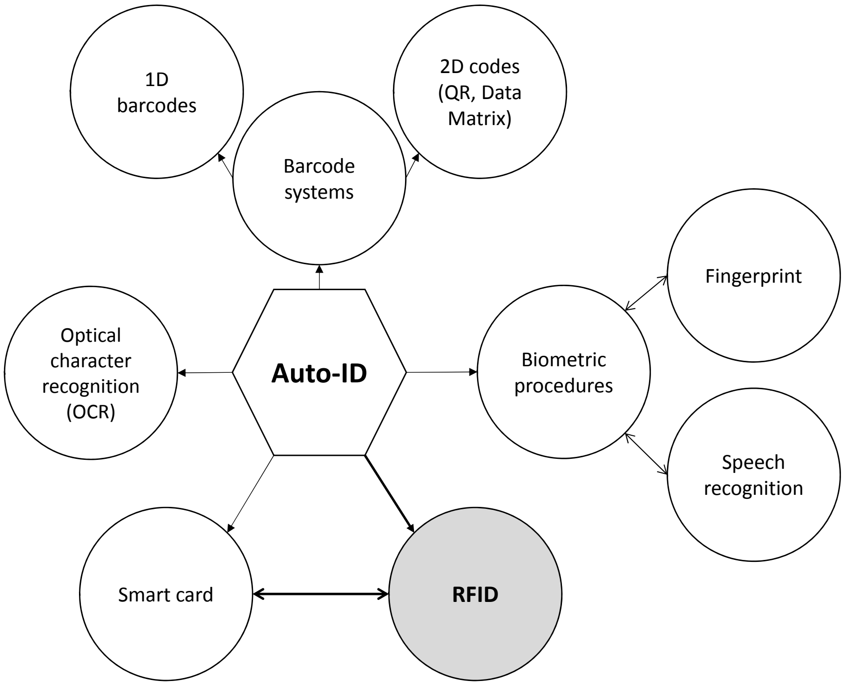

Figure 1.1: Overview of Auto-ID systems (Finkenzeller, 2015)

Besides the barcode, there exist other methods for automatic identification. Figure 1.1 gives an overview of the most important approaches. In addition to the classic 1D barcode there exist 2D codes such as the QR code. Also, optical character recognition and biometric identification approaches like fingerprinting or speech recognition can be attributed to Auto-ID (Finkenzeller, 2015).

1.2 Radio Frequency Identification

RFID is one of the most promising representations of Auto-ID. RFID systems store data on an electronic data carrier, the so called RFID tag. The tag is also called transponder, which is the abbreviation for transceiver and responder. With the help of electromagnetic fields the transponder is supplied with energy in order to transfer data between a receiver and a reading device (Lampe et al., 2005). One of the most common pieces of information that is saved on an RFID chip is the Electronic Product Code (EPC) which is a code that is assigned to objects in business applications in order to uniquely identify them (GS1, 2015).

Figure 1.2 illustrates the parts which are common for almost every RFID system. Usually, there exists at least a transponder which communicates with an RFID reader. The transponder is intended to be attached to the object which shall be identified. The RFID reader, which is usually connected to an application that stores and processes the received information, supplies the transponder with energy and communicates with it in different cycles. The reader can have the ability to receive data from the transponder but also to write on the transponder's data storage (Finkenzeller, 2015).

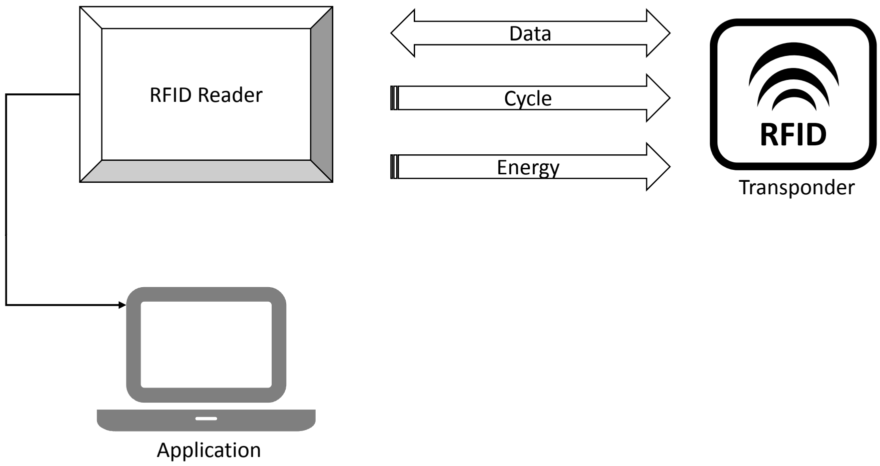

Figure 1.2: Structure of an RFID system (Finkenzeller, 2015)

A so called passive transponder (see figure 1.3) usually consists out of an antenna (coil) and a microchip. Passive transponders are only active within the reading range of a reading device that supplies them with energy via induction. There exist also active transponders which have their own battery and are not dependent upon energy from an induction process (Lampe et al., 2005).

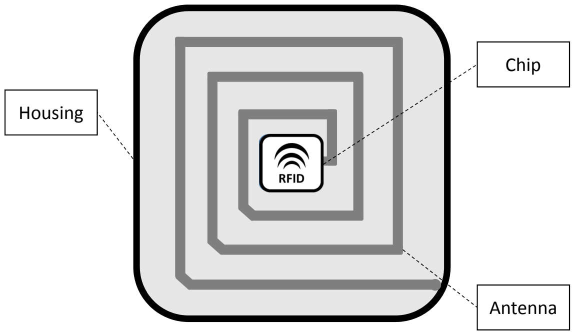

Figure 1.3: Structure of an RFID tag (based on Finkenzeller (2015))

Within this dissertation we focus on RFID devices that were present at a large German fashion retailer with whom we cooperated for our research. The readers include RFID-enabled points of sales (used for an efficient checkout process), mobile handheld reading devices (usually used by employees to perform cycle counts) and transition gates. Transition gates are used to distinguish between different positions of an RFID tag. This means in most cases to distinguish if a tag and consequently the item to which it is attached is on the sales floor or in the stockroom. However, RFID is also used as an anti theft technology in which case the gates are positioned at the entrance of a retail store and used for electronic article surveillance. In these cases the position of a tag can be either inside the store or outside. Besides the before mentioned "standard" reading devices we also incorporate novel RFID-enabled applications. The more advanced applications we consider in our research encompass RFID-enabled inventory robots and RFID-enabled smart fitting rooms.

Not only the hardware but also the software plays an important role for the successful deployment of RFID within a company. The software which coordinates all readers and communicates with the enterprise systems is called middleware.

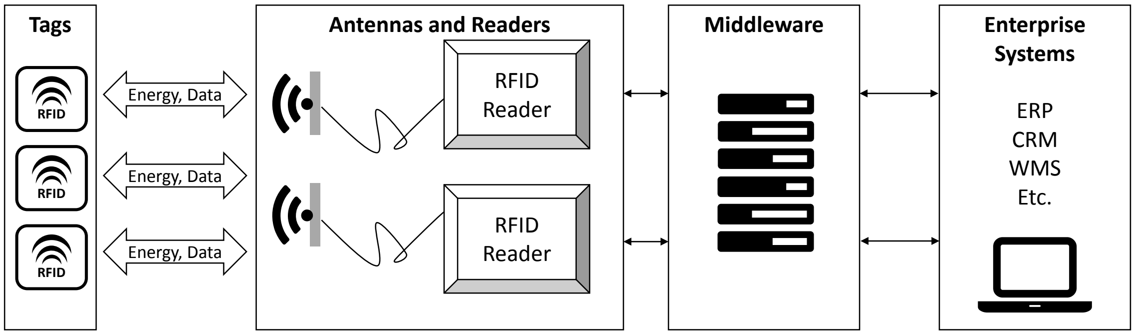

Figure 1.4: Components of an RFID infrastructure (based on Smiley (2016))

Figure 1.4 gives an overview of the components of an RFID infrastructure and shows where the middleware is positioned. The middleware allows a company to manage the RFID-enabled devices, e.g., to control and change the settings of individual readers. It also has the task to collect, filter, structure and integrate the data. There exist also software specifications that were released by EPCglobal (EPCglobal is a GS1 initiative for developing industry-driven standards) in order to help users to create useful data structures for their own data. The middleware also tracks the tag ID assignment, i.e., the middleware tracks which ID numbers have already been assigned in a system and can assign new ones. Finally the middleware is able to send the data to different enterprise systems which use the data further (Smiley, 2016). EPCglobal specified standard interfaces between RFID tags, readers and enterprise systems. These include

- a low level reader protocol (LLRP),
- a discovery configuration and initialization (DCI),
- a reader management (RM) and
- an application level event standard (ALE) (GS1, 2009; GS1, 2010; GS1, 2007).

LLRP defines a protocol between a reader and software. With over 100 standard commands it allows to control a single reader. Many vendors of RFID readers support LLRP in addition to their proprietary commands (GS1, 2010). The DCI standard defines an interface between RFID readers, so called access controllers and the network. It has the purpose to allow the readers and clients to use the network to which they are connected (GS1, 2009). The RM is a "wire protocol used by management software to monitor the operating status and health of EPCglobal compliant RFID Readers" (GS1, 2007). In order to obtain filtered and consolidated event data, the ALE standard specifies an interface for delivering decoded data (i.e., it does not deliver raw binary data but high level data like the EPC of an item) (GS1, 2007).

1.3 Scope and structure of the dissertation

Although there are technical standards and RFID is more widespread than a few years ago, little scientific work has been published on how to actually leverage RFID implementations. In concrete terms, there is little research on how to evaluate novel RFID-based applications and how to use RFID data for managerial decision making. We therefore aim at contributing to the following three areas that are relevant for a manager, particularly in the retail sector:

- Analyzing customer acceptance and privacy concerns with regard to novel RFID applications
- Evaluating novel RFID infrastructure components and their influence on a retail store with simulation modeling
- Utilizing RFID data in order to support managerial decision making

First, we investigate how customers perceive the implementation of a novel RFID-based customer application - in our case, a smart fitting room - and provide a model that enables retailers to evaluate novel customer-centric RFID applications with a particular focus on the privacy perspective. Second, we show how a retail manager can use simulation models to assess whether new RFID infrastructure components should be implemented and illustrate this with the example of an RFID-enabled inventory robot. We therefore provide a simulation model and evaluate under which circumstances the implementation of an inventory robot outperforms traditional RFID-based inventory taking methods. Third, we investigate how RFID data can be used in order to generate management-relevant information and insights. We therefore propose three methods for RFID data-based analyses and propose a generic process for the information extraction from RFID data.

CHAPTER 2

Explaining adoption of pervasive retail systems with a model based on the UTAUT2 and the Extended Privacy Calculus

2.1 Introduction

The advent of e-commerce has changed the retail landscape dramatically and puts traditional retail companies under a lot of pressure. Although customers still visit retail stores to see, touch and feel products, they often end up purchasing products online (MacKenzie et al., 2013; PwC, 2015). According to a recent customer survey (PwC, 2015), most customers prefer shopping online because of lower prices and the possibility to shop 24 hours a day, 7 days a week without the need to go to a physical store. The survey, however, also reveals that many customers decide against offline retail because the online counterpart provides better services (e.g., product reviews and product recommendations). In consequence, Vend (2016) expects so-called offline pure plays (i.e., retailers that only sell their products offline) to disappear. This, however, does not imply that retail stores are expected to disappear completely in the near future. In contrast, recent studies suggest that companies with an online shop and physical retail stores have competitive advantage against pure online and offline players as long as they integrate their online and offline businesses (Herhausen et al., 2015).

Pervasive computing systems (also referred to as ubiquitous computing systems) offer great opportunities for the integration of online and offline businesses (Gregory, 2015; Manyika et al., 2015). The idea of pervasive computing is best explained with the famous words of Mark Weiser, former chief technology officer of Xerox: “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). The objective of pervasive computing is to make “our lives simpler through digital environments that are sensitive, adaptive, and responsive to human needs” (Saha et al., 2003). We focus on pervasive computing systems in retail environments which we in accordance with P. E. Kourouthanassis et al. (2007) in the following refer to as pervasive retail systems. Examples of such systems in retail environments are for example checkout systems that automatically detect products (Hauser et al., 2017; Smith, 2005), shopping carts that navigate customers through shopping isles (P. Kourouthanassis et al., 2003) shelves that provide additional information on items (Parada et al., 2015) and fitting rooms that offer for example product recommendations based on the garments brought into them (Hauser et al., 2017; Thiesse, Al-Kassab, et al., 2009). Such systems allow retailers to provide services from their online shops on the retail sales floor which promises enhanced customer experience (e.g., detailed product information, product recommendations, no waiting at the checkout desk). In addition, the applications generate valuable customer data such as customer walking paths through the store which a retailer could, for example, use to improve store layouts (Gregory, 2015).

The collection of customer data, however, does not only offer new opportunities for retailers but also bears the risk of being perceived as a privacy threat by customers. Introductions of new technology in retail environments in the past have shown that not sufficiently considering privacy concerns can have severe consequences for retailers. When retailers in North America and Europe started to roll out Radio Frequency Identification (RFID) technology in the early 2000s a public debate started on the potential misuse of the data that could be collected with that technology (Thiesse, 2007). The Metro Group, for example, had to face a demonstration in front of its Metro Future Store and was given the infamous Big Brother Award after introducing an RFID-based loyalty card (Albrecht et al., 2005). As a consequence, legislative bodies had to cope with the fears of the public and introduced new legislation to mitigate potential privacy threats through pervasive technology (Lockton et al., 2005). Also, a recent survey on smart applications shows, for example, that only 22% of respondents felt that the benefits of these applications outweigh any privacy concerns (TRUSTe, 2014).

Against this backdrop, we investigate the trade-off between customers' perceived benefits and their perceived privacy concerns towards pervasive retail systems. To this end, we propose a model that integrates the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) from Venkatesh, Thong, et al. (2012) with the Extended Privacy Calculus Theory from Dinev et al. (2006). The purpose of our study is to gain a better understanding of retail customers' usage intentions towards pervasive retail systems and their underlying privacy disclosure behavior. To achieve this, we first determine the antecedents of people's usage intentions towards pervasive retail systems. Here, we particularly focus on people's willingness to provide personal information, which reflects the trade-off between the costs of disclosing private information and the perceived benefits of using a pervasive retail system. In a second step, we determine the antecedents of people's information disclosure behavior. We validate the applicability of our research model considering an RFID-based smart fitting room. This application detects garments within cabins and uses privacy-related data (e.g., customer identity, purchase history) to offer additional personalized services such as product recommendations.

2.2 Related literature

Research on the adoption of pervasive systems that incorporates privacy aspects can be roughly categorized into (i) studies that investigate people's information disclosure behavior and its influence on the adoption of pervasive systems and (ii) studies that use technology acceptance models in combination with privacy constructs.

The first group of studies uses privacy calculus models to identify privacy related determinants of people's adoption behaviors towards pervasive systems. Xu et al. (2009) investigate people's privacy concerns towards location based services. Their model explains 40.2% of the variance of people's intentions to disclose personal information but does not investigate the intention to use the service. In contrast, H. Li et al. (2016) focus on the intention to use pervasive systems. The authors investigate the adoption of wearable healthcare devices and develop a model that explains 15% of the variance in the intention to use them. Because of the low explanatory power of their model, H. Li et al. (2016) propose to use additional constructs from technology acceptance models in further research.

The second group of studies uses classical technology acceptance models and extends them with privacy constructs. Cazier et al. (2008), Müller-Seitz et al. (2009), and Kowatsch et al. (2012) extend the Technology Acceptance Model (TAM) from Davis (1989). The first two studies investigate the adoption intention towards the Auto-ID technology RFID. The first study introduces the constructs privacy risk likelihood and privacy risk harm; the second study the construct security concerns. The results of both studies indicate that the privacy constructs have an influence on people's adoption intentions towards RFID technology. To the best of our knowledge, Kowatsch et al. (2012) are the only group of authors that not only add additional constructs but combine the TAM with the Extended Privacy Calculus Theory. They consider people's usage intentions towards four IoT-based services (e.g., navigation or healthcare monitoring services). Although the idea of the study is very interesting, the results are questionable because they test each of their hypotheses with only 23 completed questionnaires.

Similar to the studies that extend the TAM, Gao et al. (2015), Nysveen et al. (2016), and Zhou (2012) extend the more recent technology acceptance models UTAUT and UTAUT2. In contrast to the studies that extend the TAM, none of the studies fully integrates the privacy calculus theory. Instead they all consider additional privacy constructs from different sources. Gao et al. (2015) refer to the privacy calculus theory; they do, however, only consider the construct privacy risk. Nysveen et al. (2016) use the construct privacy risk harm, and finally Zhou (2012) the constructs privacy concerns, trust and perceived risk. Gao et al. (2015) investigate users' adoption behaviors towards wearable healthcare devices and show that the construct is one of the most important predictors of the model. Nysveen et al. (2016) consider people's adoption behavior towards RFID-enabled services. In contrast to Gao et al. (2015), however, they are not able to show any effect of their privacy construct on the intention to use. Zhou (2012) investigates the adoption of location based services. Similar to Gao et al. (2015), the author finds an effect of privacy risk on the usage intention. In addition, she is able to show an effect of the construct trust, but no relationship between the construct privacy concerns and the usage intention.

Similar to Kowatsch et al. (2012), our study integrates the privacy calculus theory (see first group of studies) with technology acceptance models (see second group of studies). We use the Extended Privacy Calculus from Dinev et al. (2006) because it is a well-accepted theory and covers many important nuances of people's privacy disclosure behavior. In contrast to Kowatsch et al. (2012), however, we consider the UTAUT2 instead of the TAM. We choose the UTAUT2, because the model was developed to explain the adoption of consumer applications (Venkatesh, Thong, et al., 2012). As pervasive retail systems fall into the category of consumer applications (P. Kourouthanassis et al., 2003), we expect a better explanation of people's adoption intention towards these systems by integrating the UTAUT2 with the Extended Privacy Calculus.

2.3 Research model

Figure 2.1 depicts our proposed research model. As mentioned in the last section, we combine the UTAUT2 from Venkatesh, Thong, et al. (2012) with the Extended Privacy Calculus introduced by Dinev et al. (2006). We propose to substitute the construct price value from the UTAUT2 - which captures the trade-off between the perceived costs and the perceived benefits of using a technology - with the Extended Privacy Calculus. The Extended Privacy Calculus captures the trade-off between the perceived value of using a technology and the perceived costs of disclosing private information. Thus, we think that it is a well-suited substitute for the price value construct from the UTAUT2.

2.3.1 UTAUT2 constructs and hypothesized relationships

Venkatesh and other researchers validated the applicability of the UTAUT2 across many disciplines and showed that the model is able to explain more than 70% of the variance in a person's behavioral intention to use a technology. We use five of the UTAUT2's nine constructs in our model, namely performance expectancy (PE), effort expectancy (EE), social influence (SI), hedonic motivation (HM) and behavioral intention (BI). We explain our reasoning in the following.

Besides the price value construct, which we substitute with the Extended Privacy Calculus, we exclude three more of UTAUT2's original constructs. We first do not consider the actual use of pervasive retail systems because the implementation of such systems is still at the very beginning. Following SALINAS SEGURA et al. (2015), we furthermore exclude the construct habit, because it would require customers to already have experience with pervasive retail systems. In addition, we exclude the construct facilitating conditions because some of the underlying questions are not suited for pervasive retail systems. Customers do, for example, not need particular resources to use them because such systems are implemented in retail stores and can be used without purchasing them first (see question FC1 in VENKATESH, THONG, et al. (2012)). In addition, the technology is novel and it is thus not obvious for customers how it is compatible with other technologies they use (see question FC3 in VENKATESH, THONG, et al. (2012)).

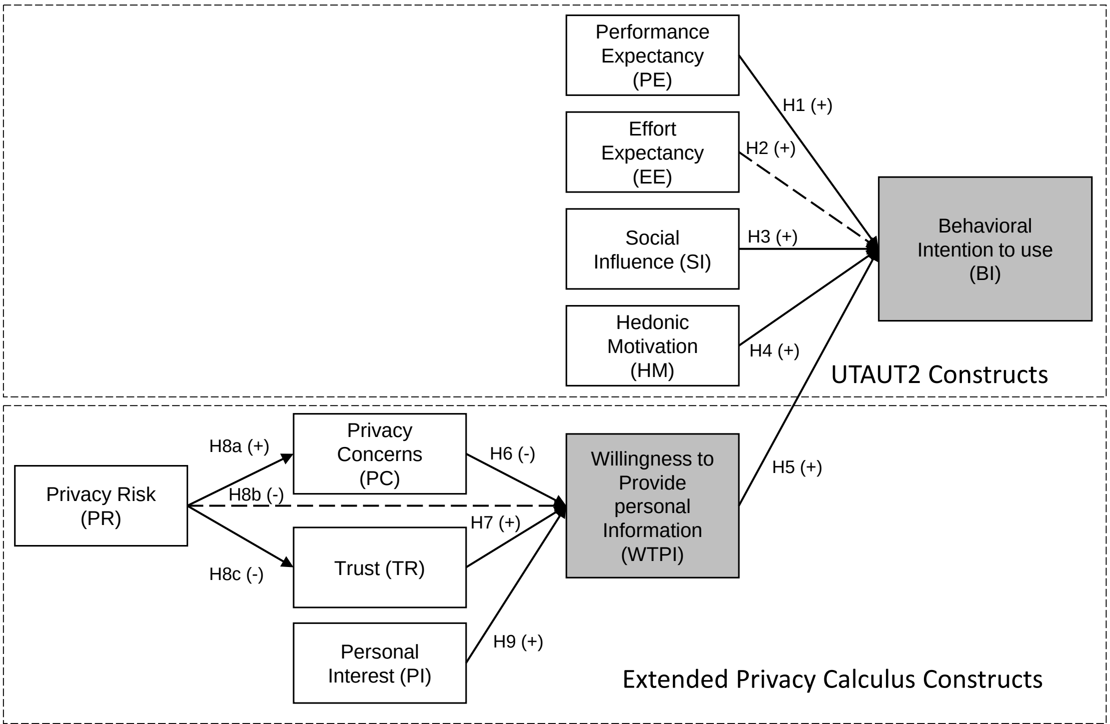

Figure 2.1: Research model and hypothesized relationships between the constructs

The first construct we incorporate is performance expectancy, which describes how much a technology user expects to improve the performance of a process through the use of a technology (VENKATESH, MORRIS, et al., 2003). The idea of pervasive retail systems is to provide customers with features that aim at improving their shopping experience. In a smart fitting room, for example, users automatically receive personalized recommendations based on their current garment selection and their purchase history, which enables them to make better decisions in less time. We thus formulate the following hypothesis:

H1: PE has a positive effect on the behavioral intention to use a pervasive retail system.

Effort expectancy is “the degree of ease associated with consumers’ use of technology” (Venkatesh, Thong, et al., 2012) and is thus positively related to BI. Obviously, if customers perceive the usage of pervasive technologies as intuitive they will be more likely to use them. Thus, we hypothesize:

H2: EE has a positive effect on the behavioral intention to use a pervasive retail system.

Social influence describes to what extent others influence one’s decision to use a technology (Venkatesh, Morris, et al., 2003). Others are in our case people who are important to a retail customer (e.g., friends and family). Various studies examine the impact of the variable social influence on a person’s behavioral intention to use a technology. Studies validated this relationship empirically for the adoption of smart kiosks (Chiu et al., 2010), mobile payment solutions (Oliveira et al., 2016), and RFID-based applications in the healthcare sector (Chong et al., 2015). Consequently, we formulate the following hypothesis:

H3: SI has a positive effect on the behavioral intention to use a pervasive retail system.

Hedonic motivation denotes the pleasure of using a novel technology. According to Venkatesh, Thong, et al. (2012), it is one of the most important factors in predicting a consumer’s intention to use a technology. Consequently, we assume that people who generally enjoy using novel technologies will be more likely to use a pervasive system and formulate our hypothesis as follows:

H4: HM has a positive effect on the behavioral intention to use a pervasive retail system.

2.3.2 Extended Privacy Calculus constructs and hypothesized relationships

As mentioned before, the use of pervasive retail systems is free of monetary charge. We thus exclude the price value construct from the UTAUT2. However, we argue that even though customers will not have to pay money for using the systems, they will be “charged” by having to disclose private information. Venkatesh, Thong, et al. (2012) define the term price value as “consumers’ cognitive trade-off between the perceived benefits of the applications and the monetary cost for using them”. In order to capture the “costs of privacy", i.e., the trade-off between the perceived benefits and the perceived potential drawbacks of private information disclosure, we propose to replace the price value with the Extended Privacy Calculus Model. We therefore redefine the term price value as the cognitive trade-off between the perceived benefits of using a pervasive retail system and the privacy related costs. To this end, we carefully adapted the proposed constructs of the Extended Privacy Calculus from Dinev et al. (2006) and also considered the study of Kowatsch et al. (2012) who adapted Dinev and Hart's questions to the realm of IoT.

The first construct we include in our model is the willingness to provide personal information (WTPI) which refers to a person's willingness to disclose private information to use all functionality of a pervasive application (Kowatsch and Maass 2012). As we assume that people would only be willing to disclose information if they intend to use the system, we hypothesize:

H5: WTPI has a positive effect on the behavioral intention to use a pervasive retail system.

The construct privacy concerns against a pervasive retail system (PC) reflects the concern of an opportunistic behavior related to the provided information by the user (Kowatsch et al., 2012). According to Dinev et al. (2006), privacy concerns are in accordance with the expectancy theory from Vroom (1964). As a consequence, people should try to minimize negative consequences of their information disclosure behavior. We formulate the following hypothesis:

H6: PC has a negative effect on a person's willingness to provide personal information.

The construct trust (TR) towards the party that provides a pervasive application denotes people's belief that their private information will be handled secure, safe and in a competent way. Even though trust perception can be seen as the opposite of risk perception – which we also included in our model – this construct captures a different notion (Kowatsch et al., 2012). For example, a customer can trust a retailer that provides a smart fitting room application and – at the same time – be aware that providing private information to use the application can bear some risks. Consequently, we hypothesize:

H7: TR has a positive effect on a person's willingness to provide personal information.

Perceived privacy risk (PR) describes the general perceived risk related to the disclosure of personal information (Kowatsch et al., 2012). According to Dinev et al. (2006) such risk includes the sale of private information to third parties or sharing of private information with third parties. This construct also reflects the misuse of personal information such as unauthorized access to the data or data theft. We consequently formulate the following three hypothesis:

H8a: PR has a positive effect on the perceived privacy concerns against using a pervasive retail system.

H8b: PR has a negative effect on a person's willingness to provide personal information.

H8c: PR has a negative effect on the trust in the party providing the pervasive retail system.

The construct personal interest in a pervasive retail application (PI) reflects a person's degree of intrinsic motivation which overrides privacy concerns in order to use such an application (Kowatsch et al., 2012). In contrast to the construct hedonic motivation from the UTAUT2, this construct measures the degree to which the cognitive attraction to a pervasive retail system overrides privacy concerns. Consequently, we formulate the following hypothesis:

H9: PI has a positive effect on a person's willingness to provide personal information.

2.4 Research method

To validate our model we consider a smart fitting room application. The system recognizes the customers' garment selections based on RFID technology and provides suitable recommendations if customers identify themselves and allow the system to access their purchase history. In addition, the application offers the option of home delivery of chosen garments if the customer provides address and financial data to the system. The application that we consider in our study is based on a prototype that was implemented during a research project on the retail sales floor at a leading German fashion retailer.

2.4.1 Instrument development and data collection

We conducted an online survey with students from a German university. We chose to target students because young people are the target group that the retailer in our study wants to attract to its stores with the pervasive retail system. As an incentive to participate, students had the chance to win one out of five book vouchers worth 20€ each. In the survey, we described the use case and its functionalities with pictures depicting the real world prototype (e.g., the user interface). We also informed the survey participants that they would have to identify themselves and share address as well as financial data in order to use the described fitting room functionalities. We carefully adapted the questions for the constructs described above (see appendix A) and used a seven point Likert scale for the questionnaire. In total, 280 students participated in the survey. Our sample consists of 151 female and 129 male students with an average age of 23.2 years. The standard deviation is 3.5 years.

2.4.2 Data preparation

As online surveys yield higher risks of careless responding due to unmotivated or inattentive respondents than pen and paper based versions (Huang et al., 2012), we conducted a structured data screening process.

We use the methods (i) screening for unusually short response times and (ii) screening for patterns to identify inattentive respondents. The first method assumes that participants who carelessly fill out a questionnaire are more likely to rush through it (Meade et al., 2012). Based on preliminary tests, we assume that respondents who are familiar with pervasive systems and are fast readers would need at least four and a half minutes for completing the questionnaire. The second method searches for unusual patterns in the data by using the long string method proposed by Johnson (2005). The author proposes to eliminate answers with an unusual number of consecutive repetitions of the same kind of answer (e.g., ten times the answer "very likely" in a row). We computed the long strings for each participant and removed completed questionnaires of participants with ten or more consecutive answers of the same type. Four of the participants that we identified with this method also fell under the previously defined response time cut-off. The times that it took the rest of the suspicious respondents to answer the questionnaires were also very close to this predefined cut-off.

Overall, the data cleaning process lead to a removal of 28 respondents, which were suspect to inattentive and unmotivated answering. These are exactly 10% of the respondents which is in correspondence with reports from other studies with student samples (see, e.g., Kurtz et al. (2001)).

2.5 Results

Henseler, Ringle, and Sinkovics (2009) state that partial least squares (PLS) “path modeling is recommended in an early stage of theoretical development to test and validate exploratory models”. We aim at introducing a new theory and thus use PLS for the analysis of our theoretical model. Following Chin (2010), we present our results by first reporting the reliability and validity of the used item measures and then present the evaluation results of the structural model. We used SmartPLS Version 3.2.6. to conduct the analysis.

2.5.1 Model reliability and validity

In a first step, we evaluated the outer loadings of our model (A full overview of all outer loadings of all items of the model can be found in appendix B). Except from questionnaire item HM3, all items have outer loadings above the proposed value of 0.708 (Henseler, Ringle, and Sinkovics, 2009). Item HM3 asks the participants the question if they perceive the usage of the smart fitting room as entertaining. With an outer loading of 0.674, however, item HM3 is only slightly below 0.708 and we thus did not exclude it from our analysis. Consequently the latent variables of the model show a good reliability.

Table 2.1: Construct reliability and validity

	Cronbach's Alpha	Composite Reliability	AVE
BI	0.919	0.948	0.860
EE	0.882	0.915	0.731
HM	0.820	0.889	0.732
PC	0.916	0.941	0.800
PE	0.720	0.843	0.642
PI	0.807	0.886	0.721
PR	0.874	0.909	0.669
SI	0.878	0.925	0.803
TR	0.755	0.859	0.670
WTPI	0.859	0.914	0.781

Table 2.1 reports the Cronbach's Alpha, Composite Reliability and Average Variance Extracted (AVE) of each construct and shows the internal consistency of our model. All constructs have a Cronbach's Alpha value higher than 0.7 and thus display convergent validity (Garson, 2016). Furthermore, all constructs show a composite reliability greater than the cut-off of 0.8 which is considered good for confirmatory research (Daskalakis et al., 2008) and well above the proposed threshold of 0.7 that literature considers good for explanatory purposes (J. F. Hair et al., 2012). In addition, the AVE of all constructs is higher than the proposed threshold of 0.5 (Chin, 1998) which means that the error variance does not exceed the explained variance (Garson, 2016).

We use the Heterotrait-Monotrait (HTMT) ratio for analyzing the discriminant validity of our model (see table 2.2) because Henseler, Ringle, and Sarstedt (2015) lately showed its superiority over the Fornell and Larcker criterion (Fornell et al., 1981). Table 2.2

shows that all HTMT ratios are below the strict cut-off value of 0.85 proposed by Kline (2015) which indicates good discriminant validity.

The overall model fit is estimated with the Standardized Root Mean Square Residual (SRMR) which measures the difference between the observed correlation matrix and the model-implied correlation matrix. Our model shows an SRMR of 0.096 which indicates a good fit according to Garson (2016).

Table 2.2: Heterotrait-Monotrait Ratio

	BI	**EE**	**HM**	**PC**	**PE**	**PI**	**PR**	**SI**	**TR**	**WTPI**
BI	1									
EE	0.286	1								
HM	0.774	0.302	1							
PC	0.301	0.127	0.154	1						
PE	0.796	0.382	0.845	0.104	1					
PI	0.722	0.242	0.633	0.209	0.570	1				
PR	0.332	0.115	0.199	0.828	0.133	0.220	1			
SI	0.570	0.204	0.557	0.072	0.691	0.406	0.126	1		
TR	0.558	0.184	0.437	0.279	0.387	0.559	0.376	0.400	1	
WTPI	0.711	0.180	0.507	0.358	0.502	0.692	0.309	0.367	0.614	1

2.5.2 Structural model

We determine the effect size f-squared of each variable with the following formula (J. Hair et al., 2014):

$$\mathrm{f}^2 = \frac{\mathrm{R}^2_{\text{included}} - \mathrm{R}^2_{\text{excluded}}}{1 - \mathrm{R}^2_{\text{included}}} \tag{2.1}$$

In order to calculate f^2 for each construct, we first calculate the R^2 of the full model ($\mathrm{R}^2_{\text{included}}$). In a second step, we calculate $\mathrm{R}^2_{\text{excluded}}$ for each construct, which is the R^2 of the model without the construct currently under consideration. Effect sizes are considered small if they are above 0.02, medium if they are above 0.15 and large if they are above 0.35 (Cohen, 1988). Furthermore, “if an exogenous construct strongly contributes to explaining an endogenous construct, the difference between $\mathrm{R}^2_{\text{included}}$ and $\mathrm{R}^2_{\text{excluded}}$ will be high, leading to a high f^2 value” (J. Hair et al., 2014).

Table 2.3 shows the effect sizes of the variables. It reveals that WTPI and HM have the highest influence on BI and that PI has the highest influence on WTPI. TR, PC and PR, on the other hand, have only small effects on WTPI. In addition, the table indicates a large influence of PR on PC.

The results of the structural model are presented in table 2.4 (see appendix C for a visual representation). We use bootstrapping with 5000 samples to determine whether the relations between the constructs are significant and support the stated hypotheses. The table shows that all hypotheses except H2 and H8b are supported.

Table 2.3: Effect sizes

Construct	Dependent Variable	f^2	Effect
WTPI	BI	0.310	**medium**
HM	BI	0.202	**medium**
PE	BI	0.053	small
SI	BI	0.022	small
EE	BI	0.002	none
PR	PC	1.251	**large**
PR	TR	0.105	small
PI	WTPI	0.264	**medium**
TR	WTPI	0.102	small
PC	WTPI	0.039	small
PR	WTPI	0.003	small

In a next step we also calculate the indirect effects of PR on WTPI, considering again bootstrapping and 5000 samples. This calculation results in a path coefficient of -0.251. When we add this value to the direct path coefficient of 0.067, this results in a total effect of -0.184 with a p-value of 0.001.

Table 2.4: Summary of results

Hypothesis		Path Coefficient	T Statistics	P Values	Supported
H1	PE ->BI	0.192	3.392	0.001	**Yes**
H2	EE ->BI	0.027	0.691	0.490	No
H3	SI ->BI	0.104	2.335	0.020	**Yes**
H4	HM ->BI	0.368	6.374	<0.001	**Yes**
H5	WTPI ->BI	0.358	8.633	<0.001	**Yes**
H6	PC ->WTPI	-0.223	3.222	0.001	**Yes**
H7	TR ->WTPI	0.275	4.626	<0.001	**Yes**
H8a	PR ->PC	0.745	23.952	<0.001	**Yes**
H8b	PR ->WTPI	0.067	0.837	0.402	No
H8c	PR ->TR	-0.309	4.748	<0.001	**Yes**
H9	PI ->WTPI	0.430	7.647	<0.001	**Yes**

We analyze the proportion of variance explained by our model. Table 2.5 shows that the constructs of BI explain 67.1% of its variance. As stated before, WTPI and therefore the result of the privacy calculus is the most important predictor for people's intention to use a pervasive retail system. 43.1% of the variance of WTPI is explained by its predictors, whereby the constructs personal interest and trust account for the biggest portion of people's intention to use a pervasive retail system.

Table 2.5: Explanatory power

	Adjusted- R^2	P **Values**
BI	0.671	<0.001
WTPI	0.431	<0.001
PC	0.554	<0.001
TR	0.092	0.025

2.6 Conclusion

The present study investigates customers' adoption intentions towards pervasive retail systems. In contrast to consumer products, customers do not have to purchase the systems to use them. The systems, however, heavily depend on privacy-related data, which customers could perceive as a potential privacy threat. To address this issue, we propose a model that combines the UTAUT2 and the Extended Privacy Calculus. Our investigation shows that our model is able to explain 67.1% of the variance in people's intention to use a pervasive retail system. We show that people's willingness to provide personal information and the hedonic motivation from the UTAUT2 are the most important determinants of people's usage intention. WTPI accounts for more variance in the behavioral intention than hedonic motivation from the UTAUT2 ($f^2 = 0.310$ against $f^2 = 0.202$). This indicates that people weigh the perceived benefits against the perceived drawbacks of providing personal information before they decide whether they want to use a pervasive retail system. We are thus able to demonstrate with our empirical investigation that the Extended Privacy Calculus is a valid substitute for the construct price value of the UTAUT2 if the usage of a system does not come with monetary costs but requires disclosing privacy-related data. This implies that providers of such applications have to carefully consider people's privacy perceptions. If people are not willing to disclose necessary privacy-related data, they will not end up using the application even if it offers valuable benefits.

We did not only investigate the predictors of people's usage intention but also the predictors of people's willingness to provide personal information for using a pervasive retail system. Our investigation shows that our model is able to explain 43.1% of their willingness to provide such information. The most important variables for explaining the willingness to provide personal information are personal interest ($f^2 = 0.264$) and trust towards the institution that provides the application ($f^2 = 0.102$). This result is in accordance with

Dinev and Hart's (2006) study, which also found that "the three factors most strongly related to the willingness to provide personal information were [...] privacy concerns, [...] trust, and personal [...] interest" (Dinev et al., 2006). We show that the perceived benefits of pervasive retail systems must outweigh the perceived privacy costs so that people are willing to "forget" their privacy concerns (captured by the variable personal interest). If retailers are not able to achieve this, they might risk losing their customers and investing in an application that customers might not use at all. In addition, as trust towards the provider of pervasive retail systems is the second strongest predictor of the willingness to provide personal information, retailers should strive to preserve a good reputation for carefully handling customer data.

Our model, however, does not support the relationship between effort expectancy and the behavioral intention to use a pervasive retail system. One explanation could be that people perceive the smart fitting room as a fun application and do thus not perceive the process of learning to use the application as an effort. In consequence, effort does not play a role on their usage intention. Another explanation could be, that our sample comprises only students, which are digital natives and are thus familiar with pervasive systems (e.g., smart phones and smart watches). The data revealed that most of them chose high values on the Likert scale for the questions of the construct effort expectancy regardless of their usage intention towards the smart fitting room. Nevertheless, we decided to keep the construct because we think that a survey with a different sample population (i.e., a sample not only comprising digital natives) could show a relationship between effort expectancy and the behavioral intention to use a pervasive retail system. We furthermore did not find support for the direct relationship between perceived privacy risk and the willingness to provide personal information. The model, however, revealed that privacy risk has a significant indirect effect on the willingness to provide personal information, which is in accordance with our expectations.

There are also some limitations to our research. First, although the student sample is suitable for this study because young people are the target group of the retailer with whom we conducted this study, the sample characteristics limit the generalizability of our results. Second, we conducted an online experiment and even though we carefully described the application and illustrated its use with meaningful pictures, there is still the possibility that a study with a real prototype would yield differing results. Third, with the smart fitting room application we only considered one pervasive retail system to validate our research model.

We see opportunities for further research in various directions. We encourage researchers to use our model for the investigation of people's adoption intention and disclosure behavior towards other privacy related pervasive retail applications. In addition, future research should not only consider usage intention but also actual usage behavior of pervasive applications. Not least, we believe that our proposed model could be used to explain adoption intention and privacy disclosure behavior of applications beyond pervasive retail systems.

CHAPTER 3

Evaluating RFID-enabled robotic inventory taking

3.1 Introduction

Radio Frequency Identification (RFID) can generally lead to a number of benefits for retailers, like for example more efficient processes and more time for store staff to serve customers (Marco et al., 2012). One of the most important advantages, however, is the improved accuracy of a company's inventory data. Stock-out situations are still an important issue for retail companies today, because it does not matter how efficient the downstream supply chain could be in supplying a store if an inefficient shelf replenishment process - caused by incorrect inventory data - leads to empty shelves and unsatisfied customers (Rekik, Sahin, et al., 2008).

Accurate inventory information is crucial for the success of a retail company. However, out of stock rates between 10% and 15% are not unusual for European companies (Berger, 2003). The inaccuracy of the inventory is referred to as the discrepancy between the actual inventory and the recorded inventory (usually in a computer system). Studies have shown that this is a major problem and have found that discrepancies of up to 65% of the data sets of the companies examined were inaccurate (DeHoratius et al., 2008).

When there is a deviation between the actual and the recorded stock level, situations of overstock and understock can occur (Ernst et al., 1993). Overstock means that the actual stock level is higher than the recorded stock level. This can lead to higher inventory holding costs than a company originally planned. Understock denotes the opposite of the former. This means, that the actual stock level is lower than the recorded stock level which leads to a higher risk of out of stock situations (Ernst et al., 1993). Kang et al. (2005) show in their study that even the best performing companies had only 70 - 75% of the inventory records match the inventory on hand. Consequently, the discrepancy between actual stock levels and recorded stock levels is a major problem for companies.

One way to deal with inventory inaccuracy is the use of novel technologies. Since Wal-Mart tested the use of RFID along its supply chain as part of a pilot project in 2003, the so far little used technology has gained more and more attention and has fundamentally changed logistical processes in retail (Delen, Hardgrave, et al., 2007). One of the benefits of RFID is that it can lead to a higher product availability at lower costs (McEachern et al., 2005). Before RFID was available, a "[c]omplete inspection of the inventory [was] very expensive"(Ernst et al., 1993). Because of RFID's huge potential, the barcode technology is becoming less important and academic research has shifted its focus towards RFID (Kok et al., 2008).

One claim of RFID is, that it enables a firm to enhance its inventory data quality. However, through multiple negative effects like for example, theft, misplacement or imperfect read rates of the fixed RFID hardware itself (usually RFID gates), the quality of RFID-based inventory data is often not as reliable as a retailer might assume. Low data quality can lead to stock-outs and replenishment freezes and therefore cause high costs for the retailer (Thiesse and Buckel, 2015). In order to diminish the influence of these negative effects, additional data quality measures are often undertaken. Most common is the usage of RFID-based handheld readers, which enable retailers to conduct cycle counts without the need to hold and scan individual items. Consequently this approach is much faster and costs less than traditional cycle counts (Buckel et al., 2013). Although the use of RFID-based handheld scanners for inventory taking is faster than traditional inventory taking, it is still a manual process.

In order to further automate inventory correction, some retailers experiment with inventory robots equipped with RFID reading devices. These robots are able to make a full inventory every day without human intervention, thus eliminating manual labor completely from the inventory taking process (Swedberg, 2016). However, it is unclear whether the introduction of an inventory robot actually improves the quality of inventory data compared to the approach with RFID-based handheld readers. In addition, robotic inventory may not be error-free, and the introduction and implementation of an inventory robot in a retail store is an investment that should be carefully considered. It is therefore unclear, if retailers will not do better with the use of a 'traditional' RFID handheld-based cycle counting policy. Our study therefore has the following objectives: We first want to determine the influence of handheld-based RFID-enabled cycle counting and RFID-enabled robotic inventory taking on the economic performance of a retail store. Second, we want to compare both approaches and evaluate when either of the approaches is superior over the other. Third, we want to determine if robotic inventory taking renders an RFID-enabled replenishment gate obsolete.

To address our research questions, we conduct computer based simulations to examine the influence of RFID-enabled cycle counting and RFID-enabled robotic inventory taking on the economic efficiency of a retail store. We simulate different control parameters on an RFID equipped inventory management system that operates on a threshold based replenishment policy using the stock information generated by RFID. In order to use realistic assumptions, we base our simulation model on information made available by a large German fashion retailer which has already implemented RFID on a large scale. Our research aims to help practitioners decide which RFID-based inventory taking strategy to choose.

The chapter is organized as follows. In the next section we provide a review of prior research on imperfect inventory data as well as RFID-based inventory control and outline the research gap that is addressed by our study. Finally, we describe the model which we developed for this study and perform several analyses in order to compare RFID-enabled robotic inventory taking with RFID-enabled cycle counting.

3.2 Related literature

In the following we analyze the relevant streams of literature about (i) *inventory record inaccuracy and non-technological countermeasures*, (ii) *inventory record inaccuracy and perfect RFID systems*, (iii) *inventory record inaccuracy and imperfect RFID systems* and (iv) *RFID-enabled robotic inventory taking.*

3.2.1 Inventory record inaccuracy and non-technological countermeasures

Many researchers have investigated inventory record inaccuracy from different perspectives. One of the first researchers who identified inventory record inaccuracy as a major problem for supply chain operations was Rinehart (1960). He reports insights from a case study of a government agency that performs yearly inventories at its supply centers. He noticed that the discrepancy rates for so called secondary items ranged from 20% to 50% leading to high costs and to less performance of the supply centers of the government agency. By further analyzing the problem the author found out that "the discrepancies were caused by the discrepancy correcting procedures themselves" (Rinehart, 1960). Based on these findings he finally gives suggestions on how to improve the situation.

The first study that mathematically investigates the impact of counter measures against inventory record inaccuracy was conducted by Iglehart et al. (1972). The authors analytically determine the optimal combination of buffer stock and inventory counts for inventory systems with imperfect asset information (i.e., a discrepancy between the recorded inventory and the on hand inventory) in order to minimize the occurrence of inventory shortages. In contrast to Iglehart et al. (1972), Morey (1985) investigates, from a managerial point of view, how buffer stock, physical inventories and corrective actions (i.e., eliminating the causes of inventory discrepancy) can be used in order to enable managers to have a cost-effective means of reducing inventory discrepancies. The author therefore provides practical and conservative guidelines that can be used by managers in order to choose effective counter measures against inventory record inaccuracy.

In their paper Ernst et al. (1993) propose an approach for controlling and monitoring stock levels. They use the average absolute relative difference as a practical measure for the accuracy of the inventory data and visualize it in a control chart. Because of the high costs of inventory taking, the authors furthermore discuss the applicability of sampling strategies.

Fleisch et al. (2005) investigate how inventory inaccuracy influences the performance of a retail supply chain. They use a simulation model in order to show that the alignment between physical inventory and system inventory reduces the costs that occur in a supply chain and the stock-out quota. They furthermore briefly discuss possible methods in order to improve inventory accuracy and suggest that RFID technology could prove very promising for this purpose.

Gumrukcu, English, et al. (2007) investigate with a simulation of a two-echelon supply chain with multiple items how different cycle counting strategies (i.e., how often the counting is performed and what percentage of items is counted) impact the costs and the data quality of the supply chain. In a second study Gumrukcu, Rossetti, et al. (2008) elaborate their analyses further by trying out different cycle counting configurations in order to find the best cycle counting intervals for high-demand-low-cost and low-demand-high-cost items. They are able to show that a suitable cycle counting strategy leads to cost savings for the entire supply chain.

Thiel et al. (2010) analyze the behavior of a continuous-review policy (Q,R) with the help of an analytical model and a simulation model for the scenario of small and medium-sized enterprises. They investigate the relationship between safety stock, inventory inaccuracy and service level for varying demands.

In summary, the inaccuracy of inventory records was investigated from several angles, taking into account the effect of non-technological countermeasures such as optimizing buffer stock and using manual inventory counts. The next chapter examines how technology - in our case RFID - helps to alleviate inventory record inaccuracy.

3.2.2 Inventory record inaccuracy and perfect RFID systems

Several papers have investigated the impact of RFID on inventory record inaccuracy, assuming RFID to be a perfect technology. Kang et al. (2005) investigate automated inventory management processes that rely on an information system. They evaluate the inventory accuracy at a global retailer and demonstrate with an analytical and a simulation model that even a small undetected loss of stock can lead to a replenishment freeze and high subsequent costs. A replenishment freeze refers to a situation in which the information system assumes that there is inventory present even though it is not the case and fails to trigger a replenishment. Besides other methods for compensating for the inaccuracy in the inventory records, the authors also briefly investigate the impact of RFID. They, assume RFID to be a perfect technology and conclude that it allows for the lowest inventory level while simultaneously having the lowest rate of stock-outs in comparison to the other inventory correction methods.

Lee et al. (2004) investigate the impact of implementing RFID into a supply chain with the help of a simulation model. They investigate a manufacturer-retailer supply chain and show that RFID positively influences the overall service level and reduces the inventory levels. However, they propose for further research, that RFID should be expected to work with less than 100% accuracy.

Atali et al. (2009) propose an analytical model for investigating how companies should manage their inventory when inventory records are faulty. They show the value of inventory visibility and try to quantify the value of tracking technologies like RFID. The authors perform a numerical study and compare modern tracking technologies to traditional inventory management methods. The study shows, that even small discrepancies between the recorded and the on hand inventory can lead to lost sales due to stock-outs. The authors conclude that RFID can help to "reduce stock-out rates without carrying excessive and costly inventory" (Atali et al., 2009).

With the help of an analytical model Kök et al. (2007) develop an inspection and replenishment policy that minimizes the total costs of the model for a finite time horizon. In a second step, the authors also attempt to assess the value of accurate inventory information that could be delivered by RFID. The authors conclude that although RFID can have great benefits for the correct management of inventory, correction strategies such as those proposed can also deliver good inventory accuracy results if a company cannot afford to invest in RFID.

By modeling a retail supply chain with one manufacturer and one retailer Gaukler et al. (2007) investigate the influence of implementing item-level RFID. The authors focus their attention on the sharing of costs between the supply chain partners. Their study has the objective to evaluate for different scenarios how the costs of item-level RFID should be distributed between the partners in order to optimize the overall profit of the supply chain.

Saygin (2007) investigate RFID-enabled inventory management of time-sensitive materials. The authors use a simulation, in order to compare different inventory management models based on costs, service level as well as inventory and waste reduction. They show that a dynamic, forecast-integrated inventory model is best suited for using the data offered by RFID. Overall the authors conclude, that RFID in combination with the dynamic inventory model leads to reduced inventory levels and lower levels of waste.

Rekik, Jemai, et al. (2007) and Rekik, Sahin, et al. (2008) investigate the influence of misplacement type execution errors in a retail store facing the classical Newsvendor Problem. They propose an analytical inventory model in which a retail store is supplied by one manufacturer. The model incorporates execution errors at the retailer leading to missing items on the shelves of the retailer. The authors investigate what happens to the supply chain if RFID is deployed in order to eliminate the execution errors and mathematically prove the validity of their model. In a further paper Rekik, Sahin, et al. (2009) investigate the impact of theft on the inventory management of a retail store. For their analysis they compare three scenarios. In the first scenario the manager of the retail store ignores theft, in the second scenario, the manager of the retail store is aware of the theft and uses this knowledge in order to construct a better inventory policy and in the third scenario a perfect RFID system is introduced and eliminates theft completely.

With a mathematical model Szmerekovsky et al. (2008) investigate the applicability of RFID for a vendor managed inventory. They compare a scenario with continuous review and RFID to a scenario with periodic review that does not include RFID. They show under which circumstances RFID is beneficial for a centralized system and demonstrate how the tag price of RFID tags can be used in order to coordinate a decentralized supply chain.

Kok et al. (2008) perform a break-even analysis on when to introduce RFID and calculate break-even prices for RFID tags. They discuss that the break-even prices are highly dependent upon the costs of the products under consideration and the shrinkage that can be eliminated with RFID.

Ustundag et al. (2009) use a simulation model of a three-echelon supply chain in order evaluate the expected benefits of an integrated RFID solution. The model takes into account factors such as theft, lost sales, ordering costs and labor costs. The authors show, that the benefits from RFID are highly dependent upon the costs of the product and the uncertainty of its demand. They also show that not all members of the supply chain benefit equally from the implementation of RFID.

In order to perform a return-on-investment analysis for the implementation of RFID Sarac et al. (2008) create a simulation model of a three-echelon supply chain. The authors study the influence of different types of RFID implementations (case-level tagging, item-level tagging and item-level tagging in combination with smart shelves). However, they merely conclude that the economic impact depends upon the product under consideration (fast selling, expensive, cheap, etc.), the chosen RFID technology (e.g., smart shelves) and the level of tagging (item-level or case-level).

In their study Wang et al. (2008) investigate the influence of RFID on a simulated TFT-LCD supply chain. Their simulation shows that RFID leads to a decrease in the inventory holding costs and to an increase in the rate of turnover in comparison to a non-RFID supply chain.

Taking a look onto pharmaceutical inventory, Çakici et al. (2011) analyze the impact of RFID on the inventory policy and the reduction of shrinkage with an analytical model. The authors compare RFID to the barcode and perform a cost-benefit analysis for using RFID in a radiology practice. The study concludes that RFID generates high benefits for the investigated use case.

To summarize, all of the before mentioned studies do consider RFID to be a perfect technology which, in our opinion, leads to an oversimplification of the technology itself and an overestimation of the potential benefits of implementing RFID. However, there exist some studies which take the potential problems of RFID into account. We discuss these studies in the next section.

3.2.3 Inventory record inaccuracy and imperfect RFID systems

In contrast to the previously discussed papers, the following studies consider the problems of RFID technology. The first paper to mention was written by Thiesse and Fleisch (2007). The authors conduct a simulation study in order to compare shelf replenishment policies based on manual inventories to a scenario with RFID. In contrast to the studies mentioned above, however, they consider scenarios where RFID is less than 100% accurate. They demonstrate that the RFID-enabled process, depending on the reading rate and hardware costs, exceeds the traditional process in terms of item availability and cost-efficiency.

Buyurgan et al. (2010) also assume in their study that RFID is not a perfect technology. The authors investigate how the imperfect inventory information from RFID impacts a multi-echelon retail supply chain with the help of a simulation model. In order to counter the imperfect read rate of the RFID hardware the authors investigate the influence of cycle counting as a data quality measure on the supply chain. They consider scheduled cycle counting (in ranges from weekly cycle counting over to yearly cycle counting) and system triggered cycle counting on the inventory accuracy of the supply chain. The authors conclude that RFID is a valuable technology even if it does not deliver perfect inventory information.

Condea et al. (2012) investigate RFID-enabled shelf replenishment decisions in a retail store with case-level tagging. They use a simulation model that incorporates stochastic demand and shrinkage. In contrast to other research their model also incorporates bidirectional movements of inventory between the stockroom and the sales floor under consideration. They furthermore propose and evaluate a heuristic in order to improve the replenishment decisions. The authors conclude that choosing a suitable replenishment policy is highly dependent upon the cost factors and the read rate of the implemented RFID devices.

Metzger et al. (2013) mathematically analyze the influence of so called false negative reads on the performance of RFID-based shelf replenishment policies. However, in contrast to Condea et al. (2012) the authors consider item-level tagging and develop an inventory control policy that copes with the problem of false negative reads by optimizing an analytical model for an RFID-enabled infrastructure that is based on smart shelves. According to their model, the negative impact of false negative reads is moderate for medium to high read rates of the RFID hardware.

Similar to Condea et al. (2012) and Metzger et al. (2013), Thiesse and Buckel (2015) investigate RFID-enabled replenishment policies on the retail sales floor. They use a simulation model and analyze case-level tagging and item-level tagging. The authors first evaluate a scenario with smart shelves and compare it to the traditional periodic review. In a second step, they extend their model to evaluate backroom monitoring with an RFID gate, as done by Condea et al. (2012). The study shows that the read rate of the RFID hardware is not negligible and has a strong impact on the performance of the proposed replenishment policy.

In summary, the authors of the studies we consider within this chapter are aware that RFID is not a perfect technology and although it is intended to reduce incorrect inventory, it can produce errors itself. Therefore, these studies suggest that the accuracy of the RFID reading hardware must be taken into account in further research.

3.2.4 RFID-enabled robotic inventory taking

Using RFID technology helps a company streamline its inventory process, but does not eliminate the need for manual work. As the studies in the previous sections show, it is still necessary to carry out additional manual checks, e.g., with RFID handheld readers, to compensate for the errors caused by an imperfect RFID system. Therefore it would be a logical step for companies that already use RFID to automate this last step of the inventory. Robotics in particular seems to be particularly suitable for this task.

The use of robots in the industry, especially the producing industry like automobiles is not new. However, with recent developments also non-producing companies try to improve their processes with the help of robots. Amazon for example acquired Kiva Systems (a manufacturer of mobile robots) for $775 million in 2012 in order to improve inventory management in its warehouses. In late 2015 Amazon used over 30,000 Kiva robots in its warehouses. The robots not only helped Amazon to reduce the time for the "click to ship" process from 75 minutes to 15 minutes, but also allowed the company to hold more inventory in its warehouses because the robots need less space than human workers (Bhattachaya, 2016).

Some retailers are currently experimenting with robot-based inventory. Lowe's, an American retailer, has developed in collaboration with Silicon Valley company Fellow Robots, a retail robot that is able to navigate through a store's shopping aisles, identify customers with a 3D scanner and scan the inventory on the shelves on a daily basis. The robot not only increases the overall accuracy of stock levels, but also offers customers the service of guiding them to the items they are looking for (McSweeney, 2016).

The RFID industry has also recently recognized the potential of robotic inventory taking and is thus combining robotics and RFID technology. According to our knowledge, there are currently three solutions from three different manufacturers on the market that use RFID in combination with robotics for inventory taking. Table 3.1 gives an overview of the available systems.

Table 3.1: Overview of RFID-based inventory robots (sources: Keonn (2016), MetraLabs (2016), and PAL-Robotics (2016b))

Manufacturer	Name	Antennas	Positioning	Runtime	Accuracy
MetraLabs	Tory	n.a.	3D	14h	>99%
PAL Robotics	StockBot	8	3D	12h	n.a.
Keonn Technologies	AvanRobot	12	3D	12h	>99%

The German company MetraLabs offers the Tory, PAL Robotics offers the StockBot and Keonn Technologies offers the AvanRobot. All these systems have in common that they use RFID for item detection and for locating the items' positions on the shop floor. According to the manufacturers, the inventories are performed with an detection accuracy of over 99% (Keonn, 2016; MetraLabs, 2016). Two of the systems are currently being tested by several companies, the Tory is in use at Adler Modemärkte Ag in Germany (MetraLabs, 2016), the StockBot from PAL Robotics is tested at Media Markt in Barcelona, Spain as well as at the fashion company Roberto Verino (PAL-Robotics, 2016a).

The previous research about the influence of RFID on the overall inventory accuracy we discussed so far (see sections 3.2.2 and 3.2.3) considers several RFID hardware configurations, ranging from, smart shelves to RFID gates, but none of the studies considers robotic inventory taking as a data quality measure. There exist, however, a few studies that investigate the quality of RFID-enabled robotic inventory taking. The earliest paper to find was written by Ehrenberg et al. (2007) who perform a feasibility study within a library. The researchers develop a robot that has the purpose to automatically scan the shelves and to find misplaced books. The researchers demonstrate that the robot is able to reliably detect the books on a shelf and to localize each book with an accuracy of a few centimeters. In a similar study, R. Li et al. (2015) show that a robot is able to find books with an accuracy of 98.5%.

Miller et al. (2010) perform a proof-of-concept for an automated asset locating system and show that their system is able to detect and map all 143 assets that it has to map for their experiment with a mean position error of about 80 cm.

Other researchers focus on robotic inventory in retail stores. Morenza-Cinos et al. (2017), the developers of the AvanBot from PAL Robotics, published a study on the development of their system. They report the results from their experiments and compare the inventory accuracy of the AvanBot to the accuracy of a handheld-based RFID-enabled inventory. After selecting certain areas of the store for the experiment, the AvanBot beats the handheld inventory in all of them with regard to the inventory accuracy. The authors reason, that the low accuracy of the RFID-enabled handheld inventory must be explainable by human errors. While the robot always achieved an accuracy of 99.4% and higher, the accuracy of the handheld inventory ranged from 44.1% for the women's wear to 99.51% in the jeans section of the store.

However, there are also studies that investigate RFID-enabled robotic inventory taking, but show a different picture. Schairer et al. (2008) propose a system for an RFID-enabled inventory robot and test it in a simulated supermarket. However, the tests show that the robot only achieves a detection accuracy of 60% and therefore has to drive along the shelves several times in order to achieve a higher accuracy.

Zhang et al. (2016) develop a mobile robot for inventory taking in retail stores. The experimental results show, that the robot works efficiently but only achieves an average overall inventory accuracy of 87.72% (ranging from 84.05% to 100% for different item categories). The researchers conclude, that the structure of the store areas heavily influences the results, leading to the obtained accuracies.

At a first glance, the advantages of robotic inventories seem obvious. Instead of just performing periodic cycle counts, a robot can scan a whole sales floor every day without needing to be paid. Furthermore, robots do not have the problem of motivation and need no incentives in order to perform their work properly. However, the studies on the effectiveness of robotic inventory taking are mixed. While the manufacturers and some researchers claim detection accuracies of 98% and more (Ehrenberg et al., 2007; R. Li et al., 2015; Miller et al., 2010; Morenza-Cinos et al., 2017) other studies show much worse results (Schairer et al., 2008; Zhang et al., 2016).

If we summarize the research on RFID-enabled robotic inventory taking, it still unclear if the benefits of using robots for inventory taking really outweigh the associated costs and risks. Even though studies like Morenza-Cinos et al. (2017) suggest that robotic inventory taking might be beneficial in some cases we do not have much evidence that it will always outperform traditional RFID-enabled cycle counting with handheld readers. More - especially manufacturer-independent - research is necessary to clarify whether robotic inventory taking is really superior to other approaches. In order to contribute to this stream of research, we perform a simulation study to better understand the pros and cons of using RFID-enabled robotic inventory taking and compare it to the traditional approach with RFID-enabled handheld devices. We therefore evaluate its economic impact on a retail store and discuss the results from a managerial perspective.

3.3 Model building and evaluation

The following sections first describe the general assumptions of our model and its technical implementation. We then describe and evaluate the various relevant scenarios and compare them with each other.

3.3.1 General model assumptions

We consider a retailer who uses RFID with item-level tagging. Overall, the retailer's main objective in our model world is to limit costs while simultaneously reaching a reasonable service level (i.e., fulfilling as much customer demand as possible). We do not take monetary costs into account, but rather evaluate cost factors such as the number of replenishments required to achieve a certain service level. Our hypothesis is that a good in-store replenishment process can only be carried out on the basis of high quality inventory data from the retailer's inventory monitoring system.

Table 3.2 shows the most important model parameters. The available shelf space on the sales floor (S) is the maximum number of items which can be physically on the shelves. The current physical inventory is given by I_{p} while the virtual inventory - which denotes the inventory of the RFID-system - is given by I_{v}. The virtual inventory is influenced by the RFID-enabled replenishment gate which works with the read rate ϕ. The accuracy of the inventory taking process using handheld readers or the inventory robot is denoted as Φ. A replenishment is triggered as soon as I_{v} reaches the replenishment threshold s. The demand is generated according to the demand rate λ and the rate of shrinkage is given by the parameter ε. Furthermore, we keep track of the number of demanded items y_{c}, the number of sold items y_{u}, lost sales y_{L} and the number of stock-outs y_{S} during the time horizon T of a simulation run.

Table 3.2: Model parameters

Parameter	**Description**
s	Replenishment threshold
S	Shelf space
I_{v}	Virtual inventory level of the sales floor
I_{p}	Physical inventory level of the sales floor
y_{c}	Number of demanded items
y_{u}	Number of sold items
y_{L}	Number of lost sales
y_{S}	Number of stock-outs
T	Simulation horizon
λ	Demand rate per day
ε	Shrinkage rate
ϕ	RFID read rate of the replenishment gate
Φ	Inventory taking accuracy of the robot / handheld
β	Beta service level
R	Review cycle

One performance measure of the retailer is the service level β which we define as the fraction of filled customer demand:

$$\beta = \frac{y_{\mathrm{c}} - y_{\mathrm{L}}}{y_{\mathrm{c}}} \tag{3.1}$$

In order to evaluate the RFID-enabled robotic inventory and to compare it with RFID-enabled cycle counting with handhelds, we define the following model scenarios:

- Scenario 1: Traditional RFID infrastructure - no additional data quality measures
- Scenario 2: RFID-enabled cycle counting with handhelds
- Scenario 3a: Perfect RFID-enabled robotic inventory taking
- Scenario 3b: Perfect RFID-enabled robotic inventory taking (no replenishment gate)
- Scenario 4: Imperfect RFID-enabled robotic inventory taking (no replenishment gate)

Scenario 1, which serves as a benchmark, describes a traditional RFID infrastructure where the store manager is not aware of the flaws of RFID technology and does not perform any additional data quality measures. In scenario 2 the same infrastructure is present, but the store manager is aware of the imperfect read rate of the RFID hardware and advises the employees to perform cycle counts with RFID-enabled handheld readers every four weeks. Scenario 3 and 4 evaluate a retail store where the inventory is controlled by an RFID-enabled inventory robot.

While scenario 1 serves as a starting point and enables us to illustrate how additional data quality measures generally influence an RFID-enabled process, our main goal is to compare scenario 2 with scenario 3 and 4 and to evaluate the benefits of an RFID-enabled robotic inventory in general. First, we take a look at each scenario and perform an exploratory analysis for each case. We then compare the scenarios with each other.

3.3.2 Technical implementation

In order to develop the model as a software program we used the programming language Python and the package SimPy which was developed for discrete event simulation. SimPy uses Python's generator functions in order to simulate discrete events with simulated objects, like customers or vehicles. Furthermore, it can be used in order to model different types of shared resources like for example gas stations, production facilities or checkout counters (SimPy, 2017).

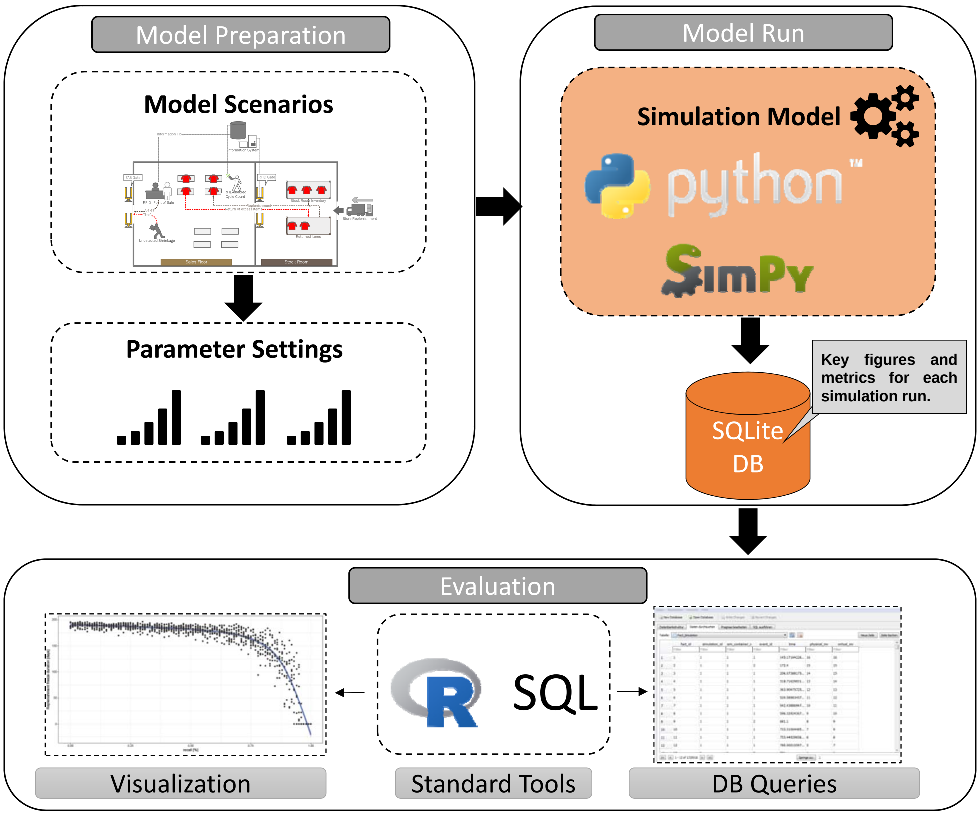

Figure 3.1: Simulation workflow

Figure 3.1 gives an overview of our simulation and evaluation approach. We first define certain model scenarios and define for each scenario a set of parameters which are used in order to configure our simulation. Via the parameters, we can, e.g., configure, if there is a replenishment gate between stockroom and sales floor, the read rate of the replenishment gate and if there are any data quality measures performed like for example cycle counting.

Each set of parameters is then used to run our simulation several times. We save the results into an SQLite database. The results of the simulation runs can then be evaluated using standard tools such as SQL or the statistical programming language R. In the following, we use 100 repetitions for our analyses for each set of parameters.

3.3.3 Scenario 1: Traditional RFID infrastructure - no additional data quality measures

The first scenario under consideration serves as a benchmark. To built upon the existing work from Condea et al. (2012) and Thiesse and Buckel (2015) the model comprises uncertain demand, shrinkage, item-level tagging and imperfect RFID hardware. Item-level tagging means, that each individual item is equipped with an RFID tag and can be identified with the help of a unique identifier. The retailer of our model world does not carry out any further data quality measures other than the use of an RFID infrastructure (i.e., no cycle counting and no robotic inventory). This scenario serves as a baseline in order to estimate the effects of additional data quality measures on the economic performance of our model store.

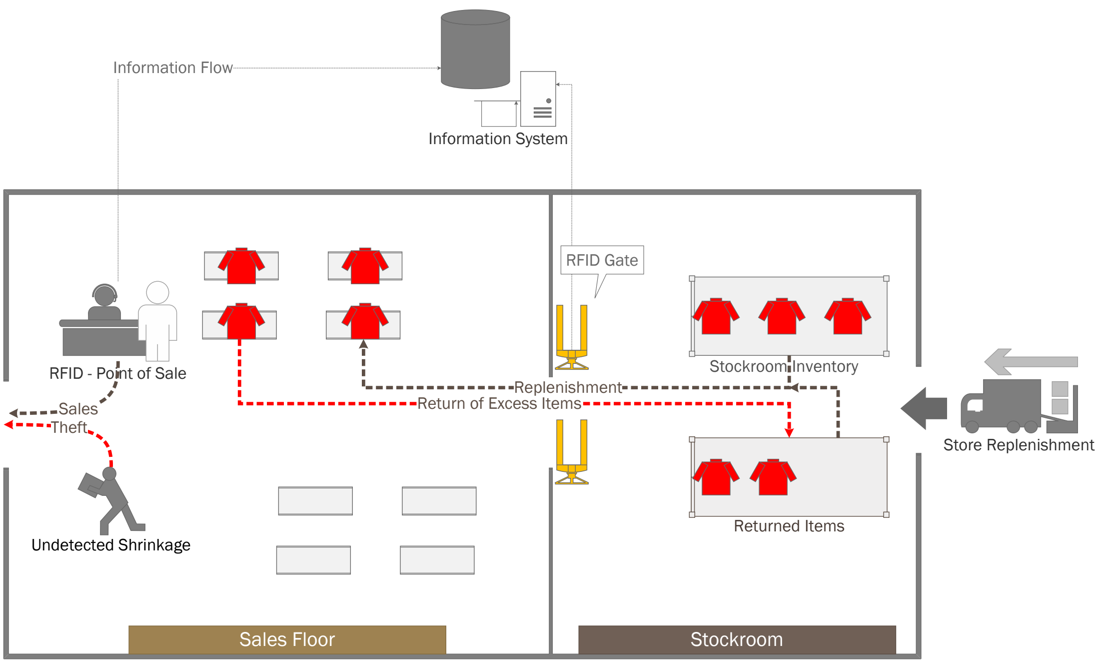

Figure 3.2: Scenario 1: Traditional RFID infrastructure - no additional data quality measures

Figure 3.2 illustrates the considered retail store with all installed RFID readers. Our model store has similarities to the models which were used by Thiesse and Buckel (2015) and Condea et al. (2012). The store is composed out of a sales floor and a stockroom. In order to distinguish the recorded sales floor inventory level from the stockroom inventory level, an RFID-enabled replenishment gate is positioned between these two areas. We assume, that the store immediately receives a shipment from the distribution center after an employee takes items from the stockroom. Consequently, the stockroom behaves as if it had unlimited inventory and was always able to replenish the sales floor. Also we assume the sales floor to have a maximum capacity S for holding garments which cannot be extended. This means if the inventory system triggers a replenishment request with more items than the sales floor is able to hold, then an employee has to bring the excess items back to the stockroom (after noticing this fact on the sales floor). The items are then returned to the inventory of the stockroom. We furthermore assume that the replenishments received from the distribution center are detected with an accuracy of 100%. We decided for this simplification, because the replenishment process between the distribution center and the stockroom is not in scope of our analysis.

It is possible that there is on hand inventory in the stockroom while there is no inventory on the shelves of the sales floor. We refer to such a situation as an *in store but out of shelf situation*. We do not include an RFID-enabled electronic article surveillance gate because its influence lies out of scope of our analyses. Finally, our analyses underly the assumption, that the RFID system is in full control of the replenishment process without human interference (e.g., employees do not replenish articles themselves that are obviously out of stock because they notice that a shelf is empty).

To make our research more comparable with the works of other researchers, we base our analysis on a medium selling article with an average demand of $\lambda = 10$ as it was used by Condea et al. (2012) and Thiesse and Buckel (2015). Similar, to the previous works on RFID-enabled replenishment policies we assume Poisson distributed demand λ and lost sales Y_L. The shelf space for the sales floor inventory S is set to 24. In order to analyze different performances of the RFID-enabled replenishment gate, the read rate is varied between 10% and 100% of detection accuracy.

The National Retail Federation estimates that shrinkage makes up for 1.38% of total retail sales. The largest shares are attributed to shoplifting with 38% and to internal theft with 34.5% (Allen, 2015). For the item under consideration, we assume a shrinkage rate ε of 2% of the total expected demand during our simulation horizon which is slightly above the average percentage reported by the National Retail Federation but still a realistic value for certain items. It is furthermore in alignment with Thiesse and Buckel (2015) and Condea et al. (2012) and thus makes our research more comparable to previous research. Also, taking more extreme values is more likely to clearly show the effects of RFID-enabled data quality measures on the in-store replenishment process. Furthermore, it may be interesting to evaluate how different data quality measures influence out of stock situations and the effectiveness of the replenishment policy of an item that is stolen quite often.

The time horizon of the simulation T is set to 300 days which roughly corresponds to the opening times of a fashion retail store in Germany for a whole year (including Saturdays). We decided against a longer time horizon because we assume that once a year a traditional full inventory takes place in every retail company. This manual inventory should theoretically set the difference between on hand inventory and system inventory to zero and thus restore the start conditions of a simulation scenario at the end of each year.

3.3.3.1 Exploratory analysis

Our first objective is it to analyze how the RFID-enabled in-store replenishment process behaves for different parameter settings of the replenishment threshold s and the read rate of the gate ϕ if a store manager does not perform any additional data quality measures. The retail manager uses an s/S policy. This means that as soon as the inventory reaches or drops below the threshold s, the sales floor is replenished up to the maximum shelf space S. We conduct the first exploratory analysis based on the observation of lost sales and the corresponding service levels. We therefore consider in the following the service level β, the total number of triggered replenishments, the lost sales, the number of excess items, the number of return transports to the stockroom as well as the occurrence and duration of replenishment freezes.

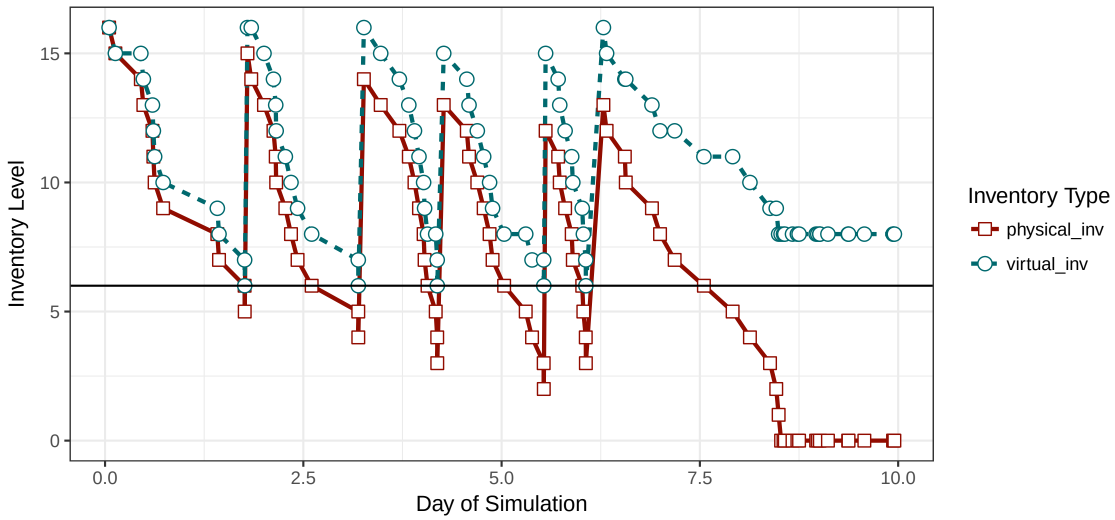

Figure 3.3: Example of a simulation run

Figure 3.3 shows how the physical inventory (on hand inventory) and the virtual inventory (system inventory) may behave over a simulation run. In this particular example, the physical inventory and the virtual inventory first move in sync but start to deviate from each other over time. This difference is caused by the detection error of the replenishment gate and by theft. Between day seven and day eight the physical inventory drops below the replenishment threshold of six items and drops further to zero between day eight and day nine. The virtual inventory, however, does not follow in the same pace and consequently stays above the replenishment threshold. This event causes a so called replenishment freeze. We define a replenishment freeze as a situation in which no further replenishments are triggered by the inventory system because the system inventory is above the replenishment threshold and the on hand inventory is at zero. The situation cannot be resolved without additional means like for example cycle counting in order to align the system inventory with the on hand inventory.

There is also a second, less obvious irregularity. Even though, according to our replenishment policy, shelves should be refilled to reach the maximum capacity of S, this hardly ever happens. This is because the replenishment amount is calculated as the difference between the system stock and the available shelf space. As in the example of the figure 3.3 the virtual inventory always remains above the physical inventory, which leads to a replenishment of too few articles.

We first analyze for scenario 1 how much sales are lost for different levels of the replenishment threshold s. In reality it is a non-trivial task for a retailer to determine the optimal replenishment threshold because the demand is most often not known for many types of articles and the costs for not having certain articles on the sales floor are hard to estimate. For example, customers may decide to just buy a related article, thus there may not occur any lost sales, on the contrary a customer could however also visit a rivaling store. In the latter case the lost sales amount would be equal to the article's sales price.

We simulated read rates of the gate in steps of 10%-units, where 10% denotes the lowest detection accuracy we evaluated and 100% the highest ($\phi \in [10\%, 20\% \dots 100\%]$). A read rate of 10% means that the replenishment gate will on average be able to detect 10% of all items transported through it. A read rate of 100% resembles a perfect gate that works without any flaws and consequently does not miss any items.

Figure 3.4 illustrates the lost demand for the simulation of scenario 1 for all possible replenishment thresholds. For each threshold we repeated the simulation 100 times and averaged the lost demand. The figure reveals a fact that may seem surprising at a first glance. The worse the accuracy of the replenishment gate, the less demand is lost in the simulation. This is also reflected in the average achieved service levels for each of the different read rates of the gate (see figure 3.5).

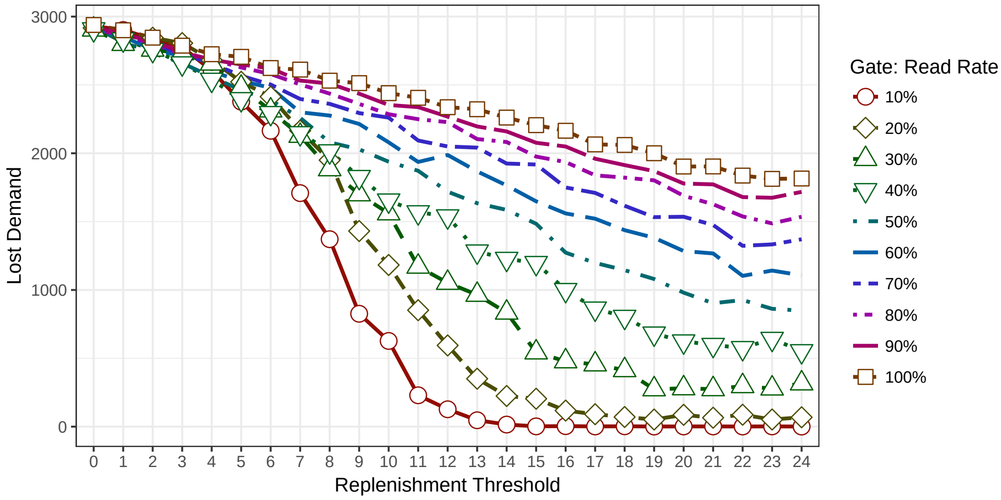

Figure 3.4: Lost demand per replenishment threshold s

Visualizing the average number of triggered replenishments for each read rate of the gate (see figure 3.6) we can observe, that in the cases with lower read rates (i.e., 10% to 50%) much more replenishments are triggered than in the cases with higher read rates (i.e., 60% and more). As in our model a replenishment of the sales floor inventory can be performed once a day, a maximum of 300 replenishments is possible over the time horizon T if the retailer replenishes every day.

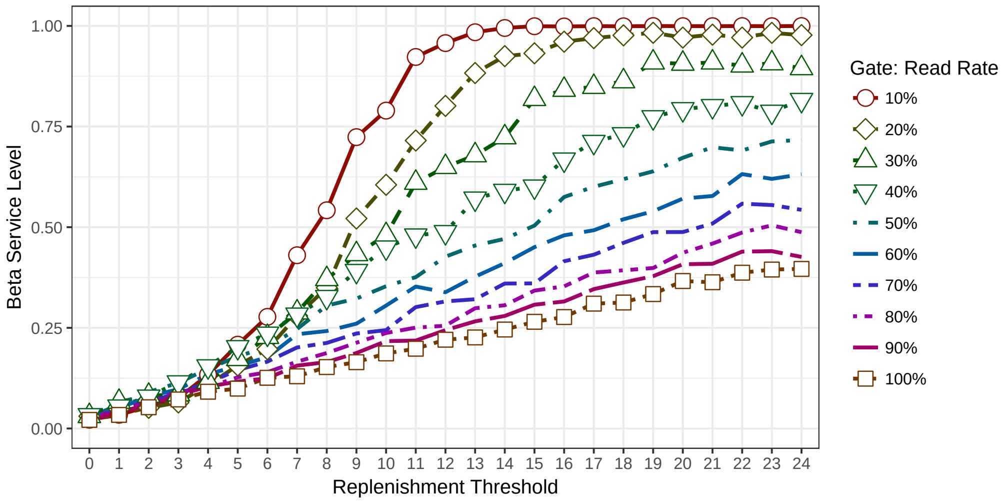

Figure 3.5: Service level β per replenishment threshold s

We can conclude from the observation of the triggered replenishments and the service level β, that the better service levels, in cases with low read rates of the replenishment gate, are related to a high number of replenishments. However, in reality it is not feasible to replenish everything every day. In the cases with low read rates, many replenishments are probably triggered falsely by the system because of a divergence between the system inventory and the on hand inventory. We therefore take a look at the excess items, i.e., the items that were transported to the sales floor but had to be taken back to the stockroom due to the limited sales floor capacity.

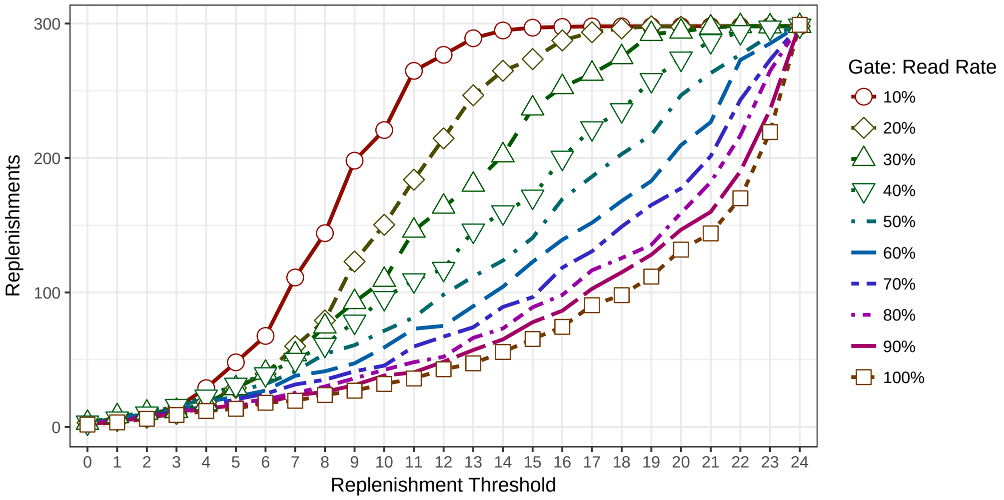

Figure 3.6: Number of replenishments per replenishment threshold s

Figure 3.7 shows that low read rates lead to high numbers of excess items - i.e., items that were replenished due to faulty inventory records. Because we assume in our model that it is not possible to overstock the sales floor, employees have to use their labor time to bring the excess items back to the stockroom where they have to put them on the intended places.

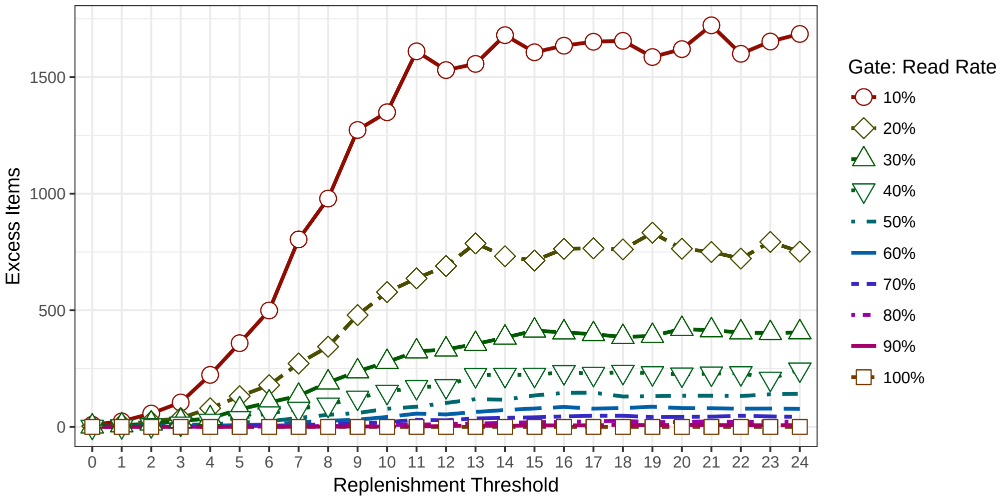

Figure 3.7: Excess items per replenishment threshold s

The numbers of the return transports to the stockroom are reported in figure 3.8. Similar to the number of excess items, the number of return transports is higher in those simulation runs in which the read rate of the replenishment gate is low. This is caused by the RFID system which systematically underestimates the inventory on the sales floor if the read rate of the replenishment gate is low.

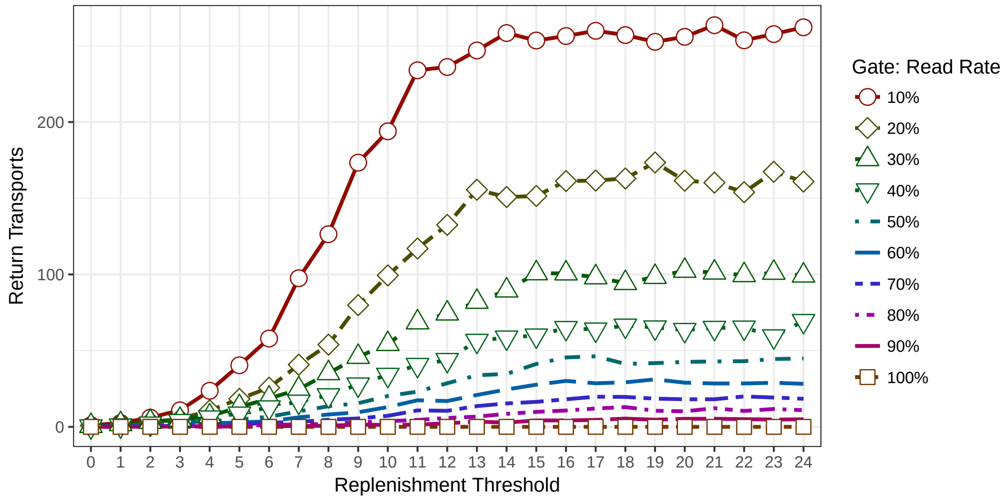

Figure 3.8: Return transports per replenishment threshold s

In order to find out if the low service levels and low number of replenishments for high read rates of the replenishment gate may be caused by replenishment freezes, we compare the days with replenishment freezes that occurred during the simulation runs for each read rate and each replenishment threshold (see figure 3.9).

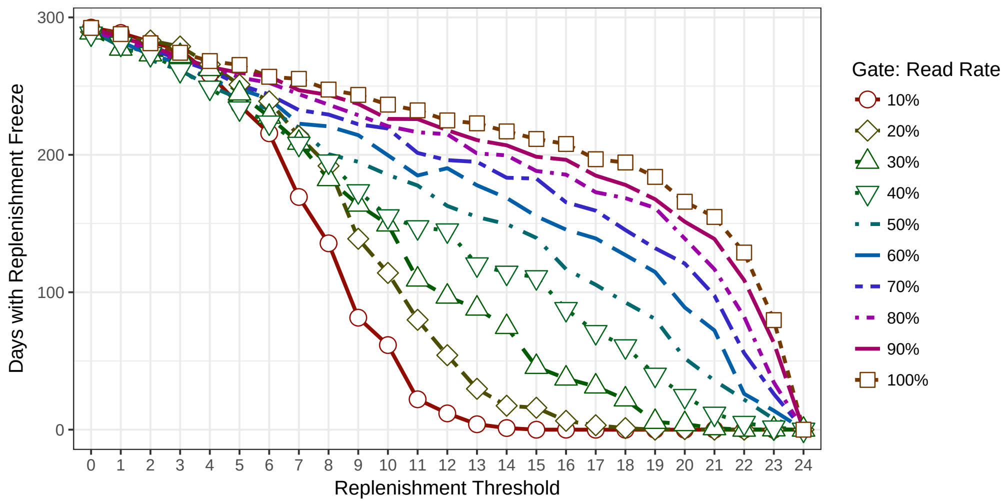

Figure 3.9: Replenishment freeze duration per replenishment threshold s

Our results show, that a high replenishment threshold and a low read rate of the replenishment gate lower the duration of replenishment freezes during a simulation run. This stems mainly from the fact, that in the cases with low read rates, the RFID system does not recognize that a replenishment of a particular item was performed and thus triggers several replenishments after another. For example in the case of an average read rate of 10%, only one out of ten items is recognized during a replenishment and thus the system will very likely trigger another replenishment the next day.

If the replenishment gate works with a high read rate it notices most of the items which travel to the sales floor and back. However, the items that are lost through shrinkage are not recognized by the system. Also when articles have to be taken back to the stockroom, the gate has another opportunity to miss them (eventually leading to a high sales floor overstock according to the virtual inventory). While scenario 1 only serves as a benchmark for the other scenarios it demonstrates that additional data quality measures are necessary for an RFID-equipped retailer in order to be able to trust the inventory data of its RFID system.

3.3.3.2 Conclusions for scenario 1

Not surprisingly, the benchmark scenario is not satisfactory from the perspective of a manager. As table 3.3 shows, a good working RFID-enabled replenishment gate does not by itself lead to a high service level. In the case of a perfect gate (i.e., with a read rate of 100%) the maximum achievable service level β was just 63%, meaning that 37% of all customer demand was lost in the best case. This mainly stems from the occurrence of long replenishment freezes which are not resolved till the end of the simulation. In the cases with a better service level, many return transports have to be performed by the store staff in order to transport the excess items back to the stockroom.

Table 3.3: Overview statistics of scenario 1

ϕ	**min.** β	**max.** β	**Avg. days with freeze**	**Std. freeze**
10%	1%	100%	93.49	120.71
20%	1%	100%	110.31	120.87
30%	1%	100%	122.65	112.27
40%	1%	100%	139.27	101.29
50%	1%	99%	156.86	93.74
60%	1%	95%	172.71	88.01
70%	1%	87%	185.66	83.04
80%	1%	78%	196.13	78.51
90%	1%	77%	204.45	73.51
100%	1%	63%	213.20	70.17

If the retailer does not undertake any additional data quality measures in order to account for the effects of shrinkage and the imperfectness of RFID, the economic performance of the retail store may not comply with the high expectations that are put into RFID technology. Consequently, additional measures are necessary in order to better align the virtual inventory with the physical inventory of a retail store.

3.3.4 Scenario 2: RFID-enabled cycle counting with handhelds

In scenario 2 we investigate the influence of RFID-enabled cycle counting on the simulated retail store. Besides, this additional data quality measure the scenario is similar to scenario 1. RFID-enabled cycle counting is performed in predefined intervals on the sales floor by the store staff with handheld readers in order to align the system inventory with the actual on hand inventory.

In order to be able to use realistic intervals for the RFID-enabled cycle count (i.e., counting cycles that are actually feasible in a large retail store) a large German fashion retailer supplied us with its RFID cycle counting plan for the year 2017 for all of its planning groups. We use these intervals as the basis for simulating the RFID-enabled cycle counts. The intervals for the RFID-enabled cycle counts for different product groups range from four weeks for some groups to eight weeks for the majority of groups for the store under consideration. Since we assume a six day week from Monday to Saturday, we translate these intervals for our simulation into cycle counts every 24 days or every 48 days. To be better able to compare RFID-enabled cycle counting against a robotic inventory we decided to simulate an RFID count that is performed every 24 days.

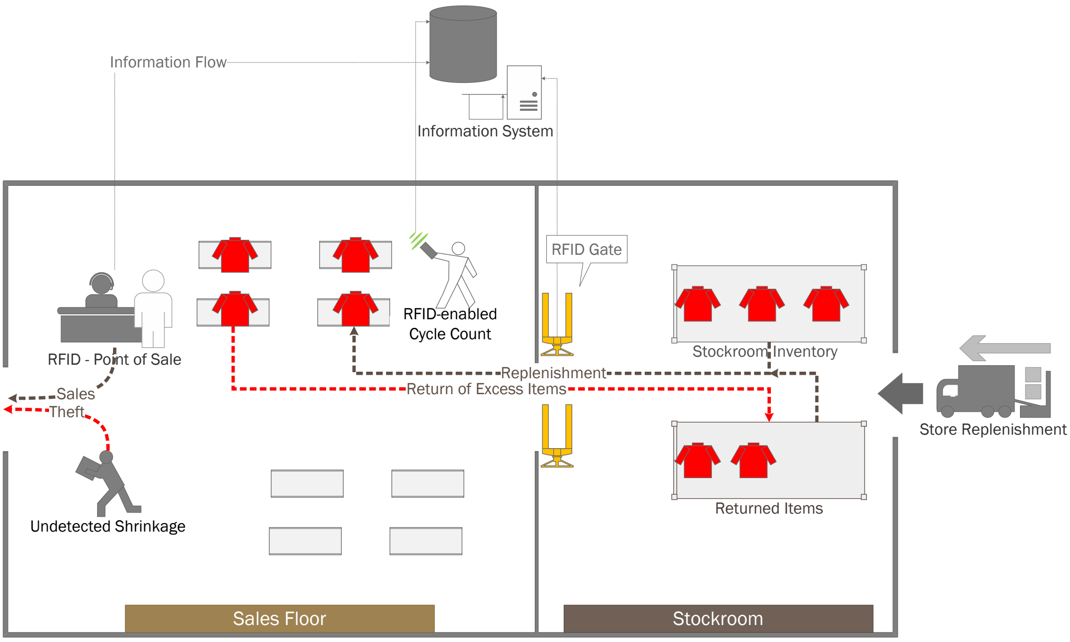

Figure 3.10: Scenario 2: RFID-enabled cycle counting with handhelds

In order to simplify the model for our first analysis, we assume that the RFID-enabled cycle counting is carried out by well-trained employees who are able to capture all articles perfectly. This assumption allows us to better compare the cycle counting against the robotic inventory without having to consider different levels of accuracy for the respective inventory taking methods.

3.3.4.1 Exploratory analysis

We simulate RFID-enabled cycle counting with intervals of four weeks (assuming six day weeks). Figure 3.11 illustrates the average service level that is reached for each replenishment threshold during 100 simulation repetitions.

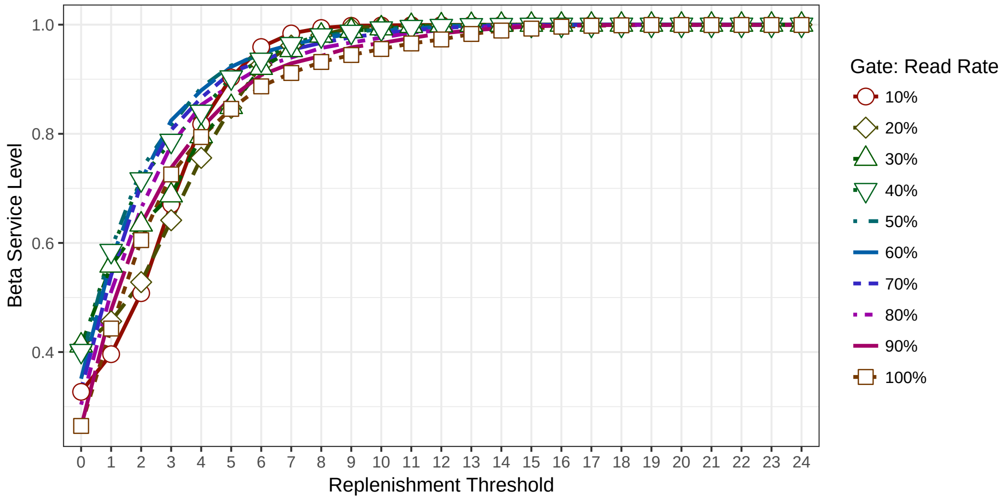

Figure 3.11: Service level β per replenishment threshold s for $R = 24$ days

As expected, the cycle counting aligns the system inventory to the on hand inventory every 24 days, leading to closer service levels between the different simulated read rates of the replenishment gate. Consequently, the RFID cycle count makes choosing the right replenishment threshold easier for a retailer because the read rate of the replenishment gate is less relevant and can thus be neglected when choosing a threshold in order to reach a satisfactory service level.

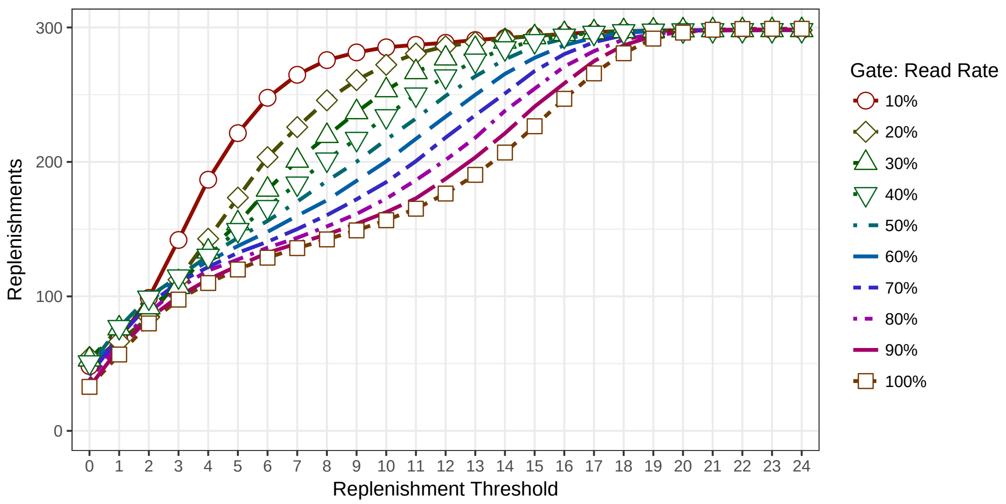

Figure 3.12: Replenishments per replenishment threshold s for $R = 24$ days

With regard to the replenishments per respective threshold, high read rates of the gate lead to fewer replenishments than low read rates (see figure 3.12). In comparison to scenario 1 (see figure 3.6), the RFID inventory system performs at least as many or more replenishments.

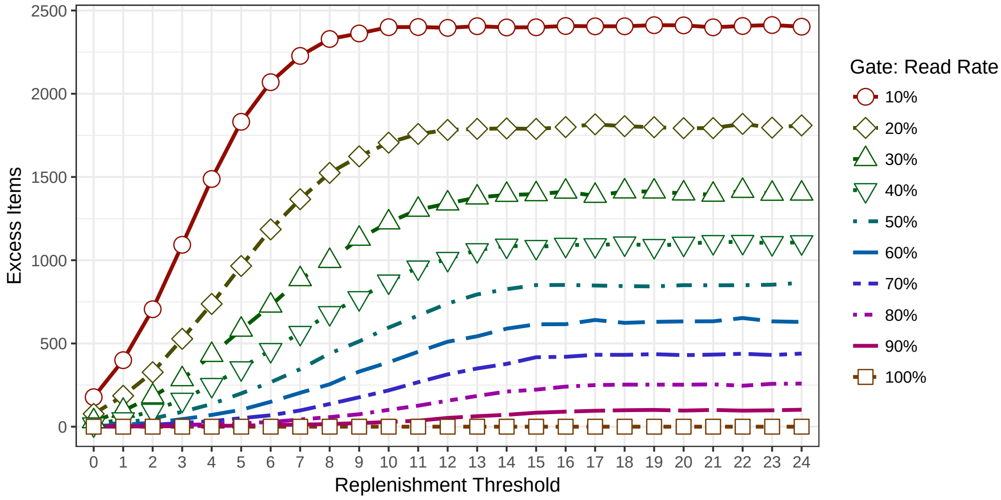

Figure 3.13: Excess items per replenishment threshold s for $R = 24$ days

The number of excess items (i.e., items falsely transported to the sales floor) is reported in figure 3.13. Surprisingly, the number of excess items is higher than in comparison to the figures reported in scenario 1, especially for the low read rates of the replenishment gate.

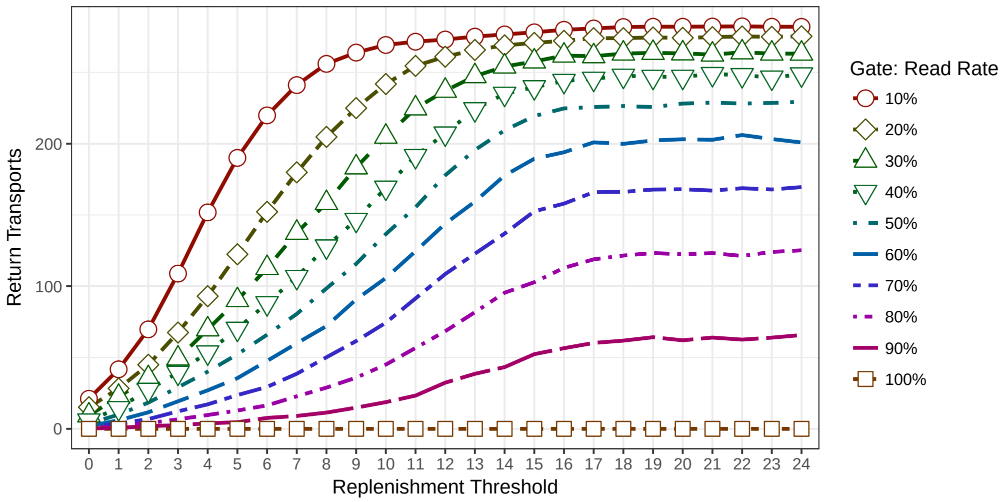

Figure 3.14: Return transports per replenishment threshold s for $R = 24$ days

The overall number of return transports the employees had to perform (see figure 3.14) also increased in comparison to scenario 1. These numbers are influenced by several factors, such as the difference between the physical and virtual inventory, the influence of theft and the difference between the physical stock situation and the available shelf space S

at a certain point in time during a simulation run. Even though it might seem that RFID-enabled cycle counting leads to unnecessary work, one major reason for the rise of excess items and return transports is quite logical. Scenario 1 had large timeframes with replenishment freezes in which no further replenishments were triggered and in which consequently no return transports were performed. Less replenishments lead to less excess items and to less return transports. In order to verify our conclusion we take a look at the actual number of days on which replenishment freezes occurred during the simulation of scenario 2. Figure 3.15 shows the average number of days with replenishment freezes for each read rate of the replenishment gate. Comparing figure 3.14 with figure 3.15 we can see that a decrease of the duration of replenishment freezes comes with an increase in the number of return transports.

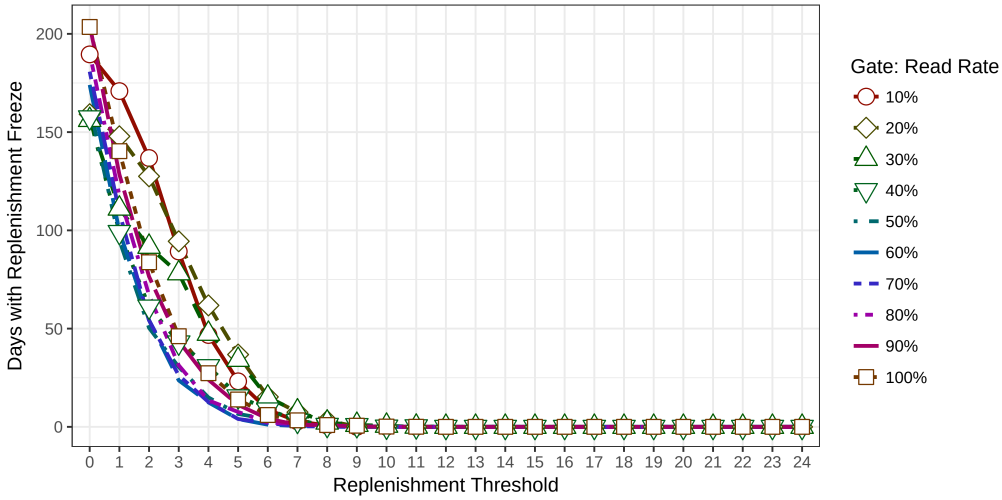

Figure 3.15: Replenishment freeze duration per replenishment threshold s for $R = 24$ days

If we set the replenishment threshold high enough, there happen almost no replenishment freezes. In our case the threshold for all read rates of the replenishment gate that prevents freezes is roughly a threshold of ten articles. Furthermore, the total duration of the replenishment freezes is capped at a maximum of four weeks (assuming a six day week) regardless of the read rate of the gate, because every four weeks the system inventory is corrected by an RFID-enabled cycle count. Consequently, RFID-enabled cycle counting reduces the duration of replenishment freezes and the likelihood of a replenishment freeze to occur when compared to scenario 1 in which no additional data quality measures were performed by the store manager.

3.3.4.2 Conclusions for scenario 2

All in all, the four-weekly RFID-enabled cycle counting in our simulation enables the retailer to achieve a maximum service level β of 100% regardless of the read rates of the

RFID-enabled replenishment gate (see table 3.4). This means for each read rate exists a replenishment threshold that leads to a service level of 100% which was not the case in scenario 1. Also, the minimum service level β regardless of the read rate of the replenishment gate is at least 10 percentage points higher than in scenario 1.

Table 3.4: Overview statistics of scenario 2

ϕ	**min.** β	**max.** β	**Avg. days with freeze**	**Std. freeze**
10%	22%	100%	26.75	56.31
20%	25%	100%	26.15	50.92
30%	21%	100%	21.80	43.48
40%	21%	100%	16.86	38.64
50%	22%	100%	14.63	38.24
60%	18%	100%	14.78	40.23
70%	14%	100%	15.58	42.07
80%	18%	100%	17.26	44.94
90%	13%	100%	19.79	48.64
100%	17%	100%	21.04	49.94

Comparing the results further to scenario 1, the average number of days with replenishment freezes decreased. Due to the cycle counting intervals, replenishment freezes cannot last longer than 24 days. Thus we conclude that RFID-enabled cycle counting in our model not only mitigates the problem of replenishment freezes but also helps to effectively utilize the replenishment gate because it reduces the negative effects of shrinkage on the inventory data. Thus high read rates of the replenishment gate, in contrast to low read rates, lead to high service levels with less replenishments, less excess items and less return transports. However, with RFID-enabled cycle counting the service levels that can be reached with the respective replenishment thresholds are closer to each other independently of the read rate of the replenishment gate (see figure 3.11) which means that the overall importance of the gate is weakened compared to scenario 1.

3.3.5 Scenarios 3a and 3b: Perfect RFID-enabled robotic inventory taking

In scenario 3, we investigate RFID-enabled robotic inventory taking. Scenario 3a investigates a daily robotic inventory of all items in a store with an RFID gate in place while scenario 3b investigates what happens when the replenishment gate between the stockroom and the sales floor is removed. For Scenario 3a and b, we assume that the manufacturers' claims are correct and that RFID-enabled inventory robots can actually achieve an inventory accuracy of more than 99%. We therefore assume that the robot of our model is able to reconcile the system inventory with the existing inventory without errors.

In scenario 3a, a robot drives every night through the hallways of the store and scans the surrounding articles, aligning the on hand inventory with the system inventory. It differentiates to the RFID-enabled cycle count through the frequency of counts, because a daily handheld based inventory of a large retail store would not be economically reasonable. However, we assume that the robotic inventory can be performed daily because it does not cause additional costs (the consideration of acquisition costs are out of the scope of our analysis).

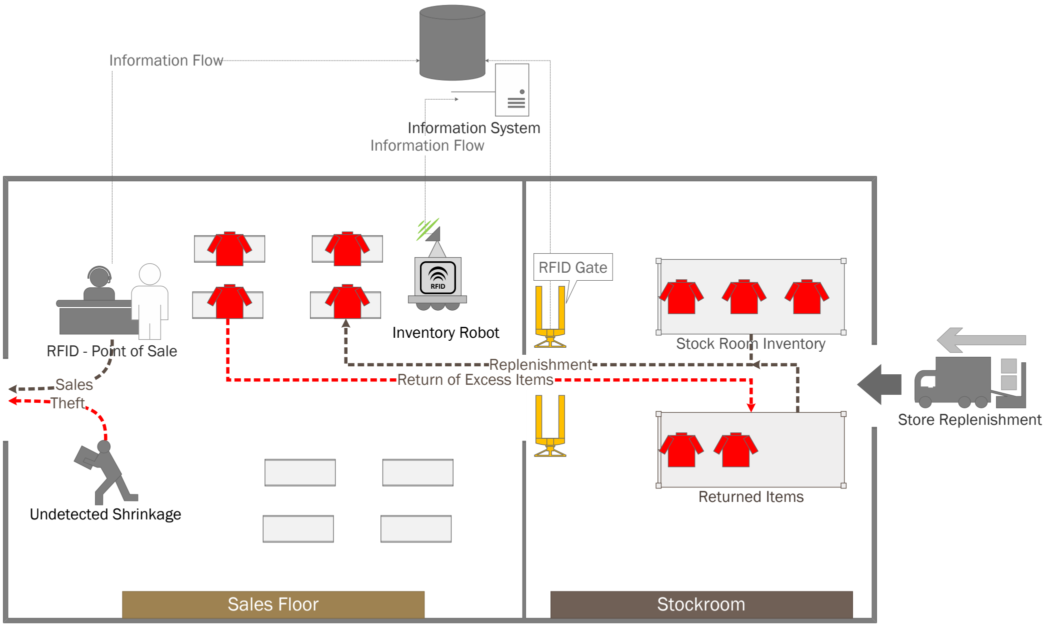

Figure 3.16: Scenarios 3a and 3b: Perfect RFID-enabled robotic inventory taking

Figure 3.16 illustrates scenario 3 in which the store manager substitutes the employee with the handheld reader with an autonomous RFID-enabled inventory robot. This substitution allows a much higher frequency of the inventories than in the human dependent case. In scenario 3b the manager of the retail store has decided to not implement a replenishment gate but to only use the robot for determining the number of articles on the sales floor.

3.3.5.1 Exploratory analysis

We start our analysis with an evaluation of the service level for each read rate of the replenishment gate and for each replenishment threshold. Taking a look at the achieved service levels of scenarios 3a and b it can be seen, that a daily robotic inventory lessens the influence of the replenishment gate.

Figure 3.17 illustrates the relationship between the replenishment threshold s and the service level β for the RFID-enabled robotic inventory. As the figure shows, the service level is almost identical for all read rates of the replenishment gate, including the case without an RFID gate. The higher the threshold for the replenishment, the higher is the average achieved service level for all simulated read rates of the replenishment gate. The daily robotic inventory seems to render the replenishment gate almost irrelevant. It is even more remarkable that the minimum service level never drops below 79% regardless of the selected threshold, while in scenario 2 the service level is in some cases below 40%. This could be due to the fact that during the time horizon of the simulation, no replenishment freezes occurred.

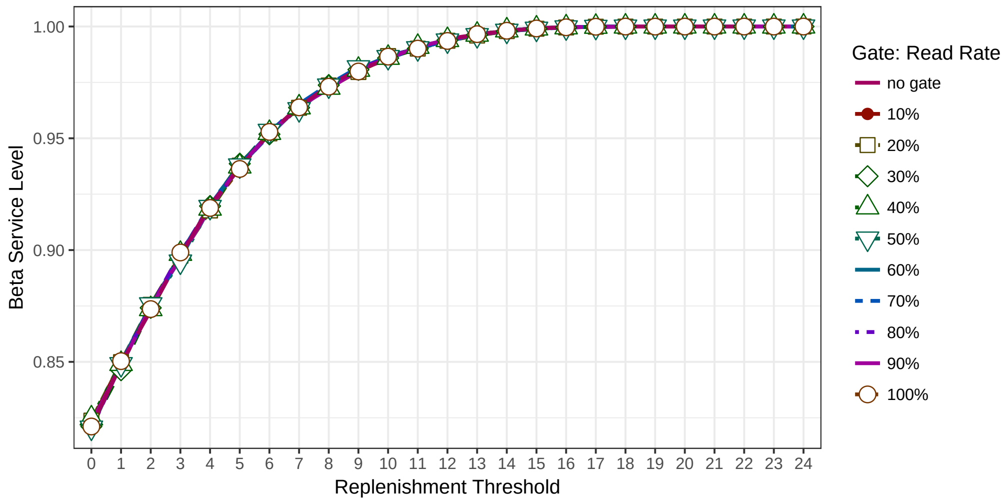

Figure 3.17: Robotic inventory - Service level β per replenishment threshold s

Taking a look at the average number of replenishments that are triggered for each threshold (see figure 3.18) it is notable that the number of replenishments is only dependent on the chosen threshold but not on the read rate of the gate.

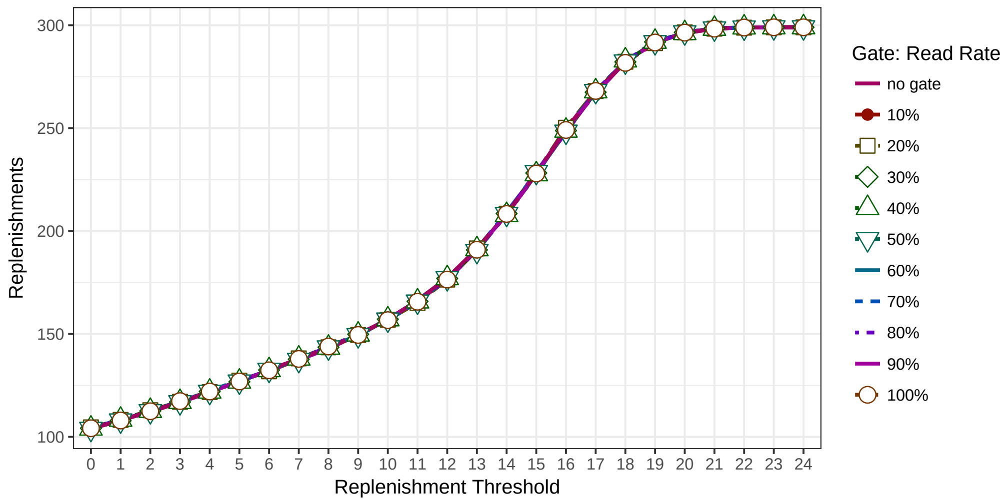

Figure 3.18: Robotic inventory - Replenishments per replenishment threshold s

Considering, that the return transports and the number of excess items were a larger problem in the previous scenarios, the daily robotic inventory eliminates them completely.

3.3.5.2 Conclusions for scenarios 3a and 3b

Table 3.5 shows that, no replenishment freezes occurred during any of the simulations with daily robotic inventory. This is because the robot aligns the system inventory with the on hand inventory over night, before the RFID system checks the inventory level and triggers the replenishment. Consequently, the situation necessary for a replenishment freeze (i.e., the system inventory is above the replenishment threshold and the physical inventory is at zero) cannot occur. The maximum achievable service level β is 100% for each scenario under consideration. Furthermore, the minimum achievable service level is 79%, independent of the read rate of the replenishment gate. As we have seen in figure 3.18 the average number of replenishments per scenario is almost equal for each read rate of the replenishment gate and even for the case without a replenishment gate ($\phi = 0\%$). Consequently, if a retailer performs a daily (perfect) robotic inventory, a replenishment gate seems irrelevant.

Table 3.5: Overview statistics of scenario 3a and 3b

ϕ	**Min.** β	**Max** β	**Avg. days with freeze**	**Std. freeze**
0%	80%	100%	0.0	0.0
10%	80%	100%	0.0	0.0
20%	79%	100%	0.0	0.0
30%	79%	100%	0.0	0.0
40%	80%	100%	0.0	0.0
50%	80%	100%	0.0	0.0
60%	80%	100%	0.0	0.0
70%	79%	100%	0.0	0.0
80%	80%	100%	0.0	0.0
90%	79%	100%	0.0	0.0
100%	79%	100%	0.0	0.0

To conclude, the daily robotic inventory makes the replenishment process very exact, as it eliminates falsely triggered replenishments and excess items. This indirectly reduces the workload of store staff by improving the overall quality of inventory data.

3.3.6 Comparison of scenarios 1, 2 and 3b

We compare scenario 1 (no data quality measures) with scenario 2 (RFID-enabled cycle counting) and scenario 3b (robotic inventory without replenishment gate). We excluded scenario 3a from the comparison, because its results were almost similar to scenario 3b. For our comparison we focus on the read rates between 80% and 100% of accuracy of the replenishment gate, since this range appears realistic when looking at the literature (see section 3.2.4) and based on the talks with the retailer that provided us its cycle counting plan. Figure 3.19 illustrates the achieved service levels for all scenarios under consideration. If we solely compare the scenarios with regard to their beta service levels it is clear, that the benchmark scenario always performs worse than the scenario with the RFID-enabled cycle count which in turn always performs worse or at least equal to the scenarios with daily robotic inventory taking. This means, that if a retailer chooses to use robotic inventory taking, the retail store will always achieve a higher service level for its products than with handheld based cycle counting. Also the retailer will have a higher margin for error when deciding to choose a certain replenishment threshold because even in the worst case the robotic inventory leads to a service level of 79% while the other scenarios have a minimum of 25% (scenario 2) or 1% (scenario 1).

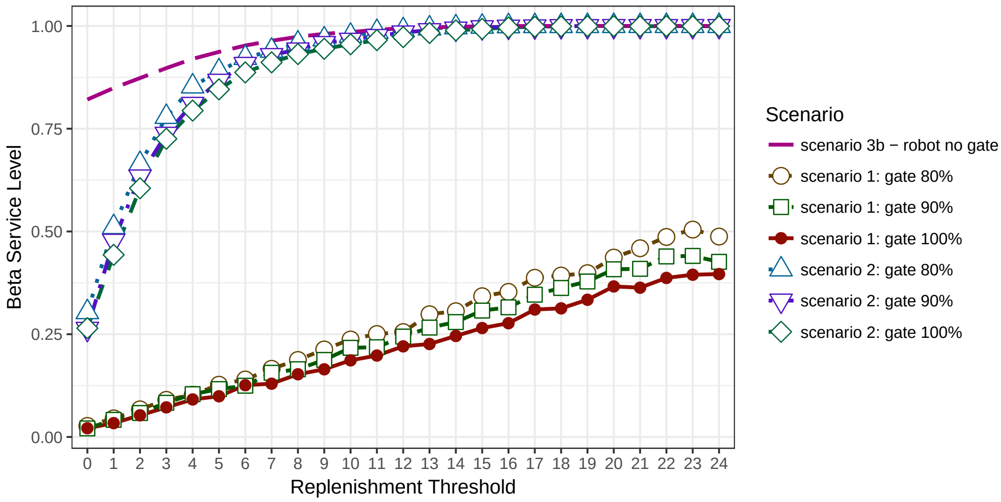

Figure 3.19: All scenarios - Service level β per replenishment threshold s

Another aspect of the scenarios is the occurrence of replenishment freezes. Figure 3.20 depicts that the days with replenishment freezes are much more frequent in scenario 1 than in scenario 2. Consequently, we can state that (a perfectly performed) RFID-enabled cycle count is a good means in order to reduce this problem. However, there are still circumstances in which this method can lead to replenishment freezes. In contrast, a daily robotic inventory - assuming the robot detects all items on the sales floor - eliminates the replenishment freezes completely. We can consequently state, that with regard to preventing replenishment freezes, doing nothing (scenario 1) is inferior to performing an RFID-enabled cycle count every four weeks (scenario 2) which is clearly inferior to performing a robotic inventory every day (scenario 3).

Another aspect to compare between the respective scenarios is the occurrence of falsely transported items and the connected problems of return transports to the stockroom. Figure 3.21 shows the number of excess items transported to the sales floor. We can see from the figure that the perfect robotic inventory always reaches zero excess items and is in this aspect comparable to the scenarios with a replenishment gate working with a read rate of 100%. Also, lower read rates of the gate lead to higher amounts of excess items in the scenarios under investigation (except for scenario 3). It thus might appear that scenario 1 is superior to scenario 2, as the number of excess items is always smaller than in scenario 2, for example, in the case of a replenishment gate with a read rate of 80%. In scenario 2, the number of excess items is about four times higher than in scenario 1, but the lower number of excess items for scenario 1 is mainly caused by the higher number of replenishment freezes and without replenishments, no excess items can occur. However, the figure shows us that a higher read rate of the gate leads to fewer excess items and furthermore, that a perfect daily robotic inventory eliminates the occurrence of excess items independently of a replenishment gate.

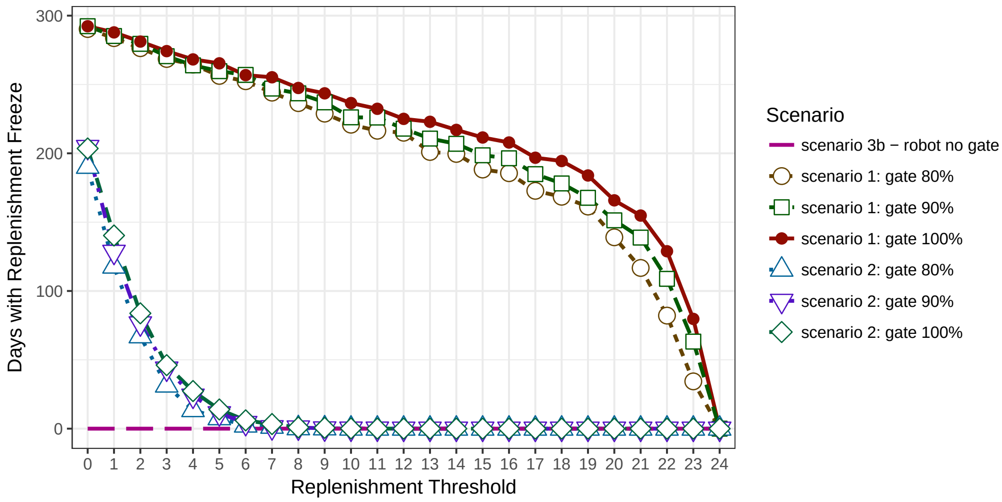

Figure 3.20: All scenarios - Replenishment freeze duration per replenishment threshold s

Based on our first analysis a daily robotic inventory, assuming the robot reaches a detection accuracy of 100%, is superior to other data quality measures. If we assume that the promises of the manufacturers of more than 99% of detection accuracy are true, then retailers should definitely go for robotic inventory taking. However, we also have to consider the case that RFID-enabled robotic inventory taking could be erroneous and be aware of the consequences. We therefore take a more skeptical perspective in scenario 4 and evaluate what happens if RFID-enabled robotic inventory taking becomes imperfect.

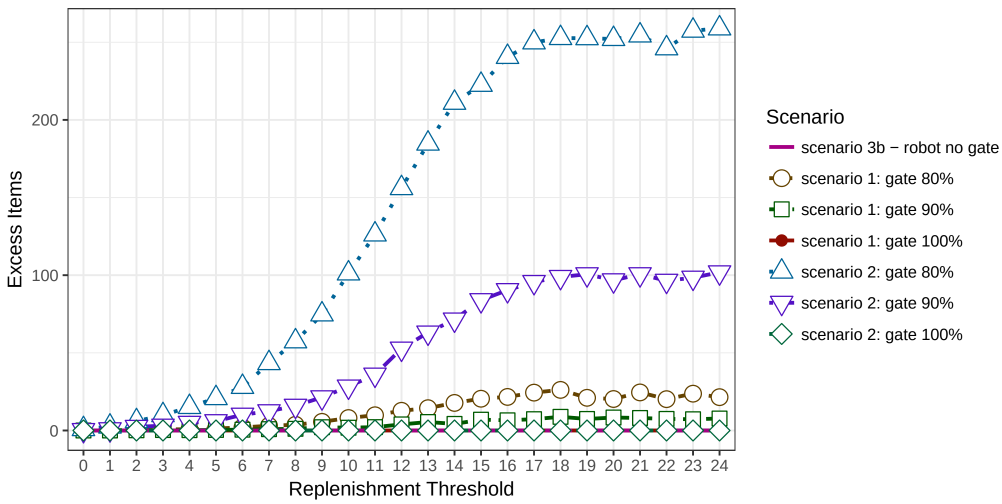

Figure 3.21: All scenarios - Excess items per replenishment threshold s

3.3.7 Scenario 4: Imperfect RFID-enabled robotic inventory taking

We could show in section 3.3.6 that a perfectly performed daily robotic inventory without an additional replenishment gate is superior to a perfectly performed four weekly RFID-enabled cycle counting strategy in combination with an RFID gate working with 100% detection accuracy. However, as we report in our literature review (see section 3.2.4) robotic inventory taking does not always work perfectly. We therefore evaluate the influence of an imperfect RFID-enabled robotic inventory on the economic performance of our model store. In order to better understand the influences of an imperfect robotic inventory, we first have to remind ourselves on what an inventory actually does: An inventory aligns the system inventory with the on hand inventory. More concretely the "old inventory" in the system is "set obsolete" and the new inventory becomes the actual system inventory. Out of this reason the inventory robot (assuming daily inventories) renders an RFID gate less important because it basically "overwrites" the data generated from the gate with the data from its next inventory. We therefore conduct several simulation runs with an imperfect inventory robot. As we know from the literature and the data from the manufacturers, the reported accuracies range from 60% to 99%. To get a comprehensive picture we decided to evaluate the following accuracies Φ of the inventory robot:

$$\Phi \in [10\%, 20\%, 30\%, 40\%, 50\%, 60\%, 70\%, 80\%, 90\%, 95\%, 97\%, 99\%] \tag{3.2}$$

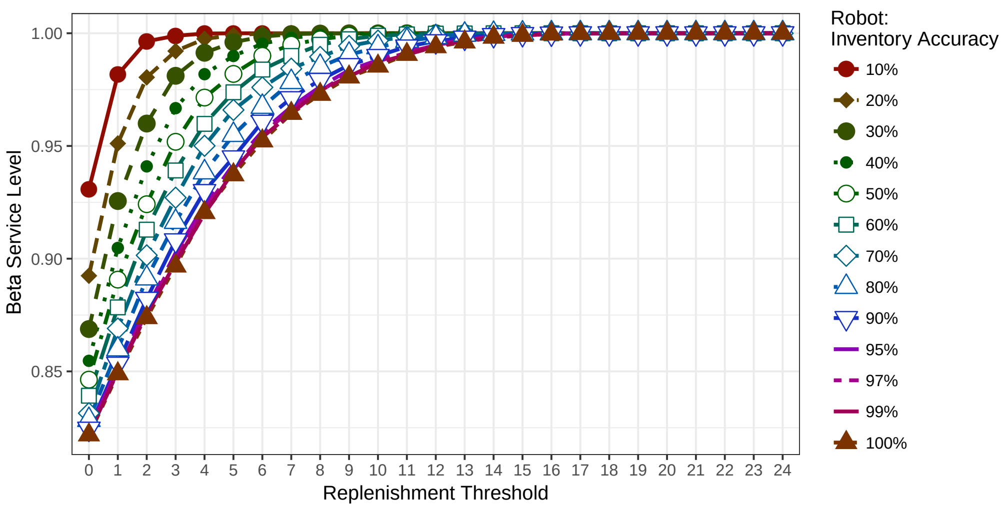

Figure 3.22: Service level β per replenishment threshold s

We also simulate worse detection rates for the inventory robot than the literature indicates to see how the model behaves in the worst case. Assuming the same set up as in scenario 3b we first evaluate the reached service level for each simulated replenishment threshold. We do not consider a replenishment gate because we have already shown in section 3.3.5.2 that the daily robotic inventory renders its influence to almost zero. As figure 3.22 shows, the service levels do not drop below 79% (for $s = 0$).

Lower levels of accuracy lead to higher service levels. For example a detection accuracy of 10% leads to a higher or equal service level as an accuracy of 20% (dependent on the chosen replenishment threshold). This is due to the fact that more replenishments are triggered in these cases, as figure 3.23 shows. However, the better service levels are bought expensively with more excess items (see figure 3.24) and more return transports to the stockroom (see figure 3.25).

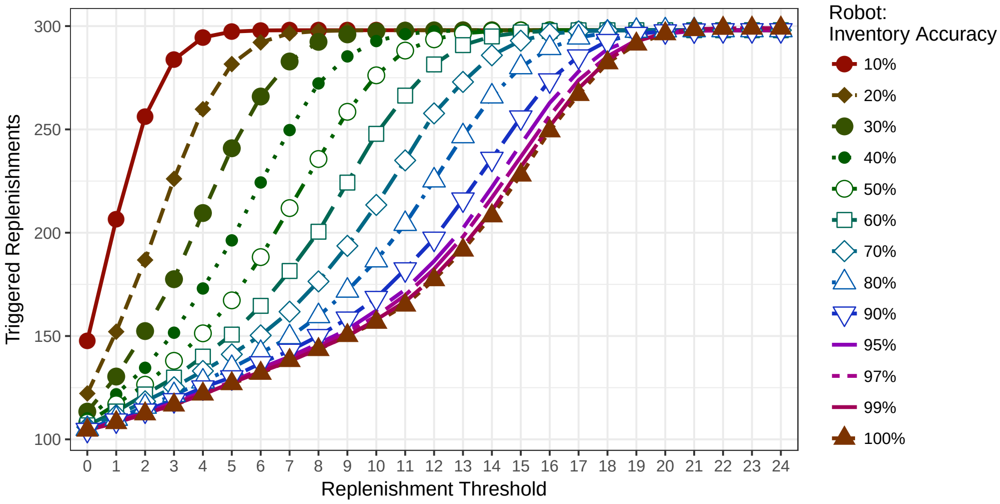

Figure 3.23: Replenishments per replenishment threshold s

Our analysis also reveals a problem of robotic inventory taking. A slight deterioration of the robot's detection accuracy, i.e., loosing a few percentage points of accuracy, doubles and triples the number excess items and return transports. A retailer has to be aware of this fact as it influences the reliability of the RFID system. This leads to indirect costs because employees will perform unnecessary replenishments and have to take care of the items which have to be taken back to the stockroom. Consequently, a higher accuracy of the inventory robot leads to less triggered replenishments per respective threshold.

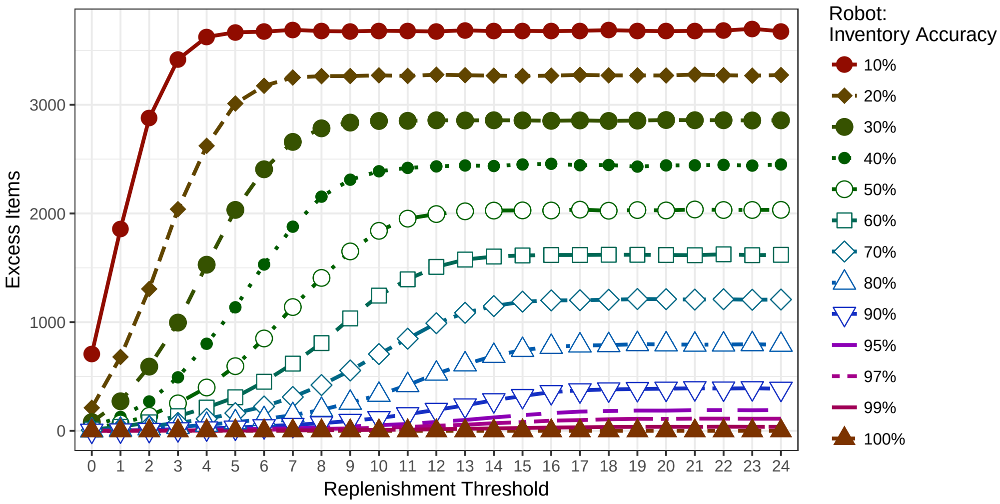

Figure 3.24: Excess items per replenishment threshold s

The most surprising fact about the RFID-enabled robotic inventory taking is, that replenishment freezes are completely eliminated independently of the accuracy of the inventory robot. What might seem surprising at the first glance has a reasonable explanation which we illustrate in figure 3.26. The reason for the elimination of replenishment freezes simply is, that the robot checks the inventory daily thus eliminating any situations in which a replenishment freeze may occur.

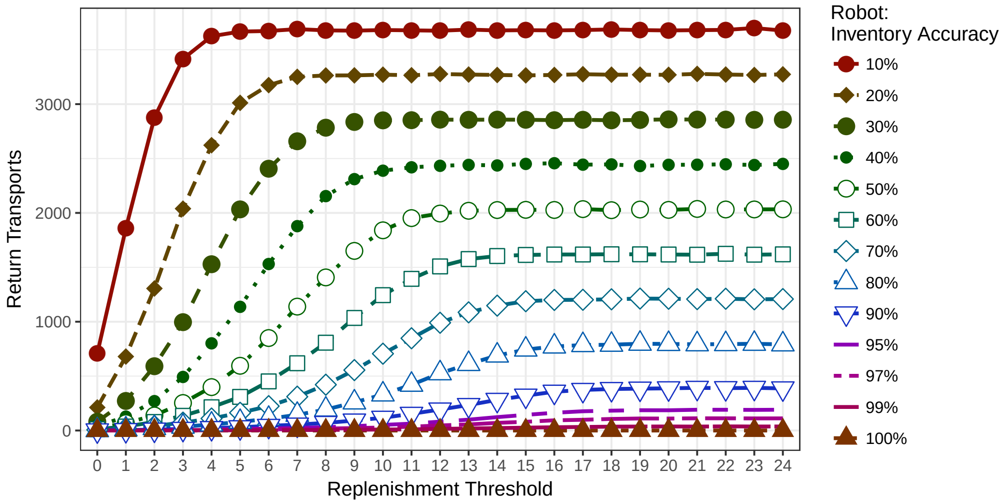

Figure 3.25: Return transports per replenishment threshold s

As the example in figure 3.26 shows, the virtual inventory is at the level of 10 units before the inventory of the robot and the physical inventory already dropped to zero. This is according to our definition a replenishment freeze if it is not resolved before the next replenishment control check by the inventory system. However, as soon as the inventory robot performs its inventory, the virtual inventory is set to zero and is thus below the threshold of 5 units of our example. Consequently, the requirements for a replenishment freeze are resolved.

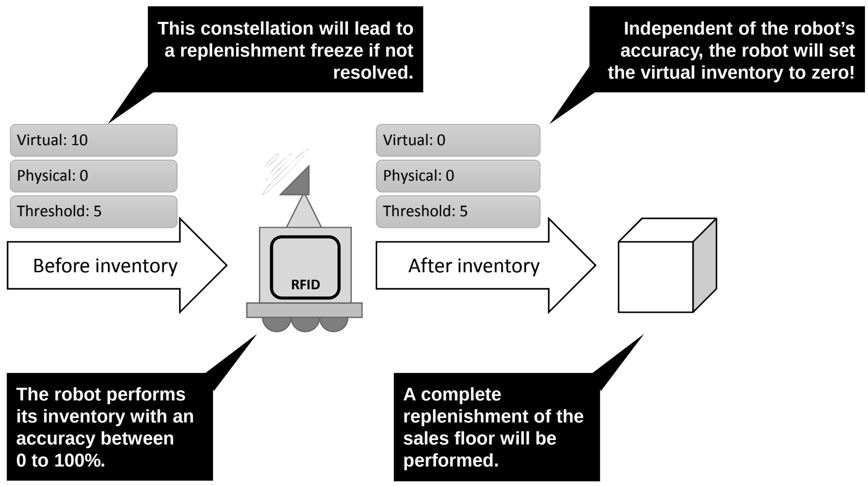

Figure 3.26: Explanation of why no replenishment freezes can occur when using robotic inventory

Interestingly, the accuracy of the inventory robot is irrelevant for resolving replenishment freezes. We know that the robot reads the articles with an accuracy that is between 0% and 100%. If we assume an accuracy of 100% it is clear that the robot will scan the sales floor correctly and thus does not find any items, which leads to a system inventory of zero. In the case of an accuracy of 0% the robot always finds zero items. A case that is in between, for example an accuracy of 50% would translate to the following outcomes: The inventory robot will have a 50% chance to correctly "find" the zero items and a 50% chance of "missing" the zero items. So either case will lead to the same outcome.

3.4 Conclusion

The results of our simulation study reveal several key takeaways. We are able to show within section 3.3 that a a simple RFID infrastructure just consisting out of a replenishment gate and an RFID-enabled point of sale is not able to achieve appropriate service levels because replenishment freezes eventually occur. The freezes are caused by undetected shrinkage and false replenishment orders by the RFID system itself. This means that the system does not replenish when it is supposed to and replenishes when it should not. Furthermore, it orders wrong quantities of items from the stockroom.

Additional data quality measures are necessary to mitigate the before mentioned problems. We show in section 3.3.4 that RFID-enabled cycle counting with a handheld device is an effective counter measure against data inaccuracy. Using a four weekly count resolved the replenishment freezes, leading to higher service levels. However, RFID-enabled cycle counting is still a manual process that draws upon the labor time of the store staff, it is also not able to completely eliminate replenishment freezes and according to reports (e.g., Morenza-Cinos et al. (2017)) it may not work with the high accuracy we assume for our simulation. We therefore evaluate the improvement through a robotic inventory.

While RFID-enabled cycle counting can only be performed in longer time intervals (i.e., a certain product group in intervals of several weeks) the robotic inventory can be performed in much shorter time intervals. Evaluating a daily robotic inventory against a four weekly handheld count, the robotic inventory (assuming also a perfect read rate) proved superior even when the RFID-enabled replenishment gate was removed from the model.

However, the reviewed literature shows that an RFID-enabled robotic inventory may not always work as flawless as we assume in our first evaluation. We thus consider in a second evaluation the effects of an imperfect robotic inventory on our model. The results show that robotic inventory taking is still effective, e.g., it completely prevents replenishment freezes to occur independently of the robot's accuracy. However, it has the same disadvantage as the non-robotic scenarios (see section 3.3.7). A low accuracy of the robot leads to many falsely replenished items which have to be brought back to the stockroom. Already small deteriorations of the detection accuracy double and triple the number of excess items and the connected return transports.

If the robotic inventory fails, then the RFID system orders the employees to replenish many articles which have not to be replenished at all. We assume this would lead the employees to lose trust in the RFID system and may cause them to just ignore it. Consequently, robotic inventory should only be used if it works very reliably.

Based on our simulation model, RFID-enabled robotic inventory is clearly in favor against "traditional" RFID-enabled cycle counting if it works as promised by the manufacturers (i.e., with accuracies of 99% and more). The improved data quality that can be achieved by a robot-based inventory allows retailers to execute their replenishment strategy as originally intended. Also a daily robotic inventory prevents replenishment freezes from occurring. One very important point is that a replenishment gate seems not necessary for our evaluated case. However, in reality a gate could nevertheless prove beneficial because it could be used to crosscheck the results of the robotic inventory (see section 4.3.5.2 for a proposal of such a method). In addition a replenishment gate might be necessary if products have a very short shelf life and have to be replenished several times a day. In that case a daily robotic inventory at night may not be enough in order to control the sales floor inventory. However, this could also be compensated with a continuous robotic inventory check of the sales floor.

Our research also has some limitations. As we use the means of simulation modeling our research also inherits its weaknesses. This means that our model is only a simplification of reality and does not cover all influences on the inventory accuracy of the retail store. We do for example not evaluate how a robotic inventory of the stockroom would influence our model world. Also, we do not consider overstocking and also neglect errors that might be caused through the replenishment process by the distribution center of the retailer under consideration.

There are several reasons for a retailer to implement robotic inventory that go beyond the scope of our simulation study. First, robotic inventory seems to be cheaper than manual cycle counting if we neglect the costs of acquisition. While an employee has to be paid at least 8.84€ per hour in Germany (DGB, 2017), a robot just costs electricity. Also it is thinkable that the robots can perform additional tasks like it is already done at Lowe's, thus improving the overall customer experience (McSweeney, 2016). Furthermore, the collected data can be used for analytical purposes (see chapter 4). However, in small stores a robot might not pay off and a retailer could be better off with just using manual

RFID-enabled cycle counts. We therefore believe that a retailer should invest in robotic inventory when owning a large retail store. When the replenishments happen more than once a day, like for example in the food industry, then a replenishment gate should be used in addition, because a daily robotic inventory would be too slow to recognize the missing items. Furthermore, a replenishment gate is an additional data source for checking the reliability of the inventory data generated by a robot. In the case of a malfunction additional data from the replenishment gate may allow to perform some kind of a sanity check and allow a retailer to react to changes in the robot's performance.

To conclude, if robotic inventory works as promised by the manufacturers it will outmatch all other data quality strategies by a wide margin and prove as a valuable tool in the hands of a store manager. If robotic inventory, however, works with significantly less accuracy than promised, it could worsen the inventory data and lead to high costs. Consequently, researchers should use the insights from our simulation study and perform manufacturer-independent field studies in order to prove if robotic inventory taking can meet the high expectations that are put into it. Our study also demonstrates that simulation modeling can be a cost-effective tool for managers who need to evaluate novel RFID-based applications.

CHAPTER 4

RFID data-based in-store analytics

4.1 Introduction

Companies most often implement Radio Frequency Identification (RFID) technology in order to streamline their processes and to obtain more accurate and timely inventory data (Ngai et al., 2009). However, besides improving operative processes and the accuracy of the inventory data, RFID has the potential to support managerial decision making (Al-Kassab et al., 2013). Analysts can combine the data from several RFID readers and other data sources in order to uncover hidden insights. There are only few reports from industry and research that evaluate how to actually perform RFID data-based analytics and only few researchers have proposed approaches for using RFID data in order to aid managerial decision making (e.g., Chongwatpol (2015)). Based on this observation, RFID data still seems to be an untapped source for business insights and strategic decision making. We therefore want to contribute to this stream of research and focus our study on the following three objectives:

- Summarize the scientific literature on RFID data-based analytics
- Propose methods for extracting management-relevant information from RFID data
- Propose a generic process model for the extraction of management-relevant information from RFID data

In the first part of our study we summarize and evaluate the scientific literature that covers RFID data-based analytics. In the second part of our study we develop novel approaches and ideas for extracting management-relevant information from RFID data. We base our research on a dataset that we obtained from a large German fashion retailer. Our work extends and goes beyond of what has already been done by other researchers. We also illustrate how our analyses can be practically used by integrating them into a prototypical in-store analytics dashboard prototype for the apparel and fashion industry.

We finally use the insights from our work and the literature in order to derive a generic process model for the extraction of management-relevant information out of RFID data. Our proposed model shall help practitioners and researchers to develop useful management support tools and to harness the potential of their RFID data.

4.2 Related literature

Our literature review encompasses papers which discuss how RFID may aid managerial decision making. We are particularly interested in contributions that suggest how RFID data can actually be used to generate management-relevant information. This can include calculating performance indicators, visualizing data, or applying data mining methods. The results of our review can be divided into the following two categories:

1. Papers that discuss the impact of RFID on standard measurement systems (e.g., the balanced scorecard or the SCOR model)
2. Papers that investigate, with an actual dataset, how relevant information can be extracted out of RFID data

Under the first stream of research fall papers like Bendavid et al. (2009). The authors investigate the impact of RFID technology on a supply chain in a B-to-B setting. They perform a perennial field study with a duration of two and a half years and determine the impact of the introduction of RFID on certain key performance indicators of the Supply Chain Operation Reference Model (SCOR). The supply chain under consideration ranges from a first-tier supplier for components for electricity power grids to a public utility company at the end of the supply chain. The authors define horizontal key performance indicators and vertical performance indicators for their setting. While horizontal indicators are high level indicators like the quality of deliveries which is measured at all levels of the supply chain and interesting for all its members, vertical performance indicators are only important for one specific member of the supply chain. All in all, the authors conclude that real time RFID data is a valuable source for better performance measurement in supply chains. Consequently in the authors' opinions the introduction of RFID enhances the possibilities to measure traditional performance indicators from the SCOR model. However, they do not propose any novel RFID-enabled performance indicators.

Another study we categorize into research stream one was performed by Pigni et al. (2009) who investigate how the benefits of an RFID implementation can be measured in the supply chain context. The authors therefore, similarly to Bendavid et al. (2009) identify all supply chain indicators from the SCOR model that are potentially impacted by an RFID system. However they do not propose how to extract novel management information out of RFID datasets.

Another paper that falls into research stream one was published by Kasiri et al. (2012). The authors focus their study on operations in retail stores and propose an item-level balanced scorecard model for RFID. They determine cause and effect relationships between different performance measures by employing system dynamics methods. The main goal of the study is to develop a balanced scorecard framework in order to investigate the financial impact of item-level RFID in retail operations. By conducting a Delphi study with ten experts, the authors attempt to validate the performance indicators and causal relationships between the respective indicators in the dimensions of the balanced scorecard model. At the theoretical level, they show that it is possible and sensible to link RFID-enabled performance indicators with the balanced scorecard. As in the papers discussed above, however, they do not show how the performance indicators can actually be generated from RFID data.

Consequently, in research stream one the usage of RFID for managerial decision making is only discussed hypothetically, but there are no concrete approaches or proposals on how to perform RFID data-based analytics on actual datasets. We therefore take a look at research stream two.

The first paper that falls under research stream two was written by Delen, Hardgrave, et al. (2007) who explore the business case for RFID by analyzing the RFID readings that were tracked during the shipping process between a supplier and a retailer. The authors identify and compute several performance metrics out of the collected data. The metrics are basically the average times between product movements at different locations which allow inferences on the underlying processes. The authors then discuss how these metrics can be used in order to improve the processes between the distribution center of the supplier and the stores of the retailer.

A very interesting study was performed by Chongwatpol (2015). The author developed "an RFID-enabled track and traceability framework" in order to leverage the information visibility at trade shows. During a field experiment which lasted three days, 140 of the trade show visitors were equipped with RFID-badges. The experiment had the goal to capture their movement patterns. The author tracked which exhibition booths the attendees visited and how often. Furthermore, he kept track of the order of visits and the duration of an attendee staying at a particular exhibition booth. The author then combined these data with existing enterprise data like for example demographics and credit card information. In a next step, he applied several machine learning methods on the dataset. The data were then used in order to derive useful information for the generation of marketing strategies for tradeshow exhibitions.

Two promising papers of research stream two are the two related studies by Thiesse, Al-Kassab, et al. (2009) and Al-Kassab et al. (2013). Both studies are based on an

RFID project that was performed at Galeria Kaufhof, which was a subsidiary of the Metro Group and sold in 2015 to the Canadian Hudson's Bay Company (Metro, 2015). While the main goal of the paper from Thiesse, Al-Kassab, et al. (2009) was to (i) describe the trial, (ii) theorize about the effects of RFID on the business processes and (iii) to compare the trial to a previous one that was conducted five years earlier, Al-Kassab et al. (2013) focused on generating RFID-enabled reports and performance indicators out of the collected RFID data. The proposed reports encompass amongst others, the analysis of out of stock data, smart fitting room data and the usage of inventory data from smart shelves.

In summary, it can be said that in the second research stream there exist a few interesting papers, that discuss how to extract management-relevant information from RFID data. While Delen, Hardgrave, et al. (2007) show some very basic approaches for calculating the average times for product movements, Al-Kassab et al. (2013) and Chongwatpol (2015) perform more sophisticated analyses. While Al-Kassab et al. (2013) evaluate the usefulness of RFID data analytics in a retail setting with different reading devices, Chongwatpol (2015) investigates how to combine RFID data gathered at tradeshow exhibitions with other data and how to apply data mining methods in order to obtain management insights. The results of the above mentioned work show the relevance of the second research stream.

In order to contribute to the second stream of research, the present study aims at proposing novel approaches for utilizing RFID data in order to develop novel RFID-enabled performance indicators and reports. In a second step we want to add to the existing literature with the proposal of a generic process model for RFID data analytics. Our research is based on RFID data that were collected at a large German fashion retailer which made us these data available.

4.3 Extracting management-relevant information from RFID data

Within the scope of this chapter, various methods for extracting management-relevant information from RFID data are evaluated. The data, that we use for our research, come from the RFID middleware of a major German fashion retailer. Our study is structured as follows: We start with an overview of the business case and the involved RFID devices. First of all, we show how statistical methods can be used to derive information about the queuing process at an RFID-enabled point of sale. Second, we show how to use visualization techniques to carry out sales floor analyses. Third, we show how to derive estimates of the quality of RFID data generated by the RFID infrastructure by combining the data from multiple RFID readers with knowledge of the environment and the RFID-enabled processes.

4.3.1 Business understanding

The retail store from which we obtained the data and which serves to illustrate our approach is one of the flagship stores of the retailer in question. The shop consists of two floors, with the ground floor containing the ladies' clothing and the first floor containing the men's clothing. The retailer is interested in selling its products, optimizing the location of the products, providing good customer service and making better use of its employees. Nearly all products are equipped with RFID tags and the retailer has installed the following RFID hardware:

- One replenishment gate between the stockroom and the sales floor area
- One EAS gate at the entrance of the store
- Two point of sale systems
- Four smart fitting rooms (Three in the ladies' department and one in the men's department)
- Handheld readers for the store staff
- One inventory robot

The retailer uses a similar setting to the one we describe in section 3.3.3. In addition an RFID-enabled electronic article surveillance (EAS) gate was introduced in order to substitute the traditional EAS. Furthermore, the retailer decided to perform a robotic RFID-enabled inventory similar to simulation scenario 3a which we describe in section 3.3.5. Furthermore, there exists a replenishment gate between the stockroom and the sales floor. The retailer has also implemented four smart fitting rooms within the store in order to offer a better customer service. The smart fitting rooms are able to track the items that are brought into the cabins and to offer recommendations on a screen which is placed inside the cabins. In addition, customers can also browse through the garments of the store and of the eshop.

4.3.2 Data understanding

In the following we describe the data provided by the retailer and use them as the basis for the following analyses. The retailer delivered two different sets of RFID data from its middleware, namely *RFID log data* (see table 4.1) and *RFID bookings data* (see table 4.2). Both datasets are pre-filtered by the middleware which means that they do not contain all readings of an RFID tag but only the "relevant" ones. For example, if an item travels through an RFID gate, the middleware only keeps one reading instead of all (e.g., a tag could be read twenty times when passing a gate). This is enough in order to suffice the retailer's information needs without bloating the database with redundant events. However, while the log data contain the readings of an RFID tag in combination with its SGTIN, a timestamp and the corresponding RFID reading device that read the tag, the bookings dataset contains the related bookings. This means the bookings dataset contains the bookings from the middleware system that were performed in conjunction with the reading of the respective RFID tags. For example if an item was read at the point of sale, the RFID log would contain one reading and the RFID bookings data would contain the booking that the item was sold.

As the example of the RFID log dataset in table 4.1 shows, an entry contains

- a timestamp (column Date),
- the serialized global trade item number (SGTIN),
- the device that read the RFID tag (e.g., point of sale or inventory robot),
- a movement direction (column Direction),
- X, Y and Z coordinates and
- the respective floor (column Area).

The timestamp denotes the time a tag was actually read and is accurate down to seconds (see column *Date*). The *SGTIN* serves as unique identifier of an item. The devices in the *Device* column can either be one of the two point of sale readers, the replenishment gate, the EAS gate, one of the smart fitting rooms, one of the handheld devices or the inventory robot. The column *Direction* gives information about the movement of the articles. It either denotes if an item travels to the sales floor, to the stockroom or if it enters or leaves a certain smart fitting room. This information is only important if the device is the replenishment gate or a smart fitting room - in all other cases it serves no purpose and has a value of *NULL*. Furthermore, the *X*, *Y*, and *Z* coordinates are only tracked if a tag is read by the inventory robot. The column *Area* is also only relevant in conjunction with the inventory robot and denotes on which floor the robot performed its inventory when it read a certain RFID tag.

Table 4.1: Example of the RFID log data

Date	SGTIN	Device	Direction	X	Y	Z	Area
2017-01-09 06:54:38	(01)040576558...	Replenishment	2	NULL	NULL	NULL	NULL
2017-01-09 08:41:52	(01)040576557...	SFR_DOB	IN	NULL	NULL	NULL	NULL
2017-01-09 08:45:06	(01)040576555...	SFR_HK	OUT	NULL	NULL	NULL	NULL
2017-01-09 08:42:46	(01)040581146...	POSREADER1	0	NULL	NULL	NULL	NULL
2017-01-09 08:45:07	(01)040581146...	WA01	0	NULL	NULL	NULL	NULL
2017-01-09 19:09:02	(01)040179939...	Robot	0	850	11674	890	OG

Table 4.2 gives an example of the RFID bookings that may be performed in connection with a reading in the RFID log table. First, the column *Date* in this table denotes the timestamp of the booking from the middleware. In addition to the data fields from the RFID log table, the table contains the *booking type*, a textual short *description* of an article, the *planning group* (column PG), as well as the columns *From* and *To*. The column From denotes the last known position of an article. It can either be stockroom (2), sales floor (1), outside the store (3) or unknown (4). The column To denotes the area in which a tag was actually read and can take the same values as the From column. Consequently, the values in these two fields can be used in order to recognize a position change of an article.

Table 4.2: Example of the RFID bookings data

Date	Booking Type	Description	PG	From	To	SGTIN	Device
...	425	MKG Shirt	57	1	2	(01)04058114546736(21)400122	MLVF01
...	360	Leichtsteppe	26	1	1	(01)04059182110904(21)400190	POSREADER1
...	425	KB Jeans	57	2	1	(01)04057655845131(21)400540	Transition
...	360	Triumph BH	9	1	1	(01)07611358891313(21)400166	HANDHELD

Furthermore, one reading in the RFID log table usually corresponds to several bookings in the RFID bookings table. For example if an article is sold and there is one entry in the RFID log table, then three corresponding bookings are created in the RFID bookings table. First the article is booked as sold, second the EAS alarm for this article is deactivated, and third the article is removed from the store's inventory. Also, the timestamp of the reading event in the RFID log differs from the timestamp in the bookings table. This means, that the booking is performed slightly later than the actual reading (e.g., the reading in the log at the POS denotes the start of a customer transaction, while the booking denotes the end of a transaction). In the following subchapters we either use the RFID log, the bookings table or a combination of both in order to perform our analyses.

The data we use for our experiments have a volume of 838409 readings in the log file and 184844 corresponding bookings. There are more readings than bookings because not all readings lead to a booking in the middleware. For example, a reading of the robot has no corresponding entry in the bookings table (except if an item changes its position) but is just used to verify the inventory. In addition to the RFID data, we also received the floor plan of the shop in question, which we use for visual analyses of the sales areas. We also visited the relevant store to verify our analyses.

4.3.3 Method one: Estimation of queue metrics from data from an RFID-enabled POS

The purpose of this section is to illustrate the applicability of statistical algorithms for deriving information about an RFID-enabled process. We therefore take a look at the RFID-enabled checkout process and the problem of deriving information about its performance from its data.

4.3.3.1 Motivation

Queues at the point of sale can be annoying to customers. Especially during rush hours, customers may have to wait several minutes in line - a fact that can drastically diminish customer satisfaction. In a recent study Lu et al. (2013) investigate in a retail store how queues at the point of sale influence customer purchase decisions. They use video recognition for their analysis and find that customers' purchase decisions are much more influenced by the length of the line at the POS rather than the actual waiting time. They also find that the perceived queue length can reduce the chance of a customer joining the line in order to buy a product and that an increase of a line from 10 to 15 customers leads to an average drop in sales of about 10%. Consequently, it is important for retailers to mitigate this problem as good as possible. Managers therefore have to investigate if the checkout process in their retail stores poses a bottleneck and if they may have to open more cashiers and to allocate more personnel to certain times of the day or days of the week.

Technology can help to reduce the length of queues and customer waiting time. One of the major claims of RFID is to reduce customer waiting time and queue length through the reduction of the time needed for scanning items at the point of sale (Roussos, 2006). However, the checkout process consists out of many parts and scanning items is only one of them. It is therefore unclear what impact RFID actually has on this process. In order to be able to verify the claims of RFID, it is necessary for a retailer to have performance indicators about the checkout process. More knowledge about the performance of the checkout process not only helps to verify the impact of RFID but also to better allocate resources to this bottleneck. Better information about the performance of the checkout can thus be a useful asset in the hands of a manager. However, in order to obtain this information retailers have to rely on manual counting of queues or the aforementioned video recognition systems.

In contrast to the above-mentioned costly approaches we propose to use a statistical and more cost efficient method that uses the transactional data generated by the RFID-enabled POS. We combine a data aggregation method for RFID data with the work of Larson (1990) who developed a statistical approach for estimating performance indicators about queues from transactional data. The work of Larson (1990) lead to an algorithm called "the queue inference engine". We integrate this algorithm with our aggregation procedure and use it to infer queue information from RFID data of the RFID-enabled POS. The inference engine enables us to estimate important performance indicators, namely the average number of customers in line and the expected waiting time for a random customer. In a final step we show how the generated information can be aggregated further in order to derive managerial insights about the RFID-enabled checkout process.

4.3.3.2 Problem description

We investigate the queuing process at the RFID-enabled points of sale. Figure 4.1 shows a simple example of how a queue develops at the checkout. In our example there exists only one cash desk equipped with an RFID reader with one employee who serves customers.

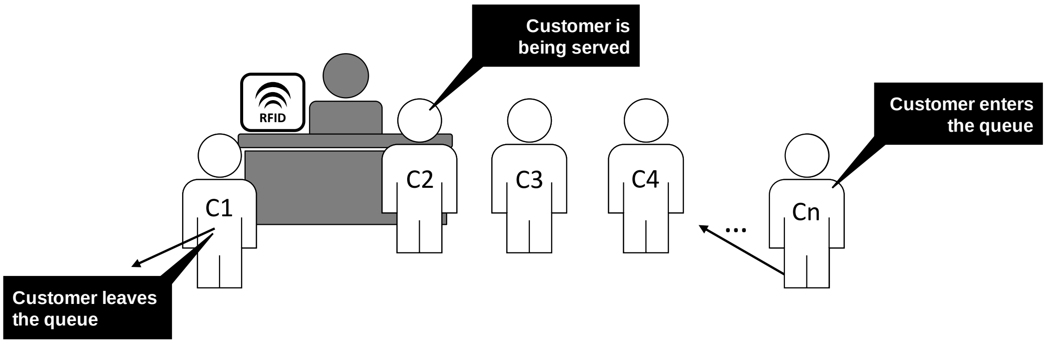

Figure 4.1: Customers queuing at an RFID-enaled point of sale

In our example, customers denoted by C1, C2, C3, C4 up to Cn enter and leave the queue according to the FIFO (first in first out) principle. This means that the customer who enters the queue first also leaves the queue first. A queue starts to build if a customer wants to step in front of the cash desk but the cash desk is already occupied by another customer. In the example, customer 1 leaves the queue and customer 2 is served at the cash desk. Customers 3 and 4 queue up and have to wait. This also applies to all customers who join the line after them.

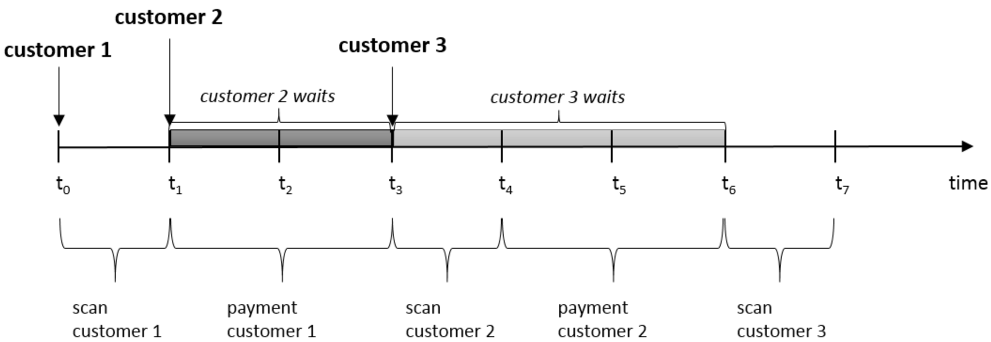

Figure 4.2: Customer arrivals, checkout process and waiting times

Figure 4.2 gives an example on how the the waiting and arrival times of customers can be distributed. For each customer there exist two events namely the scanning of products with the RFID reader and a payment. At t_0 customer 1 steps to the cash desk and the process starts. Because customer 1 is served immediately, (s)he does not have to wait. The cashier scans the items of customer 1 and customer 1 pays afterwards. While customer 1 is being served customer 2 steps into the line at t_1. Customer 2 has to wait till customer 1 leaves the cash desk. In the example from figure 4.2 a third customer enters the queue at t_3 exactly when customer 1 leaves the queue. At t_3 the checkout process for customer 2 starts. Consequently, customer 3 has to wait until the scanning process and the payment process of customer 2 have been completed.

Even though, the queuing process seems simple at a first glance, inferring queue information out of transactional data is a non-trivial task because the arrival times of the customers are not available. This is due to the fact that the data from the cash desks only tell when the items of a customer were scanned with the RFID reader and when the payment process of a customer was completed. To be more precise, each of the customers' purchases at the RFID-enabled cash desk produces transaction data. The RFID middleware tracks for the RFID-enabled POS for each article, when it was scanned on the desk and when corresponding bookings were performed in the middleware.

In our real world dataset, the first scan of a sales transaction is found in the *RFID log* and the completion time of the transaction can be found in the *RFID bookings*. This information gives us a decent estimate for the start of the checkout process for a customer and the completion of the process (this means the time (s)he leaves the queue). We furthermore know from the data, the sequence in which the customers must have stepped into the line (assumed customers do not change their positions while waiting). Consequently, the data only tell us when a customer was served and when (s)he left the cash desk. However, the data do not tell us the time a customer stepped into the line which makes estimating customer waiting times and the length of a queue at a certain point in time difficult. We demonstrate this issue with two extreme scenarios.

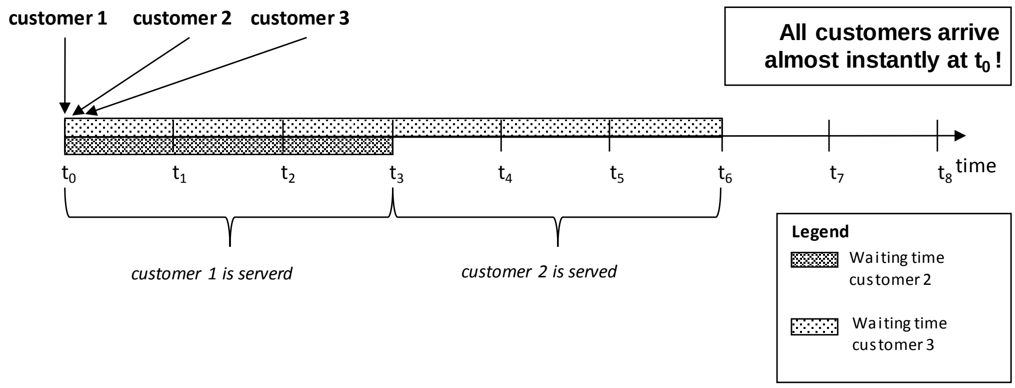

Figure 4.3: Example for the worst case arrival times for customers 1, 2 and 3 if the checkout process takes exactly three time units

In the *worst case scenario* (i.e., the scenario in which the waiting time for all customers is longest), all customers arrive almost instantly at the same point in time. The scenario is illustrated in figure 4.3. Let us assume, that the payment process takes exactly three time units for each customer. This means that if customer 1, 2 and 3 arrive almost instantly at

t_0, (note: the sequence is always C1 < C2 < C3) customer 2 has to wait three time units until customer 1 leaves the cash desk and customer 3 has to wait for six time units until customer 1 and customer 2 leave the queue. Consequently, the overall waiting time within the queue is zero time units for customer 1 plus three time units for customer 2 plus six time units for customer 3 which totals nine time units.

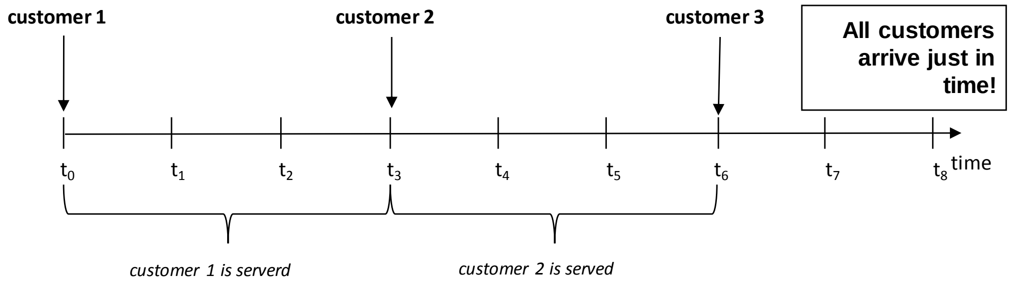

Figure 4.4: Example for the best case arrival times for customers 1, 2 and 3 if the checkout process takes exactly three time units

In contrast to the previous example we can also imagine a *best case scenario* for the arrival times of customers 1, 2 and 3. This is illustrated in figure 4.4. In this example all customers arrive *just in time*. This means that customer 1 arrives at t_0 and is immediately served, customer 2 arrives just when customer 1 leaves the cash desk at t_3 and is also immediately served. Then customer 3 arrives at t_6 and is also immediately served. In this example, which reflects the best case scenario, customers 1, 2 and 3 do not have to wait at all.

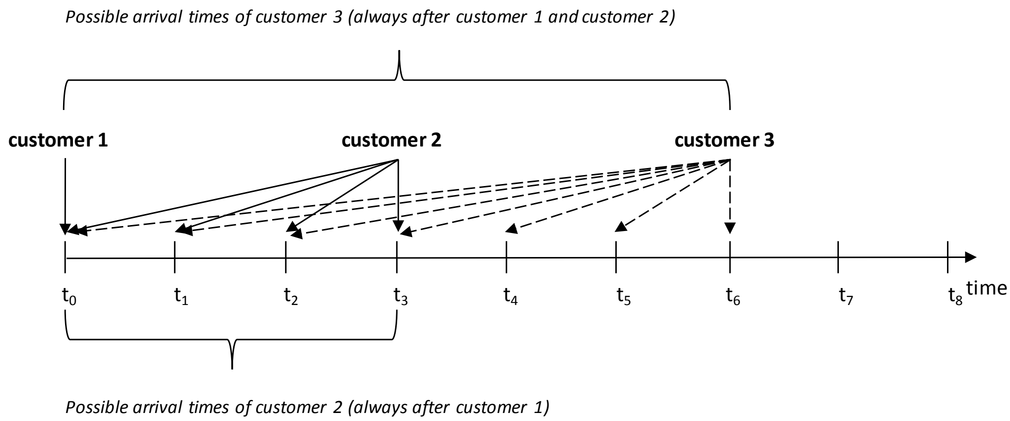

Figure 4.5: Possible arrival times for customers 1, 2 and 3 if the checkout process takes exactly three time units

Unfortunately, the data from the RFID-enabled POS do not tell us when exactly a customer arrives. If we take a closer look at the possible distribution of arrival times (see figure 4.5) this becomes a combinatorial problem. The arrival of a customer is always dependent upon the arrival of the previous customers, leading to an infinite number of possible combinations of arrival times (assuming time units can be split indefinitely). To solve this problem statistically we draw upon the work of LARSON (1990) who proposes a method based on order statistics and a Poisson assumption in order to derive queue metrics from transaction data.

4.3.3.3 Inferring queue metrics and aggregated performance indicators

Within this chapter we detail our approach of deriving queue metrics out of RFID-based POS data. We base our approach for the inference of economic queue metrics from RFID data on the work of LARSON (1990) who proposed an approach for deducing queue statistics out of transaction data from automatic teller machines (ATMs) in order to help bank managers to decide if customer waiting times in a bank are too long and if a bank needs more or less ATMs. We transfer Larsons's method to our use case and integrate it into our approach, in order to obtain meaningful aggregated indicators about the checkout process of an RFID-equipped retail store. Our proposed general approach is depicted in figure 4.6.

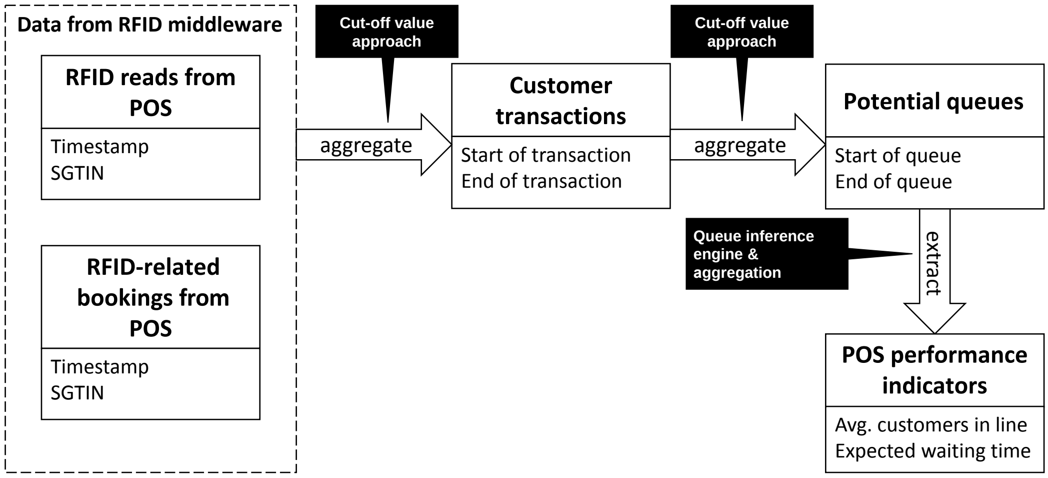

Figure 4.6: Process of queue inference based on RFID-enabled POS data

We start our process by aggregating RFID readings and corresponding bookings to customer transactions and customer transactions to potential periods of congestion at the point of sale (i.e., potential queues). These data are then used as the basis for the queue inference algorithm of LARSON (1990). In a final step we use the metrics which we derive with Larson's algorithm and aggregate them further in order to obtain aggregated POS performance indicators. The data from our real world dataset were generated by the RFID readers at the points of sale. We demonstrate our approach on an excerpt of the data which is shown in table 4.3.

Table 4.3 shows only the relevant columns which are needed in order to perform the analysis as we describe it within this chapter. In our example, there are six readings of different

SGTINs in the RFID log table. These readings belong to three customer transactions at the RFID-enabled POS reader (POSREADER1). All items were read at April the 4th 2017. As it can be seen by the timestamps in the RFID bookings, there are certain bookings which happen within a few seconds. We know that these consequently must belong to the same customer transaction. This holds for the first row in the table with the first reading in the log at 13:23:25, indicating the start of a customer transaction and the according booking at 13:24:09 indicating the end of the customer transaction (Note: all transactions are ordered by date and time). The second customer transaction, which constitutes out of two SGTINs, starts at 13:24:29 (see table 4.3 row 2) and ends at 13:25:56 (see table 4.3 row 3). The bookings for each SGTIN that belong to the same customer transaction happen slightly after one another within a timeframe of two to three seconds.

Table 4.3: Connected database entries in the RFID log and the RFID bookings from transactions at the RFID-enabled POS reader

RFID log			*RFID bookings*	
SGTIN	**StartDate**		**SGTIN**	**EndDate**
(01)04056905197129(21)24	01.04.2017 13:23:25	»»	(01)04056905197129(21)24	01.04.2017 13:24:09
(01)04059182050989(21)232	01.04.2017 13:24:29	»»	(01)04059182050989(21)232	01.04.2017 13:25:53
(01)04059182024256(21)366	01.04.2017 13:24:29	»»	(01)04059182024256(21)366	01.04.2017 13:25:56
(01)04059491090188(21)400027	01.04.2017 13:31:05	»»	(01)04059491090188(21)400027	01.04.2017 13:32:36
(01)04059182116302(21)286	01.04.2017 13:31:05	»»	(01)04059182116302(21)286	01.04.2017 13:32:38
(01)04059182115671(21)370	01.04.2017 13:31:12	»»	(01)04059182115671(21)370	01.04.2017 13:32:40

We use the timestamps of the respective bookings for identifying customer transactions, because the readings in the RFID log data can have larger time ranges than the corresponding bookings. The larger time ranges in the log can occur due to human errors or process variations. For example if a customer brings so many items that not all of them fit on the desk at once, the items have to be scanned in batches. However, the bookings of the articles are always performed at the end of a customer transaction, one after the other, and are thus preferably used for our approach.

The first step of our approach is to identify a customer transaction and its duration. This information can either be obtained by using certain timestamps and a customer id from the ERP if such an information is available or as it is in our case, to aggregate the respective scanning and booking events in the database tables based on their timestamps and the reading device.

We used the programming language R (R-Foundation, 2017) in combination with the package dplyr (CRAN, 2017) for the practical data analysis and data aggregation. This allowed us to combine the functionality of a programming language with SQL-like data manipulation abilities. However, in order to describe our approaches in a more general way without having to consider the peculiarities of the programming language R and its package dplyr and because we assume most readers to be familiar with SQL, we illustrate our approaches in *pseudocode* and *SQL*.

In a first step we determine all relevant RFID reading events from the POS. This can be achieved with an SQL statement as given in algorithm 1.

Algorithm 1 Select RFID POS readings from RFID log

Require: Table: RFID_log {RFID reading events from the RFID middleware}
SELECT SGTIN, Timestamp **AS** Startdate, Device **FROM** RFID_log
WHERE Device = "POSREADER" {POSREADER denotes the cash desk}
return Table: RFID_POS_Log

In a second step we determine the relevant bookings from all RFID bookings from the middleware which are connected to sales events at the POS. This can be achieved with the SQL statement given in algorithm 2.

Algorithm 2 Select relevant bookings from RFID-enabled POS

Require: Table: RFID_bookings {Bookings from the POS}
SELECT SGTIN, Timestamp **AS** EndDate, Device **FROM** RFID_bookings **WHERE** Device = "POSREADER" **AND** Type = "SALES" **AS** RFID_POS
return Table: RFID_POS_Bookings

After having selected the POS events from the table RFID_bookings and the table RFID_log we use an INNER JOIN in order to create a combined table based on the SGTINs (see algorithm 3).

Algorithm 3 Combine bookings with reading events

Require: Tables: RFID_POS_Log; RFID_POS_Bookings
SELECT * **FROM** RFID_POS_Log **INNER JOIN** RFID_POS_Bookings **ON** RFID_POS_Log.SGTIN = RFID_POS_Bookings.SGTIN
return Table: RFID_POS_Events

We now identify customer transactions based on a time based cut-off value of 15 seconds. As already mentioned before, the bookings of the SGTINs occur within a short timeframe one after another. We therefore use a cut-off value approach in order to aggregate the database entries based on their SGTINs and timestamps. This means we look at the booking transactions for each SGTIN that was read at the POS. If the next booking happens within 15 seconds we assume it belongs to the same customer transaction. Even though most of the bookings occur within 2-3 seconds after one another, there are times when the system of the retailer under investigation seems to have a high workload and the bookings are performed in slightly larger time intervals. We decided out of this reason to use a 15 second timeframe in order to not mistakenly aggregate booking events from different transactions. Based on our analysis of the RFID data, a time window of 15 seconds is large enough to not accidentally miss a booking event but still small enough to differentiate between different customer transactions. After having identified the relevant bookings, we use the timestamps and SGTINS in the RFID log in order to find the corresponding readings that mark the start of the checkout process. The approach for actually identifying the customer transactions is given by algorithm 4.

Algorithm 4 Identify customer transactions

```
Require: Table: RFID_POS_Events {The result of algorithm 3}
Add COLUMN "Time_To_Next_Booking" to TABLE RFID_POS_Events
Add COLUMN "Customer_Id" to TABLE RFID_POS_Events
Time_To_Next_Booking = [TIMESTAMP[-1], NULL] - TIMESTAMP
  {The time to the next booking is calculated by shifting the vector of column TIMES-
  TAMP by 1 and subtracting the vector of column TIMESTAMP from it. Furthermore,
  assume NULL - something = NULL}
row_number = 1
id = 1
for each time in Time_To_Next_Booking do
  set Customer_Id[row_number] = id
  if !isNull(time) and time > 15 then
    id = id + 1 {If time > 15, the next transaction belongs to another customer}
  end if
end for
return Table: RFID_POS_Events
```

The final grouping is then performed with the following SQL-like statement given by algorithm 5. The algorithm takes the first timestamp in the RFID log as the beginning of the customer transaction and the first timestamp in the bookings data as the end of the particular customer transaction.

Algorithm 5 Identify customer transactions

```
Require: Table: RFID_POS_Events {The result from algorithm 4}
SELECT Customer_Id, MIN(Start_Date) AS Start_Date, MIN(End_Date) AS
  End_Date, Time_To_Next_Booking FROM RFID_POS_Events GROUP BY
  Customer_Id
return Table: Customer_Transactions
```

We take the first timestamp from the bookings, because this is the time when the cash desk reports the finalization of the checkout process and thus roughly marks the actual end of a customer transaction. Using algorithm 1 to 5 on the example data from table 4.3 will result in a dataset as shown in table 4.4.

Table 4.4: Aggregation of RFID data to customer transactions

Customer_Id	Start_Date	End_Date
1	01.04.2017 13:23:25	01.04.2017 13:24:09
2	01.04.2017 13:24:29	01.04.2017 13:25:53
3	01.04.2017 13:31:05	01.04.2017 13:32:36

In the second step of our framework, we use the same algorithmic approach as described in algorithm 4 in order to identify potential queues. We follow Larson (1990) who defines the pattern for a potential queue as "a service completion time followed immediately by a service initiation time" (Larson, 1990). We thus assume that a customer likely waited in line if (s)he was served immediately after the customer transaction of the customer before ended. As there is nevertheless a little time between customer transactions, we conducted a thorough analysis of the data and chose a cut-off value of 20 seconds. Therefore, we assign all customer transactions that are no more than 20 seconds apart to the same queue. We use algorithm 6 in order to identify potential queues.

Algorithm 6 Identify potential queues

Require: Table: Customer_Transactions {The result of algorithm 5}

Add COLUMN "Time_Next_Cust" to Customer_Transactions
Add COLUMN "Queue_Nr" to Customer_Transactions
Time_Next_Cust = [Start_Date[-1], NULL] - End_Date
{The time to the next customer is calculated by shifting the Vector of column Start_Date by 1 and subtracting the respective value of End_Date from it. Furthermore, assume NULL - something = NULL}
row_number = 1
id = 1
for each time **in** Time_Next_Cust **do**
  set Queue_Nr[row_number] = id
  if !isNull(time) and time > 20 **then**
    id = id + 1 {If time > 20, the next customer will be attributed to the next queue.}
  end if
end for
return Table: Potential_Queues

After this aggregation step each customer transaction is assigned to a queue number (see table 4.5). The customers with the ids 1 and 2 were assigned to queue number 1 because they were exactly 20 seconds apart (see column Time_Next_Cust). The customer with id 3 was assigned to queue number 2 because (s)he is 312 seconds apart from the customer with the id 2. It is however to note that a queue with just one person is actually not a real queue because it has a length of zero and the waiting time is also zero because there is only one person which is served immediately. However, as we are interested in the performance of the RFID-enabled checkout process when there are potentially customers standing in line, we only consider instances with two or more potential customers for further analysis.

Table 4.5: Aggregation to queues

Customer_Id	Start_Date	End_Date	Time_Next_Cust	Queue_Nr
1	01.04.2017 13:23:25	01.04.2017 13:24:09	20	1
2	01.04.2017 13:24:29	01.04.2017 13:25:53	312	1
3	01.04.2017 13:31:05	01.04.2017 13:32:36	NULL	2

With the result of algorithm 6 we are able to utilize the ideas of LARSON (1990) which we briefly outline within the next few paragraphs. Larson's main idea is to deduce queuing behavior from transactional data only by using a Poisson assumption. He bases his work on the theory of order statistics from which he uses the following equations:

$$E[N(t)] = \frac{t}{T}N \tag{4.1}$$

$$VAR[N(t)] = N\binom{t}{T}\binom{T-t}{t} \tag{4.2}$$

$$Pr\{N(t) = k\} = \binom{N}{k}\binom{t}{T}^{k}\binom{T-t}{t}^{(N-k)} \tag{4.3}$$

Where N denotes the number of Poisson events that occur and $N(t)$ denotes the number of arrivals over a time interval of $0 \leq t \leq T$. Larson then uses these assumptions in order to derive the following recursive algorithm to compute the "[f]undamental A Priori Conditional Probability of the event that the transactional data indicate has occurred" (LARSON, 1990):

$$\alpha_{ki}(t) = \sum_{j=0}^{k-i+1} \binom{k}{j} \alpha_{(k-j)(i-1)}(t) \left(\frac{t_i - t_{i-1}}{t_N}\right)^{j}, k \leq i. \tag{4.4}$$

He then uses the a priori probability in order to compute the cumulative probabilities of arrival times, i.e., the probability that the kth arrival precedes the ith departure, where $\beta_k i(t) = 1$ for $k \leq i$ (HALL et al., 1991):

$$\beta_{Ni}(t) = \frac{\alpha_{Ni}(t)}{\alpha_{NN}(t)}, 1 \leq i \leq N, 1 \leq i \leq N \tag{4.5}$$

$$\beta_{ki}(t) = \beta_{(k+1),i}(t) + \frac{\binom{N}{k}\alpha_{ki}(t)}{\alpha_{NN}(t)}, 1 \leq i < k < N \tag{4.6}$$

The mean cumulative number of arrivals at time t is calculated via:

$$\overline{N}_a(t_j) = \sum_{k=1}^{N} \beta_{ki}(t) \text{ for all } j = 1, 2, ..., N. \tag{4.7}$$

Also if defined $t_0 := 0$ then for $t_{j-1} < t \leq t_j$, $j = 1, 2, ..., N$,

$$\overline{N}_a(t) = \frac{t_j - t}{t_j - t_{j-1}}\overline{N}_a(t_{j-1}) + \frac{t - t_{j-1}}{t_j - t_{j-1}}\overline{N}_a(t_j) \tag{4.8}$$

Larson uses the recursive algorithm (equation 4.4 to equation 4.8) in order to calculate economic indicators namely (i) the time average queue length for a potential period of congestion $\overline{N}_Q$ (see equation 4.9) and the mean delay in a queue which is the expected total number of time units spent in queue by customers during a congestion period $\overline{W}_Q$ (see equation 4.10):

$$\overline{N}_Q = \frac{1}{2T}\sum_{i=1}^{N}(t_i - t_{i-1})[\overline{N}_Q(t_i-) + \overline{N}_Q(t_{i-1}+)] \tag{4.9}$$

$$\overline{W}_Q = \left(\frac{T}{N}\right)\overline{N}_Q \tag{4.10}$$

Using our aggregation approach and the recursive algorithm of Larson on our real world dataset we obtain information about each potential queue. An excerpt of the output from the algorithm on some example data is given in table 4.6. Table 4.6 shows the determined queue number, the start time of the queue, the end time of the queue, the number of people that were assigned to the queue (column Size), the average number of customers (column Avg_Cust) and the mean waiting time for a given queue under the Poisson assumption (column Mean_Delay).

Table 4.6: Queue data for queues with size > 1

Queue_Nr	Start_Time	End_Time	Size	Avg_Cust	Mean_Delay
1187	04.02.2017 12:34:48	04.02.2017 12:36:55	2	0.50	63.50
1188	04.02.2017 12:37:38	04.02.2017 12:39:29	3	0.69	38.26
1189	04.02.2017 12:41:01	04.02.2017 12:44:25	2	0.50	102.00
1190	04.02.2017 12:46:15	04.02.2017 12:49:50	4	0.77	55.25
1191	04.02.2017 12:50:46	04.02.2017 12:51:52	2	0.50	33.00
1195	04.02.2017 13:01:22	04.02.2017 13:05:38	5	0.82	52.16
1200	04.02.2017 13:14:58	04.02.2017 13:19:31	4	0.87	78.84
1202	04.02.2017 13:23:11	04.02.2017 13:29:47	7	1.42	93.94
1203	04.02.2017 13:32:23	04.02.2017 13:33:28	2	0.50	32.50

We not only want to know statistics about a single queue, but also about the overall performance of our POS process. This means we want to know the expected waiting time and the number of customers a customer probably has to face during busy times at the POS. In order to achieve this objective, we have to further aggregate the metrics that were delivered by the queue inference engine. We therefore propose to calculate the averages out of the individual queue metrics. This gives us the average queue size and the average customer waiting time. We believe that this can be a very useful information for a retailer. We also propose to further aggregate the performance information about the cash desks over longer time periods in order to obtain more robust indicators. This can be achieved by using a simple average over the timeframe of interest. The timeframe could be a week, a month or any other wished time period. We therefore propose to calculate the mean waiting time during periods of congestion, which we denote as $\overline{W}_\tau$, as the sum of the average waiting times of all queues during that period divided by the number of queues during that period denoted as m_Q (see equation 4.11):

$$\overline{W}_\tau := \frac{\sum_{i=1}^{m_Q} \overline{W}_{Q_i}}{m_Q}, \forall \text{ queues } i \text{ to } m_Q \text{ under consideration during time period } \tau \quad (4.11)$$

Similarly we define the average number of customers in queue during a certain time interval of interest $\overline{N}_\tau$ as:

$$\overline{N}_\tau := \frac{\sum_{i=1}^{m_Q} \overline{N}_{Q_i}}{m_Q}, \forall \text{ queues } i \text{ to } m_Q \text{ under consideration during time period } \tau \quad (4.12)$$

We can use the information in order to create visualizations that are easily interpretable by a store manager. For example figure 4.7 shows the average waiting time for customers, in times when there were queues before the checkout, over the course of the day. For this illustration the averages have to be calculated for the respective timeframes. A store manager could interpret from the illustration that a customer, if there are queues at the POS, has to wait about 40 to 45 seconds in line before being served, and that this value remains relatively constant throughout the day.

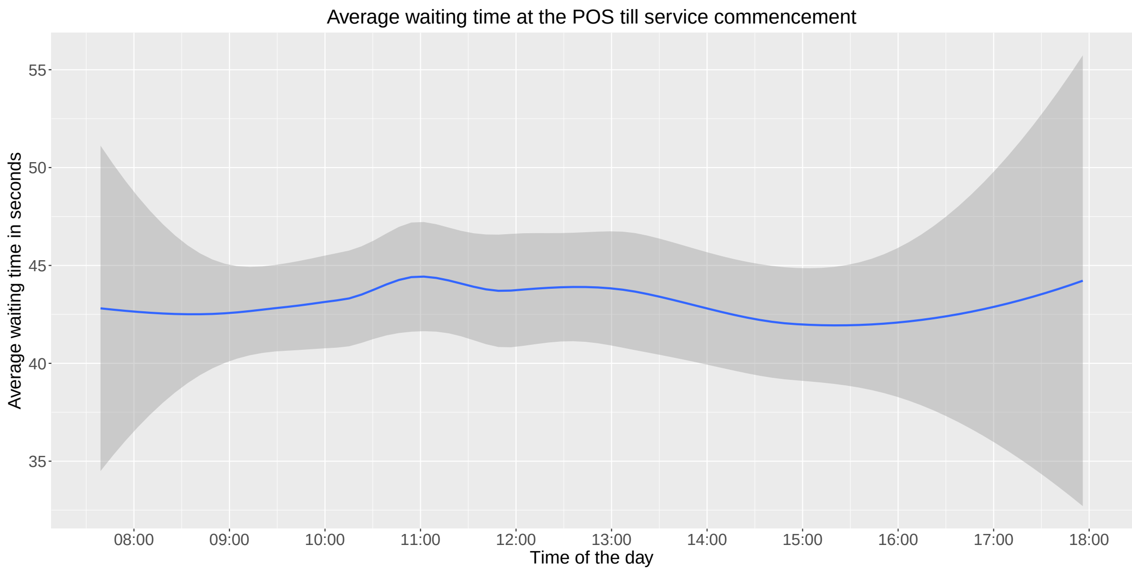

Figure 4.7: Visualization of average waiting time in a queue for times of the day.

Aggregating RFID data and using queue inference techniques is a cost efficient way to evaluate the performance of the RFID-enabled checkout process. This allows retailers to compare the performance of the checkout process in general and between different retail stores. Visualizations based on aggregated data like shown in figure 4.7 can further aid to detect time periods which show a performance drop of the RFID-enabled checkout process.

4.3.4 Method two: Visual sales floor analysis with RFID-enabled positioning data

In the following sections, we examine the possibilities of using the RFID-enabled positioning data of an inventory robot to gain useful insights for the management of a fashion and apparel retailer by means of visual analyses. The use of visualization is advantageous because people receive 80% of all information from the visual cortex (Dahm, 2006). We therefore describe the available data in a first step and then show how we combine the inventory robot's positioning data with the data from other RFID devices to create a series of visualizations of the sales floor, each providing different management insights.

4.3.4.1 Problem description

We know from the description of the retail store under investigation, that the inventory robot performs its inventory every second day on the specified sales floor area during the night, when the store is closed. This means, it performs the inventory one day on the ground floor and the next day on the first floor. Furthermore, this means that the data of a specific area are in the worst case one day old. While the robot drives through the hallways it not only recognizes all items lying or hanging on the shopping aisles, but also determines their relative positions with their respective X, Y and Z coordinates.

Table 4.7: Excerpt of RFID data from the inventory robot

SGTIN	Device	Timestamp	X	Y	Z	Area
(01)04017993911639(21)2095	Inventory_Robot	2017-01-09 22:34:38	1504	11472	1393	OG
(01)04017993911639(21)2109	Inventory_Robot	2017-01-09 22:34:38	1933	12810	1990	OG
(01)04017993911738(21)2178	Inventory_Robot	2017-01-09 22:34:38	850	11674	890	OG
(01)04021642144323(21)726100	Inventory_Robot	2017-01-09 22:34:38	1230	12223	1246	OG
(01)04021642144392(21)400135	Inventory_Robot	2017-01-09 22:34:39	794	12371	646	OG
(01)04021642170674(21)726100	Inventory_Robot	2017-01-09 22:34:39	1497	12742	1496	OG
(01)04021642170704(21)726100	Inventory_Robot	2017-01-09 22:34:39	1763	12148	1175	OG

Table 4.7 illustrates the output we receive from the robot. Similar to all the other RFID-enabled devices the inventory robot reads the SGTIN and creates a timestamp. However, in addition it also determines the X, Y and Z coordinates of the respective RFID tags. Consequently, the collected data allow us to recognize changes in article positions on the sales floor area. Furthermore, these data allow us to find the last known position of a garment. Besides the data from the inventory robot, the retail company which owns the store provided us with a layout plan. By combining the reading events of the robot with the store layout, we can carry out a visual analysis of the sales area. In concrete terms, the following sections show how to use heatmap visualizations to find interesting areas on the sales floor. Specifically, we show how to use a heatmap as a means of identifying areas with high sales volumes and areas from which customers transport their garments to the fitting rooms.

4.3.4.2 Mapping of X and Y coordinates to the sales floor area

In a first step, before performing any analysis we have to map the X and Y coordinates to the store layout. As we only perform a two dimensional analysis we do not use the Z coordinate. Because the owner of the store could not provide us with the mapping of the X and Y coordinates to the layout plan, we had to manually map the data to the sales floor area. The inventory robot delivers the coordinates relative to its position from its starting point in the stockroom of the shop. It always starts from the same place, so the coordinates can be compared with each other. In order to map the coordinates to the layout of the sales floor area, we decided to map the article positions onto the layout and to use striking structures from the layout in order to find a good estimate.

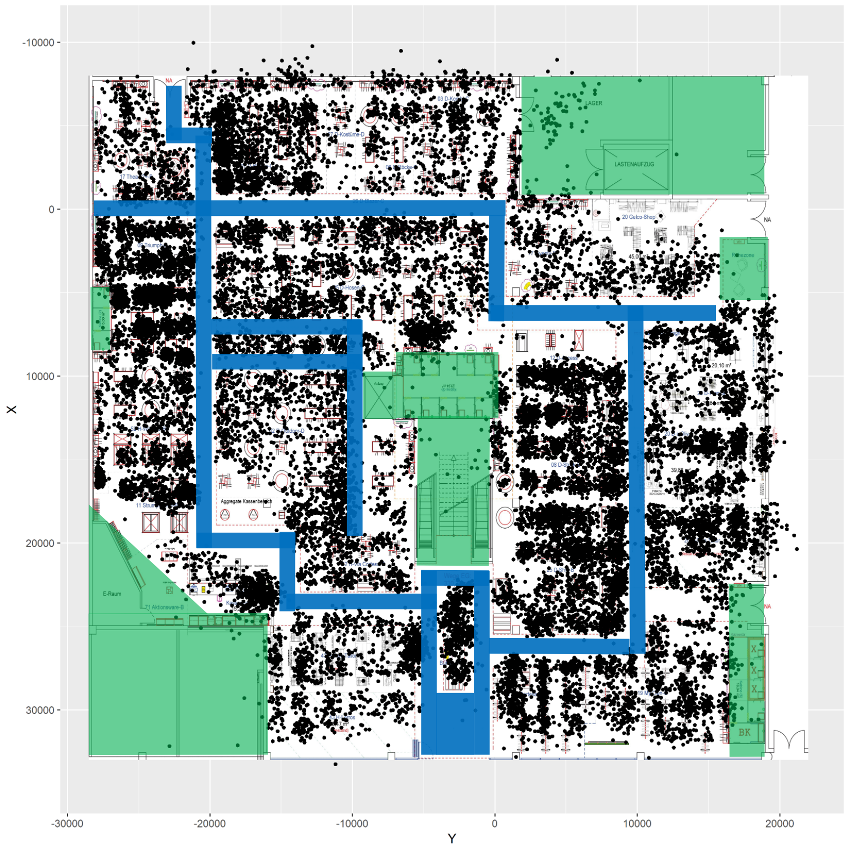

Figure 4.8: Mapping the articles onto the sales floor map

Figure 4.8 illustrates the structures of the store we used. The black dots mark the articles, the green areas mark the cashiers area, the fitting room areas and the area for the employees. The blue lines mark the biggest hallways of the sales floor area. We chose these areas because they usually do not contain many articles. We used several iterations of visual control and coordinate matching to visually map the items onto the map to match the visible structures on the sales floor. The determined coordinates were then used as a basis for the following analyses.

4.3.4.3 Heatmap visualization

In order to visualize areas with a high article density, we first determine the last known position (i.e., the last reading of an article by the inventory robot) for each article. We use algorithm 7 for this task.

Algorithm 7 Determine the last known position of an article

Require: Table: Data_Inventory_Robot {Data from inventory robot: see table 4.7}

SELECT SGTIN, X, Y, **MAX**(Timestamp) **FROM** Data_Inventory_Robot **GROUP BY** SGTIN

return Table: Last_known_Positions {Last known article position determined by the inventory robot}

We then use a visualization library from a modern programming language in order to create visualizations. We demonstrate our approach with the statistical programming language R and its visual library ggplot2. The library ggplot2 provides the stat_density2d function which enabled us to perform a density estimation for two dimensional space (Whickham, 2013). This enables us to use the *polygon* parameter and pass it to ggplot2 in order to create a visualization of areas with high article density. Figure 4.9 shows how stat_density2d lays the polygons over the sales floor area based on the article density.

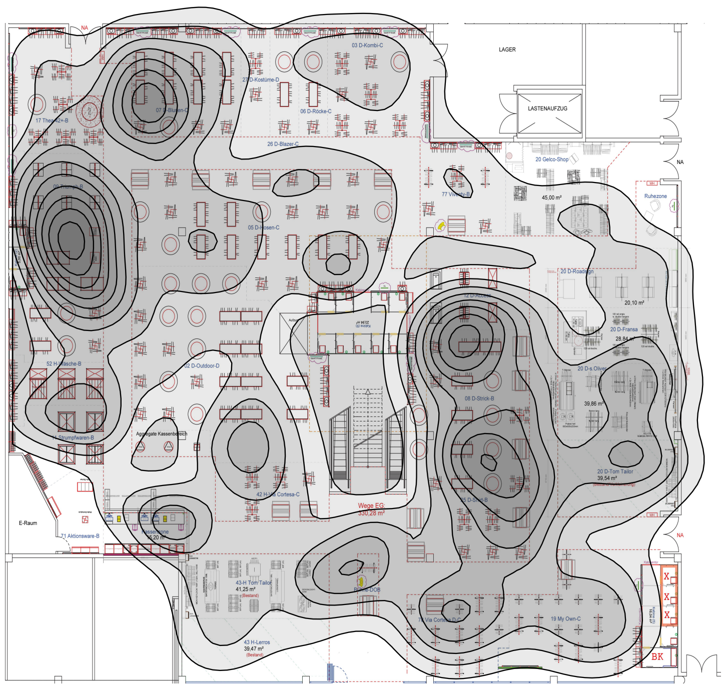

Figure 4.9: Laying polygons over the sales floor area based on the article density

In a second step we lay a green to red color scheme over the polygons in order to create a heatmap (see figure 4.11). Areas with high article density are marked red, areas with medium article density are marked orange to yellow and areas with a low article density are marked green. Furthermore, we use a transparency parameter in order to make the colored polygon areas transparent so that the underlying sales floor layout is still visible.

4.3.4.4 Visualization of areas with high sales volumes

In order to find areas with high sales volumes, we combine the sales data generated by the RFID-enabled POS with the data from the inventory robot. As the Venn diagram in figure 4.10 shows, we are interested in the intersection of sales data and data from the inventory robot. More concretely we want to know the last known position from each article that was sold during a certain timeframe, visualize its position on the sales floor area and calculate a heatmap based on the density of sold articles. So in a first step we query all sales from the POS and use the SGTINs of the sales transactions as the basis for algorithm 7 to find the last known position of each sold garment. We then use a visualization library like ggplot2 in order to create the actual visualization, in our case a heatmap.

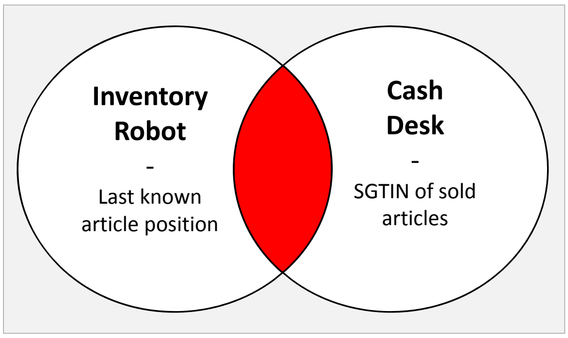

Figure 4.10: Venn diagram for analysis of areas with high turnover

Figure 4.11 illustrates the result of this operation. As it can be seen, there are several zones with a high article density (red) on the sales floor. Interestingly most of these areas are next to fitting rooms. Over a certain period of time, a manager can now evaluate how moving items from high sales areas to areas where sales are currently low would affect sales. Consequently, it could be evaluated whether a new arrangement of articles shifts the areas of interest to the new positions or whether the areas with the highest turnover remain largely unchanged despite the articles contained therein. For example, customers may not like to walk away much from the fitting rooms and thus choose more products within a certain radius around them. In addition, the effects of adjustments to certain parts of the sales area, such as changing the presentation of articles or adding seats to a certain area on the sales floor, can be visually evaluated.

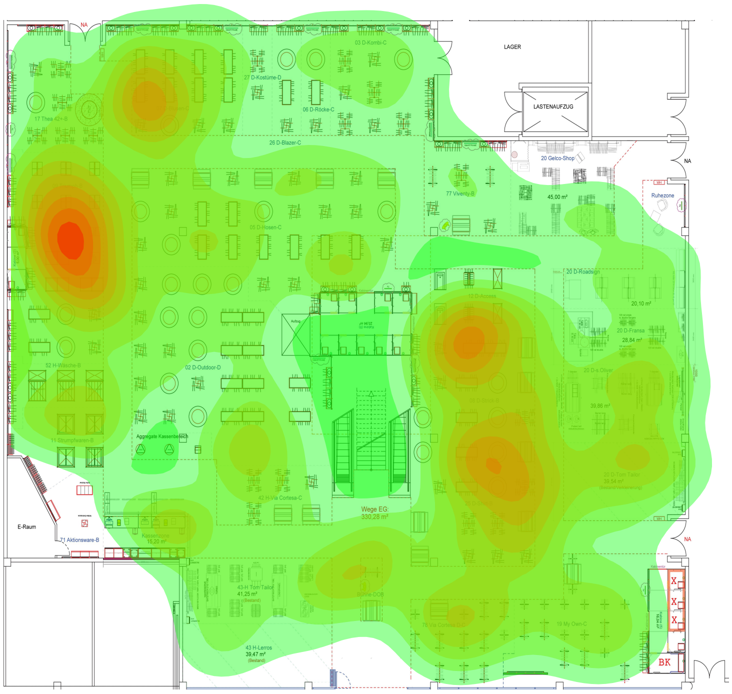

Figure 4.11: Heatmap of areas with high sales volumes

4.3.4.5 Smart fitting room catchment area

Besides combining the positioning data of the inventory robot with the sales data as we show in section 4.3.4.4, the RFID infrastructure offers more possibilities for combining the data of different devices for visualization purposes. In the following analysis, our goal is to find out from which areas of the shop customers bring garments to the smart fitting rooms.

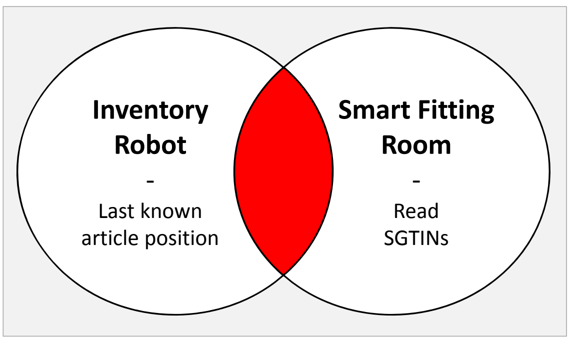

Figure 4.12: Venn diagram of smart fitting room catchment analysis

Determining the catchment areas of fitting rooms for managerial insights was first proposed by Al-Kassab et al. (2013) who used fixed smart shelves in order to find out where the catchment areas of the fitting rooms were located at Galeria Kaufhof. AlKassab's approach, however, relies on fixed installations and is consequently restricted to areas that are equipped with smart shelves. Our approach does not need any fixed infrastructure components besides the smart fitting rooms but uses the inventory robot's positioning capabilities for all garments on the sales floor and is thus more comprehensive and flexible. We use the intersection of readings from the smart fitting rooms and the inventory robot as the basis for our analysis (see figure 4.12).

Similar to what we do for the analysis of areas with high sales volumes, we first determine which articles were brought to a smart fitting room and then find their last known positions on the map of the sales floor area with the help of algorithm 7. These data then serve again as the basis for using a visualization library like ggplot2. Figure 4.13 shows an analysis that was performed for the smart fitting rooms in the ladies' department of the retailer under consideration.

The heatmap from our example provides a plethora of information. On the one hand, the heatmap provides visual feedback on the actual catchment area of the respective fitting rooms, and on the other hand, it provides information not only about where the articles come from, but also about the areas of the store that are most relevant for a particular cluster of changing rooms.

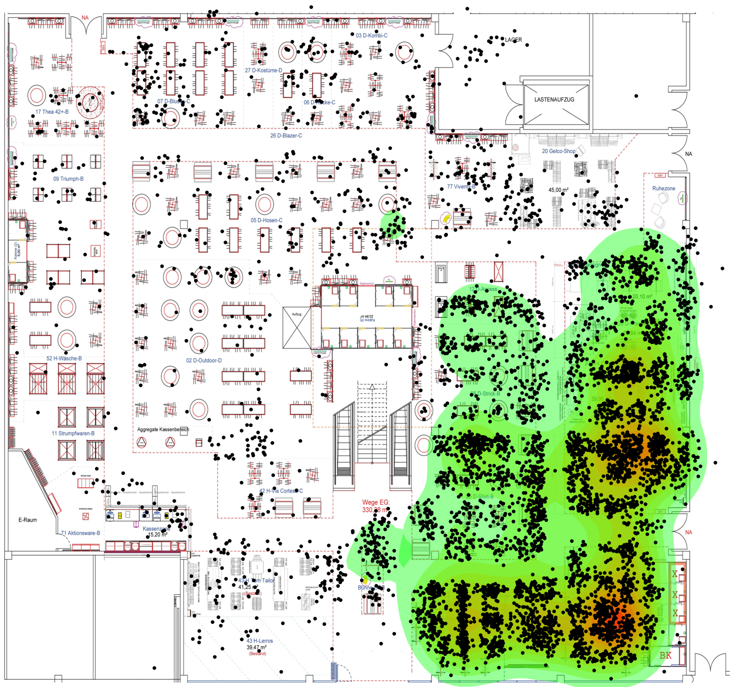

Figure 4.13: Smart fitting room catchment area in the ladies' department

Figure 4.13 also shows, that articles are brought to the smart fitting rooms (the fitting rooms are placed in the lower right corner of the store) from all over the sales floor. This analysis can be used to reposition certain valuable articles nearer to the fitting rooms in order to make it easier for the customers to reach them. A manager can also think about placing certain promotions on the pathways from which customers have to go to the changing rooms to attract the customers' attention.

4.3.5 Method three: Inferring data quality metrics with knowledge about the environment

In this section, we propose a method that enables a retailer to evaluate the quality of data generated by a retail store's RFID infrastructure by using knowledge of the environment and internal processes.

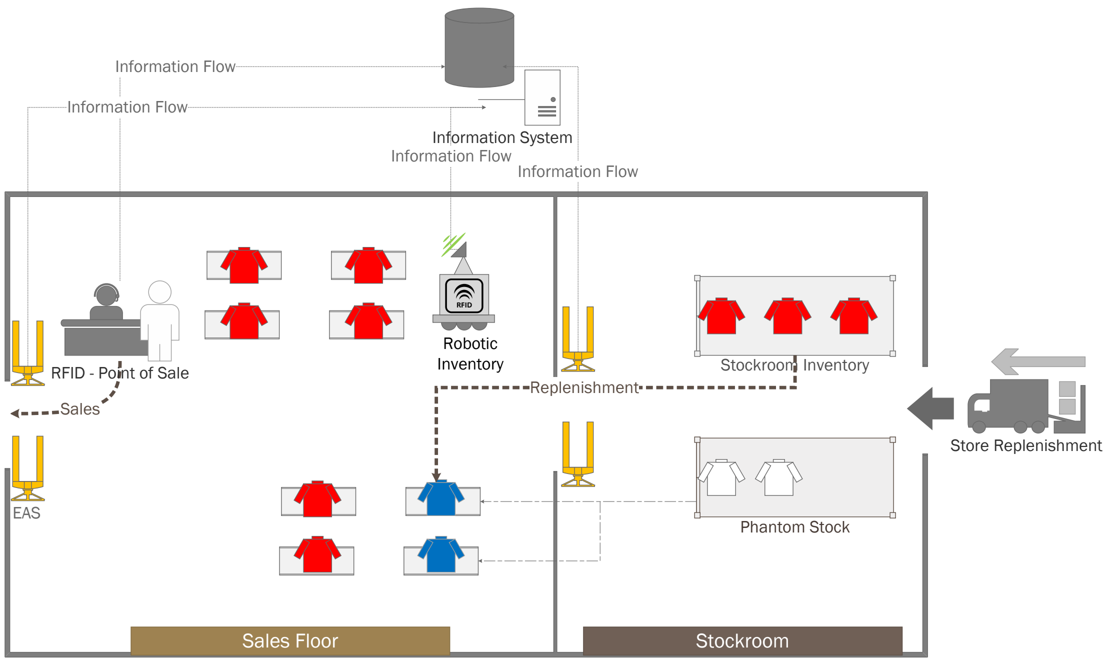

Figure 4.14: Scenario for data quality inference

Before we describe our procedure further, we take a look at the store under investigation. As figure 4.14 shows the store is equipped with a replenishment gate, an EAS gate, an RFID-enabled point of sale and an RFID-enabled inventory robot. Theoretically, all readers are prone to errors and consequently false positive and false negative readings can occur. This means, that items can be missed by a reader even if they should have been read or that items are read mistakenly by a reader when they should not have been read. This can lead to problems like that the RFID system assumes items to be in the stockroom which are actually on the sales floor. We refer to such articles as phantom stock. This can have a negative impact on the RFID-enabled replenishment process. The system could, for example, order an employee to bring items from the stockroom to the sales floor. However, since the corresponding articles are already on the sales floor, the employee loses time searching in the stockroom. Vice versa, items that are thought to be on the sales floor but that are actually in the stockroom can lead to replenishment freezes. We discuss replenishment freezes and their consequences in our simulation study in chapter 3.

Because of the problems mentioned above, a manager needs to know how reliable the data captured by the RFID infrastructure actually are. We therefore propose to make inferences about the missed readings by using knowledge about the environment of the retail store (e.g., position of readers) in order to give managers cost efficient means to estimate the reliability of the readers and the connected processes (e.g., the replenishment process). In the following, we discuss how to infer data quality metrics, namely the *false negative rate* of the replenishment gate between the sales floor and the stockroom and how to use different readers in order to estimate the *recall* of an inventory robot.

4.3.5.1 Inferring the data quality of a replenishment gate

In our first analysis we show how to infer the *false negative rate* of a replenishment gate. This indicator, which is also called *miss rate* is defined as the fraction of false negatives over the sum of true positives and false negatives (see equation 4.13) (Delen and Olson, 2008). This means we want to estimate the percentage of items, the gate misses. These errors originate for example from process errors like employees who carry a batch of items very close to their bodies when passing the gate or RFID tags lying over one another and thus shielding each other against the radio waves of the replenishment gate. Figure 4.14 illustrates this fact with the blue colored shirts. These shirts were not read by the gate, although they were transported through the gate. This makes the RFID system believe that the shirts are still at their last known position, namely in the stockroom. If the inventory system triggers a replenishment request based on these data, employees cannot find the garments when they are requested to pick them up from the stockroom, which is a waste of working time.

Table 4.8: RFID bookings data that reveal missed readings by the gate

Description	PG	From	To	SGTIN	Device
MKG Shirt	57	2	1	(01)04058114546736(21)400122	MLVF01
MKG Shirt	57	1	2	(01)04058114546736(21)400122	MLVF01
BlzLeichtsteppeM0166 kitt	26	1	1	(01)04059182110904(21)400190	POSREADER1
KB Accessoires DTT 10black	57	2	1	(01)04057655845131(21)400540	POSREADER1
Triumph BH 1PW59 LILA	9	2	1	(01)07611358891313(21)400166	HANDHELD

We propose to use the data we receive from other readers besides the gate in order to obtain an estimate on the replenishment gate's ability to detect items correctly. We know for example that if an item is read at the point of sale, but its last known position is not the sales floor but the stockroom (i.e., one of the phantom items was uncovered) then the gate must have missed this particular item. Similarly, if an article is read at the EAS or from the inventory robot on the sales floor, but its last known position stored in the system is the stockroom, we can be reasonably confident that this article has been missed by the replenishment gate and must therefore be a false negative.

The basic idea of our approach is to use the position information stored by the RFID system. We therefore propose to use the bookings of the articles that indicate a change of position. We are interested in all position changes that represent a relocation of an article to the sales floor or to the stockroom. If the stockroom has position 2 and the sales floor has position 1, we are interested in all bookings that represent a movement from position 2 (stockroom) to position 1 (sales floor) and vice versa. Table 4.8 gives an example. In line one the replenishment gate, denoted as MLVF01, recognizes that the item MKG Shirt is relocated from position 2 to position 1. In line two the item is moved back to position 2 from position 1. Row three illustrates a usual transaction at the point of sale. An item is scanned and no position change happens. In row four POSREADER1 (i.e., one of the cash desks on the sales floor) recognizes that the item that was scanned was previously on position 2 and changes the item's position to position 1 - which is the event we are looking for. Because we know that the replenishment gate is the only way the item can travel from the stockroom to the sales floor (and vice versa), we can be confident that the replenishment gate must have missed this particular item.

We know that position changes should ideally only be performed by the replenishment gate, because all articles have to pass it when being transported to the sales floor or back to the stockroom. But when such a change is performed by another device (e.g., cash desk, handheld or smart fitting room), we can almost be certain that the gate must have missed an item that was transported through it. This knowledge enables us to detect false negative readings by the replenishment gate and to estimate the false negative and the true positive rate for a given timeframe. For our case we define false negatives as items that were mistakenly not read by the gate even though they should have been read while we define true positives as the number of items that were transported through the gate and that were also recognized by it. The false negative rate is then given by equation 4.13 (Delen and Olson, 2008):

$$False\ Negative\ Rate = \frac{False\ Negatives}{True\ Positives + False\ Negatives} \tag{4.13}$$

We can also calculate the true positive rate also called recall (i.e., the probability with which the gate detects an item) (Delen and Olson, 2008):

$$Recall = \frac{True\ Positives}{True\ Positives + False\ Negatives} = 1 - False\ Negative\ Rate \tag{4.14}$$

In our use case the false negative rate tells a manager the percentage of articles which is falsely missed by the gate and the recall (true positive rate) gives information about the percentage of articles which is correctly recognized by the gate. To calculate the number of false negatives of a certain timeframe of data we can use algorithm 8.

Algorithm 8 Determine the number of false negatives of the replenishment gate

Require: Table: RFID_bookings

```
Number_False_Negatives :=
SELECT COUNT(*) FROM RFID_bookings
WHERE NOT Device = "Replenishment Gate"
AND (("From" = 2 AND "To" = 1)
OR ("From" = 1 AND "To" = 2))
return Number_False_Negatives
```

The true positives, i.e., the items that were transported to the sales floor or the stockroom and that were actually recognized by the gate can be computed with algorithm 9 (using the same timeframe of data we took for the false negatives).

Algorithm 9 Determine the number of true positives of the replenishment gate

Require: Table: RFID_bookings

```
Number_True_Positives :=
SELECT COUNT(*) FROM RFID_bookings
WHERE Device = "Replenishment Gate"
AND (("From" = 2 AND "To" = 1)
OR ("From" = 1 AND "To" = 2))
return Number_True_Positives
```

The longer the timeframe we use for this calculation (i.e., more RFID event data), the better will be our estimate of the actual detection accuracy of the gate. Assuming there are handheld counts on the sales floor and in the stockroom or that there is an inventory robot performing daily inventories, this estimation would be quite accurate and give a manager a good idea of the detection capability of the replenishment gate. Using the obtained information in order to support a data quality control plan can help a retailer in determining if the detection accuracy of the replenishment gate is reliable enough in order to be used for replenishment purposes. If the timeframe of analysis is long enough and multiple readers are used for recognizing missed items, the estimate of the actual false negative rate and the recall of the replenishment gate should become quite solid. This means that using smart fitting rooms, handheld scanners, inventory robots and the RFID-enabled cash desks will enhance the likelihood of finding items that were missed by the gate.

However, our approach also has some limitations. First, it only works if there is only one replenishment gate leading to the sales floor. If there are multiple gates (e.g., in the case of multiple stockrooms) we can only infer the accumulated detection capability of all gates, because we cannot distinguish which gate actually missed a particular item. Second, we neglect false positive readings, because the retailer with whom we cooperated shielded the replenishment gates against unintentional readings and installed light barriers in order to verify if actually someone walked through a gate and to determine the walking direction. The walking direction is then used by the RFID middleware in order to detect readings of items that did not pass the gate. The aforementioned measures lessen the probability of false positive readings to occur. Third, our approach is only able to identify missed readings caused by process errors (e.g., taking too many items through the gate at once so that they shield each other). Consequently, we are not able to detect missed readings due to defective RFID tags as we rely on RFID readers for our approach.

4.3.5.2 Inferring the data quality of an inventory robot

Besides the replenishment gate, we can also infer the detection capability of other parts of the RFID infrastructure. In this section we show how to estimate the data quality of the inventory of an inventory robot that drives through the aisles of a fashion store every night to identify and count the items of clothing on the sales floor. On its duty it tries to find all items that are on the sales floor and adjusts differences to the inventory in the inventory management system.

Robotic inventory taking is an automated process, however there can still occur errors. Some RFID tags may be shielded from each other or placed in shielded places and therefore cannot be detected by the robot's scanners. But now a store manager faces the problem of what to do with the inventory data received from the robot. For example, assuming that there is a 2% difference for some articles after an inventory, should the manager trust the robot and simply accept that 2% of the articles have disappeared, or should (s)he assign employees to look for those articles, or should (s)he run the inventory robot through the store for another round, hoping that the problem will resolve itself? A wrong decision in these cases can reduce the overall data quality with all consequences or lead to unnecessary workload for the employees. We therefore believe that a manager needs a timely indicator to assess whether the inventory robot's detection accuracy is good and trustworthy, or whether there is something wrong with the system.

To give a manager a quick and cost efficient means to assess the reliability of the robotic inventory, we propose to calculate the *recall* of the robot with the help of the RFID data generated by the RFID infrastructure of the store. The main idea is to consider all items which were transported to the sales floor on a particular day and which were detected by the replenishment gate. If the inventory robot works with 100% accuracy, it should find all of them in the subsequent inventory after the store has been closed. We only consider articles that were detected by the replenishment gate immediately before the next inventory as the basis for our procedure and not all articles that are supposed to be on the sales floor according to the inventory management system, because the stock of the sales floor is influenced daily by the inventory robot itself. We therefore use the data of the replenishment gate which gives us an independent group of articles of which we know with a relatively high certainty that it must actually be on the sales floor. In addition, we only consider the data from one day, because this allows us to timely detect changes in the quality of the robotic inventory taking process from day to day.

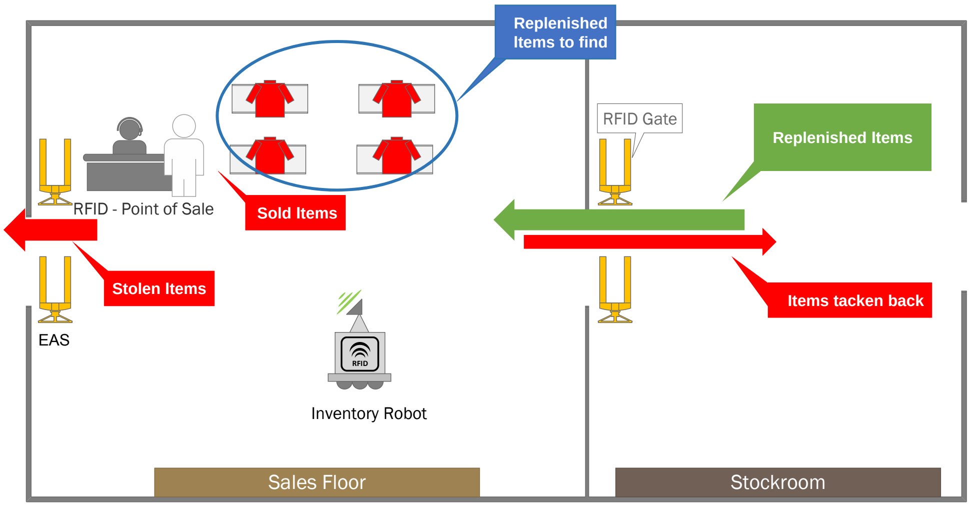

Figure 4.15: Article flows to be taken into account when estimating the inventory taking quality of an inventory robot

Figure 4.15 shows which items we consider for the process. The main idea is to count all items that are replenished on a specific day and recognized by the replenishment gate. The inventory robot must find all items during the nightly inventory. If articles are not found, we can assume that it did not recognize them during its round over the sales floor. First of all, we determine which articles need to be found. To do this, we need to consider which of the items that have recently been transported to the sales floor have been sold, stolen or returned to the stockroom before the inventory robot begins its inventory. This is necessary because the robot can no longer find these items as they have already left the sales floor (see figure 4.15).

Table 4.9: Terms used for calculating the recall

Term	Symbol
Items replenished from the stockroom:	$I_{\text{replenished}}$
Items to find during inventory:	I_{find}
Items actually found:	I_{found}
Items sold after being replenished:	I_{sold}
Items transported back to the stockroom:	I_{back}
Items stolen after replenishment:	I_{stolen}

In order to calculate the recall (i.e., the fraction of relevant items that could be found), we first define the necessary terms as shown in table 4.9. Then we define the set of items the robot has to find during its next inventory as follows:

$$I_{\text{find}} = I_{\text{replenished}} - I_{\text{sold}} - I_{\text{back}} - I_{\text{stolen}} \tag{4.15}$$

If we define I_{find} as the number of all relevant items to find and I_{found} as the number of all relevant items that were actually found, we can compute the recall of the inventory robot with equation 4.16:

$$recall = \frac{I_{\text{found}}}{I_{\text{find}}} \tag{4.16}$$

In order to calculate the respective variables, we first have to filter our RFID dataset for the data of one particular day that we want to investigate. In order to simplify the following algorithmic approaches, we assume that the filtering has been done beforehand on the RFID bookings dataset and the RFID log dataset, so that both datasets contain only the data of one day, including the relevant replenishments and the subsequent robotic inventory. Based on this assumption we can then use algorithm 10 in order to determine the replenished items of one particular day.

Algorithm 10 Determine the replenished items

Require: Table: RFID_bookings

```
SELECT SGTIN FROM RFID_bookings
WHERE Device = "Replenishment Gate"
AND ("From" = 2 AND "To" = 1)
return Table: Items_replenished
```

Algorithm 10 uses the position information from the columns From and To of the RFID bookings dataset. We first determine all items which traveled from position stockroom (2) to position sales floor (1). Then the resulting dataset, which we denote as table Items_replenished, contains only the SGTINs of the items that were actually brought to the sales floor.

Algorithm 11 Determine the items that were taken back to the stockroom

Require: Table: RFID_bookings

```
SELECT SGTIN FROM RFID_bookings
WHERE Device = "Replenishment Gate"
AND ("From" = 1 AND "To" = 2)
return Table: Items_taken_back
```

We can determine the items that were taken back to the stockroom by determining all items which made a position change from position 1 to position 2. Algorithm 11 shows how this can be achieved. The items that were sold (i.e., read at the point of sale) or stolen (i.e., read at the EAS gate) can be determined with algorithm 12. It is to note that it does not matter that the aforementioned operations may contain more SGTINs than there are in the set of Items_replenished, because these SGTINs will be filtered out by joining the previously determined datasets within the subsequent operations.

Algorithm 12 Determine the items that were sold or stolen

Require: Table: RFID_bookings
SELECT SGTIN **FROM** RFID_bookings
WHERE Device = "EAS" **OR** Device = "POSREADER"
return Table: Items_sold_or_stolen

The results of algorithms 10 to 12 can then be used in order to determine the items which the inventory robot has to find during its inventory. We use algorithm 13 for this task. Here we filter out all items (i.e., their respective SGTINS) which were taken back to the stockroom and all items which were sold or stolen.

Algorithm 13 Determine the items to find

Require: Tables: Items_replenished; Items_taken_back; Items_sold_or_stolen
SELECT Items_replenished.SGTIN **FROM** Items_replenished
LEFT JOIN Items_taken_back
ON Items_replenished.SGTIN = Items_taken_back.SGTIN
LEFT JOIN Items_sold_or_stolen
ON Items_replenished.SGTIN = Items_sold_or_stolen.SGTIN
WHERE Items_taken_back.SGTIN **IS** NULL
AND Items_sold_or_stolen.SGTIN **IS** NULL
return Table: Items_to_find

Algorithm 14 shows our approach for determining the items the robot actually found during its inventory. We use the intersection of the RFID log and the table Items_to_find in order to determine the number of items the robot has actually found for the timeframe under consideration. We use the RFID log, because only this dataset contains all readings of the inventory robot from its last inventory. We can then calculate I_{found} with a simple SELECT COUNT statement (see algorithm 14).

Algorithm 14 Determine I_{found}

Require: Tables: RFID_log; Items_to_find
$I_{\text{found}} :=$
SELECT COUNT (*) **FROM** RFID_log
LEFT JOIN Items_to_find **ON** RFID_log.SGTIN = Items_to_find.SGTIN
WHERE Device = "Inventory Robot" **AND NOT** Items_to_find.SGTIN **IS** NULL
return I_{found}

Finally, we can calculate I_{find} with algorithm 15 by performing a SELECT COUNT statement on the table Items_to_find. After having performed the algorithms 10 to 15, we are able to calculate the recall. In our case, the recall indicates the percentage of items found by the inventory robot, taking into account all replenished items that were on the sales floor during the inventory. The recall gives a manager a timely indication of how well the inventory robot has performed its last inventory. A bad recall can either indicate process errors or a malfunction of the inventory robot itself. If a large percentage of items cannot be found after replenishment, the inventory robot has either encountered problems on its route through the store (maybe it never passes a certain area) or the staff made some operational mistakes before the inventory. This could happen, if the employees do not position the articles at the designated locations on the sales floor, but rather at shielded intermediate storage locations, such as behind the cash registers, where the articles cannot be found. This can lead to an unwanted deviation between the actual stock on the sales floor and the stock the inventory management system believes to be there. We are convinced that our analysis can help to detect such errors in time.

Algorithm 15 Determine I_{find}

Require: Table: Items_to_find

$I_{\text{find}} :=$
SELECT COUNT (*) **FROM** Items_to_find
return I_{find}

There are some limitations to our approach. First, we assume that the other RFID-enabled devices such as the replenishment gate work properly, which is necessary in order to obtain reliable results. Second, we assume that the RFID-enabled inventory robot only performs its inventory on the sales floor. If the robot would also scan the stockroom, we would need a different approach in order to measure its inventory accuracy.

Our approach can also be adapted to different circumstances, e.g., when an inventory robot carries out the inventory on one day on the ground floor and the next day on the second floor. Also in this case we can still use our approach. We only have to extend the period under consideration by considering the article readings of two days. This also includes replenishments, sales, thefts and return transports to the stockroom, which are recorded by the RFID infrastructure. In order to not only rely on the recall of the inventory robot, we propose to use it as one out of many indicators and controls to assess the data quality of the robotic inventory taking process.

4.4 A generic extraction process for RFID data-based management information

We construct a generic process for generating management-relevant information out of actual RFID data based on the findings of our work and the relevant literature (i.e., Delen, Hardgrave, et al. (2007), Al-Kassab et al. (2013) and Chongwatpol (2015)).

We therefore first give an overview of the analyses that were reported in the scientific literature and within this dissertation and then construct a generic process for management information extraction.

Table 4.10 shows all performance indicators, analyses and models reported in the scientific literature, including this dissertation (denoted as Weinhard 2018). We only consider those performance indicators and reports that actually rely on data generated by RFID-enabled readers. We do not consider indicators or reports that merely measure some attributes related to RFID, such as the number of unlabeled goods in a store or the performance of a process before and after the introduction of RFID. In this way, we focus only on management information that can actually be extracted from RFID data. If the literature mentions performance indicators, models or reports several times, we have only included these indicators, reports or models once in general terms. An example of this would be an indicator that refers to the group-level and another indicator of the same type that refers to the item-level. Here we have included the corresponding indicator once, but mention both cases.

As table 4.10 shows most of the indicators and reports have an economic background. They either measure the performance of a process, like for example, the checkout process or they give more information about the behavior of the customers (e.g., the heatmap of catchment areas or the correlation of try-ons vs. sales). All reported analyses are aimed at informing operational or strategic management. In our view, the possibilities for reports, performance indicators and predictive models that can be generated using RFID data are almost unlimited. Adding a new reader to an RFID infrastructure can add new information that can lead to a variety of different reports or insights. The combination of RFID data with other types of data, such as customer profiles or position data, enables even more sophisticated analyses.

Considering, our work and the literature, we are able to structure the process of management information extraction from RFID data in a general way. The result is depicted in figure 4.16. In our work and in other studies (e.g., Al-Kassab et al. (2013), Chongwatpol (2015)) there are some basic RFID data coming either directly from the readers or from the middleware. These data usually contain the position of an item or a person and the time at which the reading occurred. In the case of a retail store the position can be for example the sales floor or the stockroom.

The basic data are then often enriched and combined with other sources of data, for example customer data, spatial information (e.g., X, Y and Z coordinates) or temperature in the case of a cold chain. The possible analyses are highly dependent upon the context and the additional data that are gathered by the RFID hardware. For example, the X and Y coordinates that we obtained through the inventory robot in section 4.3.5.2 refine the

Table 4.10: Overview of RFID data-enabled analyses, performance indicators and models for management reporting based on Chongwatpol (2015), Delen, Hardgrave, et al. (2007), and Al-Kassab et al. (2013) and Weinhard (2018) (Note: This dissertation is referred to as Weinhard 2018)

Name	**Type**	**Area**	**Source**
Average waiting time at the POS	Indicator; Report	Economic	Weinhard 2018
Average number of customers in a queue	Indicator; Report	Economic	Weinhard 2018
Heatmap of areas with high sales volumes	Report	Economic	Weinhard 2018
Heatmap of catchment areas	Report	Economic	Weinhard 2018 (Al-Kassab 2013 with smart shelves)
Customer classification	Predictive model	Economic	Chongwatpol 2015
False negative rate of a replenishment gate	Indicator	Data quality	Weinhard 2018
Recall of an inventory robot	Indicator	Data quality	Weinhard 2018
Error ratio of bulk reading at POS	Indicator	Data quality	Al-Kassab 2013
Fitting room usage distribution analysis of the number of try-ons on fitting room and cluster level	Report	Economic	Al-Kassab 2013
Time-dependent visits of fitting room	Report	Economic	Al-Kassab 2013
Correlation of try-ons and sales	Report	Economic	Al-Kassab 2013
Shelf maintenance – misplaced merchandise	Report	Economic	Al-Kassab 2013
Out of stock – store replenishment situations.	Report	Economic	Al-Kassab 2013
Front store / back store movements analysis of the occurrence of loops between front and back store	Report	Data quality	Al-Kassab 2013
Lead time analysis – identification of process inefficiencies	Indicator; Report	Economic	Delen 2007; Al-Kassab 2013

actual position of an article. With this information, we not only know that an item is on the sales floor, but also its exact X and Y position.

In the next step of our process model, the data are then usually aggregated or filtered in order to feed the method that shall be used afterwards. This means that several readings of an item at different points in time may be merged to one piece of information or that all readings but the most recent one are filtered out in order to perform an analysis. These aggregations can also serve as features for machine learning models (see Chongwatpol (2015)).

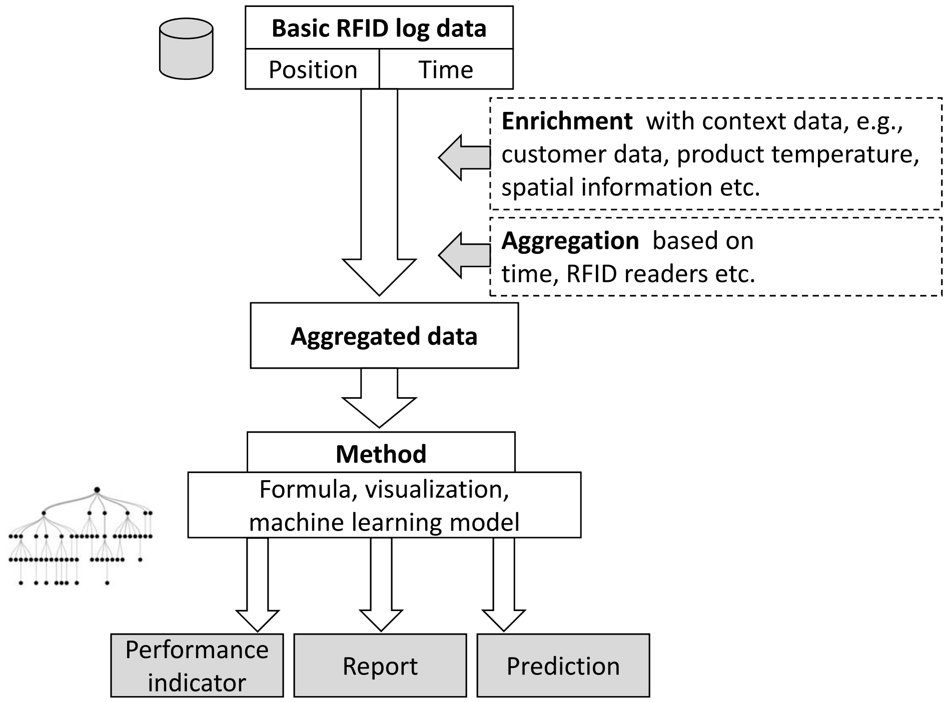

Figure 4.16: Generic process for generating management information out of RFID data

Finally, a method for generating a specific output is being applied on the aggregated and filtered data in order to (i) calculate a performance indicator, (ii) create a report or to (iii) make a prediction with a machine learning model. Managers can then use the resulting information in order to make better operative and strategic decisions. We believe that our process model can help managers to better understand how to generate value from RFID data and to better assess the potentials of their RFID data for managerial decision making.

4.5 An RFID data-enabled management dashboard for fashion retail

In order to illustrate how our work could be used for managerial decision support we created an RFID data-enabled management dashboard prototype which utilizes analyses from our work and from the literature. The programming language R and the Shiny framework (SHINY, 2017) serve as the technical basis for the dashboard.

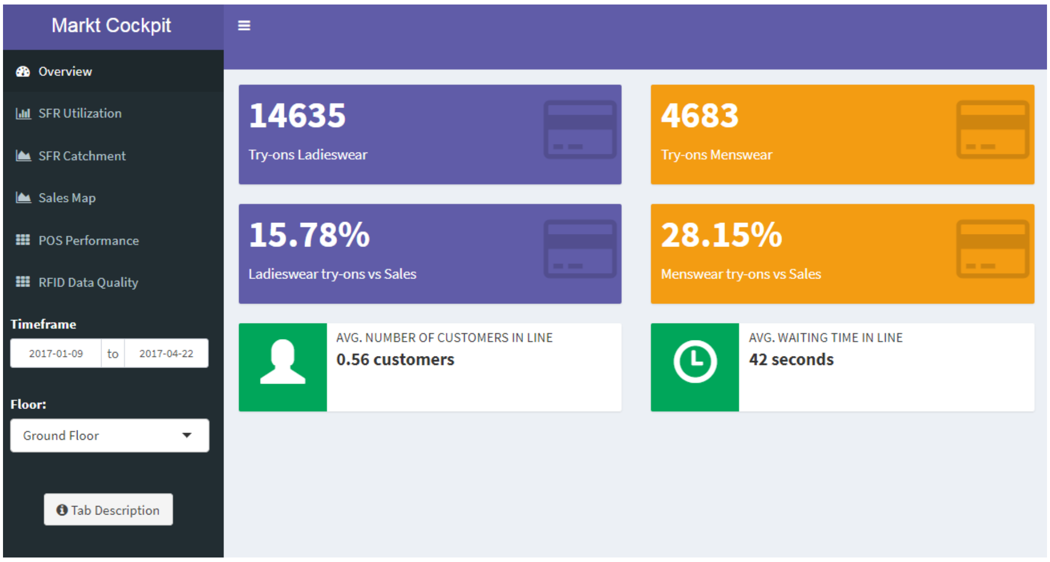

Figure 4.17: Overview screen

Figure 4.17 illustrates how an RFID data-based management dashboard could look like. We propose an overview page that contains aggregated high level indicators, like the number of try-ons in certain fitting room clusters or performance indicators about the RFID-enabled checkout process. Subpages of the dashboard could allow a manager to explore the aspects of the retail store on a more fine-granular level.

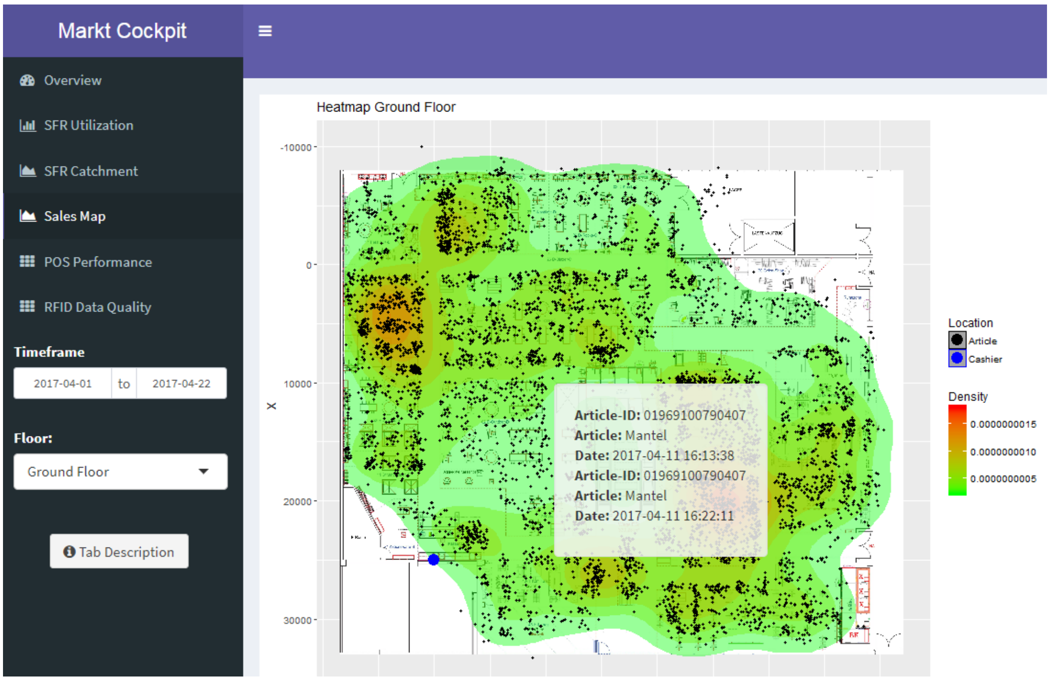

Figure 4.18: Interactive heatmap

Besides just offering certain performance indicators and just visualizing data, we believe that created reports should be made interactive, thus allowing management to explore a store or even an entire supply chain from different and novel angles. Figure 4.18 shows an interactive heatmap using the visualization of areas with high sales volumes we propose in section 4.3.4.4. A manager can display certain areas with high sales figures in a store, filter them for a certain period of time and explore the articles in the respective areas by simply hovering over them with the mouse pointer.

Keeping track of the reliability of the data generated by the RFID infrastructure should also be supported with RFID data-based reports. Figure 4.19 illustrates how a possible data quality overview could look like. The figure shows the estimates for the recall of the replenishment gate (MLFV01) and the inventory robot (TORY). These key figures, can give a quick estimate of the current performance of the RFID devices.

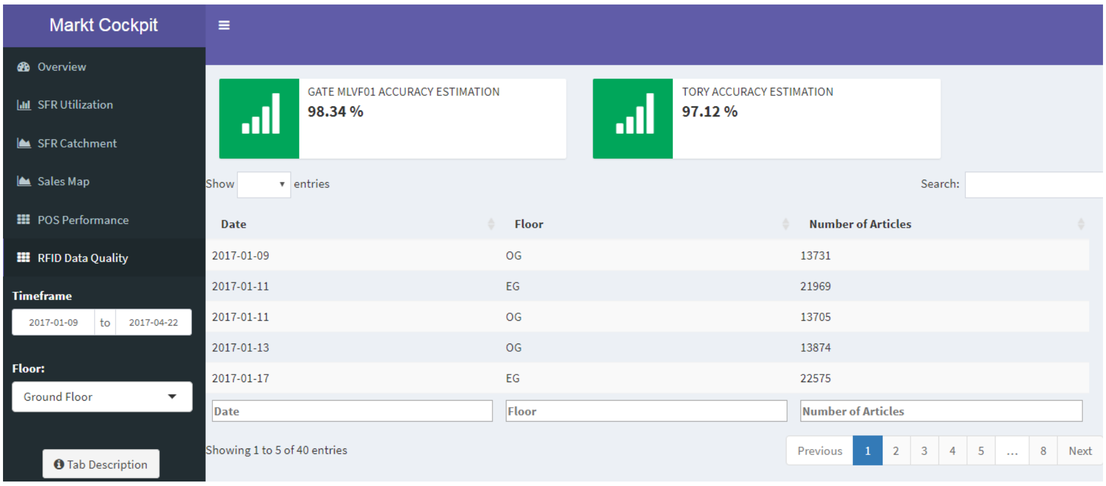

Figure 4.19: RFID data quality overview

Additional information like the last inventories of the robot and their respective areas (e.g., ground floor, first floor) can help a manager to find irregularities in the processes. As we can see in figure 4.19, the robot does not change the floors with every inventory, but executes them several times on the same floor. This indicates a process error, e.g., that the employees do not move the robot to the planned floor the next day and therefore the robot does not scan the area to be scanned. This could have a negative effect on data quality and should be addressed by the store manager.

4.6 Conclusion

RFID data-based analytics is useful to support managerial decision making. The information gathered from certain RFID readers enables new types of analyses. For example, the overview of which articles are frequently tried on and which areas of the sales floor are most frequently visited can be used to support the traditional analysis of sales data. The analysis of retail space can help to improve store layout while the analysis of try-ons can help to make better assortment decisions. From our point of view, RFID data-based analyses and reports will not replace traditional reporting, but will improve and support it and thus create added value. Table 4.11 gives an overview of the opportunities and risks of using RFID data analytics for management reporting.

Table 4.11: Opportunities and risks of using RFID data analytics for management reporting

Opportunities	**Risks**
RFID data can add additional value to existing reports	RFID data may contain errors and may thus not be reliable
RFID data are inexpensive and available in high volumes	Many data may not be useful for management reporting
RFID data may help uncover insights that cannot be found with traditional methods	Many analyses can be carried out that do not add value to a company

The use of RFID data for management reporting appears promising. The data are available at low cost and are generated continuously and automatically by the RFID infrastructure. Information distilled from RFID data can add value to existing business reports or provide new insights that could not be found using traditional methods. However, there are also some risks associated with the use of RFID data for supporting management decisions. The data may contain errors. The abundance of data can cause analysts to create reports that do not really add value to the company, but are created because it is possible to do so. We therefore recommend using RFID data carefully for management reporting.

It should be noted that our approaches have some limitations. First of all, our approaches are based on the assumption of a certain minimum data quality in order to achieve reliable results (i.e., we assume that at least parts of the RFID infrastructure work reliably). On the other hand, our approaches were only tested on a dataset from one retail store equipped with RFID. Other environments could produce different results. We therefore believe that further research in this area is necessary to further validate our results.

In summary, RFID should be combined with other technologies (e.g., photoelectric barriers in changing rooms) to exploit its full potential. Different RFID reading hardware offers new insights into the flow of goods and persons within a company. Each reader added offers new analysis options. However, there are no universally valid reports and analyses that fit every company. Different companies can have different readers and processes and therefore require different analyses and performance indicators. There are only a few studies that scratch the surface of what is possible and give companies suggestions on what they can actually do with their RFID data. Ultimately, however, it is important that an analyst or data scientist creatively merges the various data sources and extracts management-relevant information from them.

CHAPTER 5

Summary and outlook

This dissertation examines how RFID implementations can be managed and used efficiently. For this reason, we conduct three studies, each of which deals with a topic relevant to management and focuses in particular on the use of novel RFID applications.

We investigate in our first study retail customers' acceptance towards a pervasive retail application, namely an RFID-enabled smart fitting room. We investigate the antecedents of customers' usage intention towards the particular system and focus on the privacy related aspects. By utilizing the privacy calculus theory we evaluate customers' trade-off between the perceived benefits and the perceived privacy costs of using such an application. We therefore propose a model based on the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) from Venkatesh, Thong, et al. (2012) and the Extended Privacy Calculus Theory from Dinev et al. (2006). We validate our model and show that it explains 67.1% of the variance in the behavioral intention to use the system. Furthermore, we are able to explain 43.1% of the variance in a person's willingness to disclose private information. Practitioners and researchers can use our results in order to design valuable pervasive systems that are not perceived as privacy threatening.

Our second study evaluates the possibilities of RFID-enabled robotic inventory taking in a retail setting. We perform a simulation study and evaluate how an RFID-enabled inventory robot performs in comparison to RFID-enabled cycle counting with handheld devices. Since the manufacturers promise accuracy rates of 99% and more for the robotic inventory, we assume in our first evaluation that the robotic inventory works without errors. The results suggest that robotic inventory taking outperforms RFID-enabled cycle counting with handhelds and even eliminates the need to install a replenishment gate between stockroom and sales floor. However, if we take a more pessimistic view (assuming less accuracy) as suggested by a few studies, the robotic inventory quickly loses its advantages.

From this we conclude that the robotic inventory can be a good data quality measure, but only if the robots work with an almost perfect accuracy.

In the third study, we examine how valuable RFID data-based analyses are for supporting management decisions. For this reason, we first summarize the relevant literature and carry out analyses on an RFID data set. In order to illustrate the benefits of RFID data analytics, we propose three different analyses, namely the inference of performance indicators from data of an RFID-enabled POS, the visual analysis of the sales area and the inference of data quality indicators from RFID data. We then show how the proposed reports and indicators can be integrated into an interactive management dashboard and propose a generic approach to extract management-relevant information from RFID data. Our results show that RFID data analytics is useful to support managerial decision making, but will not replace traditional management reporting.

Even if the studies in this dissertation provide managers with a little guidance, they are nevertheless subject to certain restrictions. The results of our studies can only be generalized to a limited extent because they are tailored to the RFID-enabled applications examined. Our study on customer acceptance and thus our proposed acceptance model was only empirically tested with one application, namely the smart fitting room. Consequently, more work is needed to further validate the model and to validate its generalizability for other RFID-enabled applications. However, since the model is a combination of two already validated models, we assume that their combination will also be generalizable.

The results of our simulation study show that in our assumed case robotic inventory taking is superior to other methods of inventory taking. However, since simulation modeling can only contribute to a better understanding of a system and not to fully evaluate all possible configurations, we can only be sure that the results are true under our assumptions within the boundaries of our model world. In addition, other unforeseen problems can disrupt the process and reduce the benefits of robotic inventory taking. For example, it is conceivable that thieves could simply tear the RFID tags off and leave them behind in the store. In this case, a robot will not be able to detect stolen garments via RFID - a problem that is outside of our analysis (but could be eliminated by sewn-in RFID tags). Nevertheless, we show that simulation modeling is a useful tool for decision support in the evaluation of RFID-enabled applications.

The results of our study on in-store analytics show that RFID data can be used to support management decisions. However, all analyses are linked to the specific configuration of the RFID hardware and software present in the retail store under investigation. Therefore, a different configuration of hardware and software may require changes to our proposed algorithms in order to obtain the same results as we do. Nevertheless, the generic process we propose to extract management-relevant information from RFID data will be valid despite such technical configurations and can serve as a guide for researchers and practitioners. All in all, RFID technology is advancing fast, and managers will have to deal with various issues such as customer acceptance, privacy, data quality and the extraction of real value from the generated RFID data. We are therefore convinced that our work will prove useful in the hands of a researcher or manager.

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List of abbreviations

ALE	Application level event standard
ATM	Automatic teller machine
Auto-ID	Automatic identification
AVE	Average Variance Extracted
DCI	Discovery configuration and initialization
EAN	European Article Number
EAS	Electronic article surveillance
EE	Effort expectancy
EPC	Electronic Product Code
GS1	Global Standards One
HM	Hedonic motivation
HTMT	Heterotrait-Monotrait
IoT	Internet of Things
LLRP	Low level reader protocol
PC	Privacy concerns
PE	Performance expectancy
POS	Point of sale
PR	Privacy risk
RFID	Radio Frequency Identification
RM	Reader management
SCOR	Supply Chain Operation Reference Model
SGTIN	Serialized Global Trade Item Number
SI	Social influence
SRMR	Standardized Root Mean Square Residual
TAM	Technology Acceptance Model
TR	Trust
UPC	Universal Product Code
UTAUT	Unified Theory of Acceptance and Use of Technology
WTPI	Willingness to provide personal information

Appendix

A Questionnaire

Table A.1: Questionnaire with items

Item	Statement
PE1	I would find the smart fitting room useful when I would go shopping.
PE2	Using the smart fitting room would help me to do my apparel shopping more quickly.
PE3	Using the smart fitting room would help me to choose garments more easily.
EE1	Learning to use the smart fitting room would be easy for me.
EE2	My interaction with the smart fitting room would be clear and understandable.
EE3	I would find the smart fitting room easy to use.
EE4	It is easy for me to become skillful at using the smart fitting room.
SI1	People who are important to me would think that I should use the smart fitting room.
SI2	People who influence my behavior would think that I should use the smart fitting room.
SI3	People whose opinions that I value would prefer that I use the smart fitting room.
HM1	Using the smart fitting room would be fun.
HM2	Using the smart fitting room would be enjoyable.
HM3	Using the smart fitting room would be very entertaining.
BI1	I intend to use the smart fitting room in the future.
BI2	I will always try to use the smart fitting room when I go shopping.
BI3	I plan to use the smart fitting room frequently.
PR1	What do you believe is the risk that personal information that is collected by the smart fitting room could be sold to third parties?
PR2	What do you believe is the risk that personal information that is collected by the smart fitting room could be misused?
PR3	What do you believe is the risk that personal information that is collected by the smart fitting room could be made available to unknown individuals or companies without your knowledge?

PR4	What do you believe is the risk that personal information that is collected by the smart fitting room could be made available to government agencies?
PR5	What do you believe is the risk that personal information that is collected by the smart fitting room could be jeopardized by hacking activities?
PC1	I am concerned that personal information that is collected by the smart fitting room could be misused.
PC2	I am concerned that a person or an agency can find private information about me when I would use the smart fitting room.
PC3	I am concerned about the information that is collected by the smart fitting room because of what others might do with it.
PC4	I am concerned about the information that is collected by the smart fitting room because it could be used in a way I did not foresee.
TR1	Retailers would provide the smart fitting room in a safe way such that information can be exchanged electronically
TR2	Retailers would provide the smart fitting room in a reliable way such that transactions can be conducted
TR3	Retailers which provide the smart fitting room, would handle personal information in a competent fashion.
PI1	I find that my personal interest in the smart fitting room would override my privacy concerns.
PI2	The greater my interest in the smart fitting room would be, the more I would tend to suppress my privacy concerns.
PI3	In general, my need for the smart fitting room would be greater than my concern about privacy.
WTPI1	I would provide accurate and identifiable personal information for ordering products with the smart fitting room.
WTPI2	I would identify myself with a customer id card in order to receive personal product recommendations.
WTPI3	I would provide accurate information about myself in order to use all functionality of the smart fitting room.

B Outer loadings of the model

Table B.1: Outer loadings of the model

Construct	BI	EE	HM	PC	PE	PI	PR	SI	TR	WTPI
BI1	0.931									
BI2	0.904									
BI3	0.946									
EE1		0.822								
EE2		0.934								
EE3		0.924								
EE4		0.722								
HM1			0.933							
HM2			0.934							
HM3			0.674							
PC1				0.916						
PC2				0.913						
PC3				0.912						
PC4				0.835						
PE1					0.86					
PE2					0.777					
PE3					0.764					
PI1						0.859				
PI2						0.806				
PI3						0.88				
PR1							0.868			
PR2							0.89			
PR3							0.856			
PR4							0.724			
PR5							0.736			
SI1								0.906		
SI2								0.896		
SI3								0.887		
TR1									0.807	
TR2									0.826	
TR3									0.823	
WTPI1										0.857
WTPI2										0.897
WTPI3										0.896

C Structural model with significant path coefficients

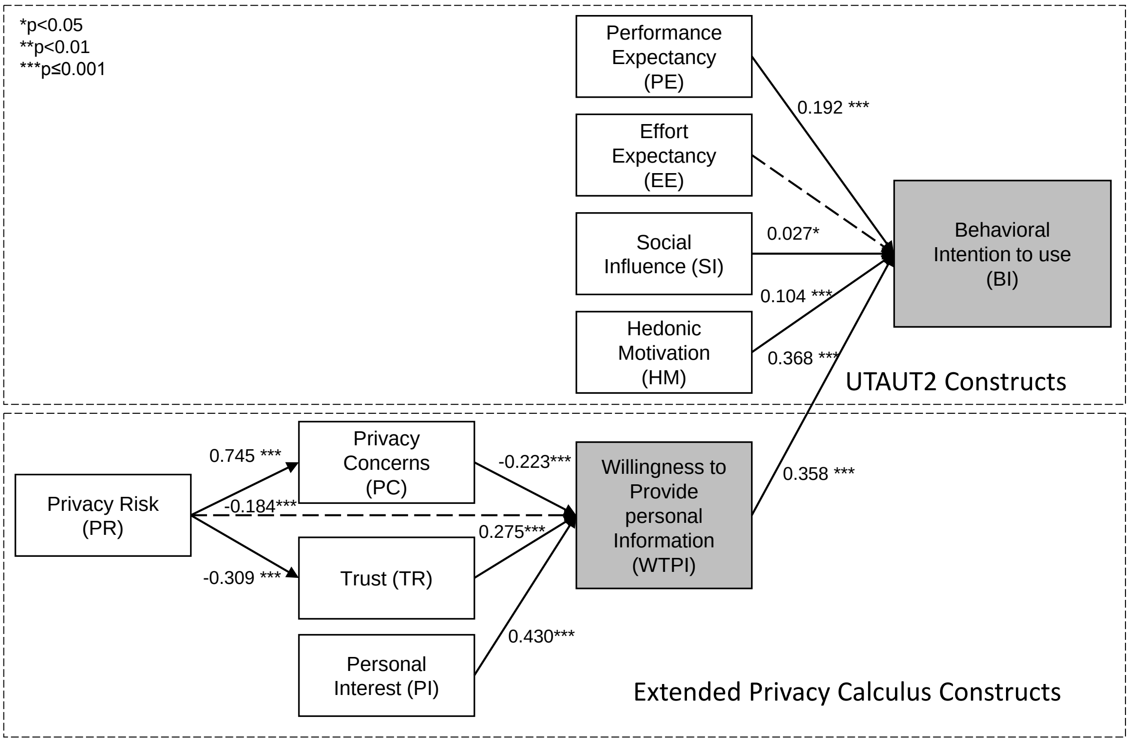

Figure C.1: Structural model with significant path coefficients

Publications

1. Bertolini, M., G. Romagnoli, and A. Weinhard (2017): ‘Proposing a Value-Added Indicators framework for the apparel and fashion sector: Design and empirical evaluation’. *International Journal of RF Technologies*, vol. 8(3): pp. 143–164.
2. Leitz, Roland, Andreas Solti, Alexander Weinhard, and Jan Mendling (2018): ‘Adoption of RFID Technology: The Case of Adler—A European Fashion Retail Company’. *Business Process Management Cases*. Springer: pp. 449–461.
3. Weinhard, Alexander, Matthias Hauser, and Frédéric Thiesse (2016): ‘Customer Intentions towards Using IoT-based Shopping Applications’. *DIGIT Pre-ICIS Workshop*.
4. Weinhard, Alexander, Matthias Hauser, and Frédéric Thiesse (2017): ‘Explaining Adoption of Pervasive Retail Systems with a Model based on UTAUT2 and the Extended Privacy Calculus’. *Proceedings of the 21st Pacific Asia Conference on Information Systems*.

Curriculum vitae