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Automating the Insurance Sector - Assessing Technology Acceptance of Emerging Technology

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Preamble

In this preamble, I express my gratitude to those who have been fundamental in creating this thesis. My appreciation extends not only to the support I received in recent months but also in the preceding years that paved the way to this point. Throughout this journey, various people have provided invaluable support and guidance.

First and foremost, I want to express my gratitude to Zenlin and Ibo for their academic supervision. Their advice and insights have played a crucial role in shaping the trajectory of this research. Additionally, I extend my thanks to all those involved in the curriculum at TU Delft. Since starting the program in 2021, I have not only gained an understanding of management and technology but have also developed personally and academically beyond the scope of my major.

Moving forward, my appreciation extends to the entire team at EY, where my internship became an incredibly enriching experience. Special recognition is due to Zara and Iven. Zara always had an open ear to my research inquiries and her insights from experience were invaluable. Iven ensured that my internship was not only educational but also a pleasant journey, offering assistance with all kinds of practical matters.

I am also very thankful for my friends who provided continuous support to achieve my academic goals. Their presence created a stable environment outside the university that I could always rely on. Special thanks are reserved for the close friends I made during my time at TU Delft — Julia, Ellen, Marleen, Masa, Thomas, Stanley, Nikki, Niklas, Renzo, Saskia, and Felix. When I moved to the Netherlands, I never thought I would make such good friends and create memories that made the master's program fly by in no time.

I would also like to thank Paul for his lifelong friendship and support. Our academic journey started 6,5 years ago together in Freising, continued on different paths, and is now coming to an end for both of us. On an exciting future that lies ahead!

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Executive Summary

Emerging technologies like artificial intelligence, big data analytics, blockchain, and the internet of things offer interesting opportunities to automate business processes. With the potential to streamline operations like claims management, underwriting, and customer service, these advancements appear to be especially promising for insurance companies. Nevertheless, digital transformation does not come without its barriers, such as IT-system legacies, regulatory demands, and business issues. One challenge for digital transformation is the rejection of innovations. Insurers, therefore, need their internal stakeholders to accept and adapt to technological change.

This study investigates this barrier to a successful digital transformation of the insurance industry. Following a literature review on innovations in this realm and technology acceptance, this thesis aims to identify factors influencing the behavioral intention to use technologies within this context.

A theoretical framework is developed throughout the research, suggesting determinants affecting the technology acceptance. To test this framework, employees of insurance companies are surveyed on their opinions and beliefs surrounding innovations that could be integrated into their workflows.

An analysis of survey data reveals that the intention to use technology, in that sector, is positively correlated with the tool's performance expectancy and a favorable organizational influence. In line, the study suggests insurers should focus on these two factors when implementing emerging technologies, to create high workforce acceptance.

In addition, expert insights were used to conclude strategies that increase performance expectancy and organizational influence, to leverage the survey findings. The professionals underpin the importance of creating awareness of the technology and establishing a level of understanding of how the tools work, by reducing the technology's complexity or providing learning and training. Additionally, technology implementations need to be flexible and approaches must be adjusted to the stakeholder group. Clear communications of implementation plans and their benefits are key.

Furthermore, this study highlights a discrepancy in perceptions between managerial and operational level employees. While insurance experts see the performance-enhancing potential of emerging technologies, employees who should work with the tools are rather reluctant. This further emphasizes the importance of bridging gaps between IT-savvy workers and employees on an operational level.

Further, the research points to future investigations on extending technology acceptance literature to the context of work process automation. The results suggest that pure performance expectancy might not be sufficient in approving technology used in automating complex and crucial work tasks; employees also seek to understand these tools for accurate and trustworthy outcomes.

In conclusion, the study provides valuable insights for implementing technology in insurance companies with a human-centric approach. It advocates for greater focus on the factors that influence employee acceptance of technology, which can directly impact a company's performance and efficiency. While highlighting recommendations to reduce technology rejection in insurance companies, the thesis also points out the potential for further research in this area.

Contents

1 Introduction

In today's fast-paced business landscape, organizations are constantly in pursuit of gaining a competitive edge through comprehensive digital transformation initiatives. This endeavor encompasses a wide array of efforts, and a particular focus lies on improving existing operational processes. Business process automation (BPA) is at the forefront of these efforts, leveraging technological advancements to reduce the need for human intervention in business tasks. Examples of such BPA implementation could be the utilization of software bots to send automated emails to customers or copy and paste data from files without assistance (Ribeiro et al., 2021).

The importance of business automation lies in its ability to free up employees from mundane and repetitive tasks, allowing them to channel their energies into more creative endeavors (Berruti et al., 2017). At its core, business process automation aims to streamline existing operations to eliminate inefficiencies (Jovanović et al., 2018). That can offer several advantages, including improved productivity, fewer errors, and cost savings, as BPA enables businesses to finish tasks more quickly and with fewer resources. BPA may also create additional value for a business by, for instance, enabling chatbots for 24-hour self-service (Feio and Dos Santos, 2022).

With the evolution of robotics, artificial intelligence, and machine learning, business automation has become smarter and more versatile (Chakraborti et al., 2020). Implementing such advancements in their businesses enables professionals to automate an ever-growing number of processes. This approach to automation, known as intelligent automation, is considered a fundamental building block for the future of business processes (Berruti et al., 2017).

However, there are also risks associated with process automation, including the complexity of implementing BPA systems and the need for robust cybersecurity measures to protect sensitive data. Businesses must have a sophisticated digital infrastructure and knowledge to properly automate business processes. For technology implementations to be successful, there must be careful planning, clear communication, and continuing oversight to maximize their advantages while minimizing potential hazards. This research centers around one crucial barrier to digital transformation: The misalignment of people and technology, which may factor into a low level of performance enhancements through process automation (Eulerich et al., 2022; Marangunić and Granić, 2015).

BPA helps with the implementation of digital solutions that support the human workforce rather than entirely automate the business landscape. Even if digitalization could theoretically enable business processes to be completed without the need for human participation, this is not always desired. For instance, customers prefer speaking with a person while handling a sensitive matter rather than completing an online self-service form (Kremer and Peddanagari, 2021). As long as businesses are not fully automated, it is necessary to look at digital transformation from a people's perspective. Next to delivering a customer-centric process, the stakeholder perspective within a company is crucial.

While BPA spans across diverse industries, its implementation varies significantly based on the industry and the nature of its tasks. Currently, digitalization and automation of business processes are most prominently seen in the service sector, including finance and insurance. In financial services, the goal of BPA is often to create straight-through processes (STP). Straight-through processing in finance refers to the automated end-to-end processing of transactions without manual intervention (Lin and Hsu, 2011). The insurance industry has heavily invested in automating business processes, with the use of software robots and artificial intelligence, which support key activities like claim handling and underwriting (Siderska, 2020). This drive for more automated and efficient processes led to a global investment of \$ 15.8 billion in InsurTech in 2021 (Ma and Ren, 2023). However, the digital transformation of the insurance sector is still evolving. Many insurance providers must further enhance their productivity and reduce operational costs to stay competitive (Erk et al., 2020). Despite the necessity of digitalization, many insurance companies struggle with implementing the new technologies (Lissy et al., 2023). 63% of businesses as of 2021 were unable to complete their business process automation initiatives on schedule. (Lazareva et al., 2022). Despite the well-known benefits of business automation, only between 0 and 7 % of insurance claims, depending on category, were carried out without human involvement (Huberty et al., 2023). For a process that shows high variance, it is not surprising. Still, considering the opportunities these technologies create, it is crucial to address the underlying barriers and opportunities for insurance businesses.

Innovations in the realm of intelligent automation appear to be promising tools to assist insurance carriers with their core processes. A crucial component for the success of emerging BPA technologies is people's perspective on digital change. One example that showcases the (mis-

)alignment of people and technology in this context is given by Kirchmer and Franz (2019). They describe the case of an insurance company, where the implementation of a robotic process automation tool led to no realized benefit. The software bot was implemented and reduced the time of some specific working steps successfully. Still, the roles of the workforce were not restructured to fit the new process, which ultimately led to no headcount reduction or efficiency gains.

A crucial factor when considering people's perspectives on digital transformation is technology acceptance. For insurers, it is necessary to know how employees perceive the digital change and how their notion is towards future adjustments to their everyday workflows. Employees may resist changes in their processes, as these can impose disruption (Liu et al., 2023). Resistance can have various origins, such as the fear of being replaced or the inability to use a tool (Bajer, 2017). Low acceptance amongst the workforce can lead to underutilization or even obstruction of automation initiatives (Ghazizadeh et al., 2012). This thesis seeks to investigate the BPA-specific digital transformation of insurers with a scope of various core procedures, technologies, and services. The research aims to investigate the phenomenon from an employee perspective on an operational level, with the main research question:

"What are key influencing factors for employees' behavioral intention to use digital innovations in insurance companies and how can adoption be improved?"

The intention is to identify whether the theoretical benefits of emerging BPA technologies can be realized, regarding employee acceptance. The report starts by first reviewing the related literature and subsequently giving an overview of the research question, objectives, and approach. Section 4 provides a theoretical framework that hypothesizes key determinants of technology acceptance in this context. Section 5 provides the methodological approach used to test the framework and how insights are gained to improve future technology implementations in insurance companies. Section 6 lists the results of the research, while Section 7 concludes and discusses them.

2 Literature Review

To uncover gaps in existing knowledge and delineate the research scope, this literature review delves into the realm of digital business process automation. This thesis will center on the digital transformation of activities within the insurance industry, a sector that stands to benefit significantly from advancements in emerging technologies that could pave the way for straight-through processes. To establish a foundation, the review will first cover process automation, as well as the role of emerging technologies for insurance processes, and later delve into the socio-technological aspects.

2.1 Emerging Technologies, Process Automation, and the Insurance Sector

This review focuses on technologies that enable business process automation (BPA), an overarching term that includes various technology-based approaches to execute processes in a digital environment (Aysolmaz et al., 2023). BPA, therefore, doesn't stand for a single technology but rather comprises the orchestration of tools that enable automation. To facilitate process automation, usually, a combination of different tools has to be applied (König et al., 2020). It is essential to examine the similarities and distinctions among the components since business automation entails a variety of terminologies and acronyms.

One term that is commonly found in the literature and that plays a pivotal role within the broader framework of BPA is robotic process automation (RPA). RPAs are enablers of BPA on a workflow or task level. RPA focuses on the automation of specific tasks that are repetitive and rule-based through the use of software robots (Siderska, 2020). The software mimics human action on computers with little or no assistance and is especially useful for tasks that fall under the characteristics described by Wellmann et al. (2020): Standardized activities that show low variation and require no subjective judgment or interpretation. Therefore, robotic process automation consists primarily of screen scraping and workflow automation.
For instance, RPA bots can scrape customer data from a file and insert it into a specific form. When implemented successfully, RPAs can reduce processing times significantly (Siderska, 2020).

BPA, on the other hand, extends beyond individual tasks to include analysis and the potential restructuring of entire workflows. This involves technologies such as business process management systems (BPMS) to map processes and connect diverse software programs through application program interfaces (APIs) (König et al., 2020). The significance and applicability of various BPA technologies may differ across industries and operational procedures. Fundamental BPA tools have become integral components throughout the business environment.

BPA extends beyond internal processes, encompassing activities that directly interact with customers—a pivotal aspect, especially within the service industry. The service sector is shifting towards automation, facilitated by digital platforms and self-service tools, including the utilization of chatbots for streamlined customer interactions. Such applications can cut costs up to 90% and reduce human involvement significantly, as described in a case by Markovitch and Willmott (2014), where an insurance company was able to cut costs significantly by implementing a digital platform for self-service of simple claim processes.

With the rise of emerging technologies in artificial intelligence (AI) and machine learning, even processes that initially appear less suitable, as they require a sense of judgment or are less standardized, can now be automated. This evolving landscape is referred to as intelligent automation (IA) or intelligent process automation (IPA), enhancing traditional automation (BPA) by enabling machines with learning capabilities to improve their methods. IA also extends beyond automating repetitive tasks, as it can handle cognitive work, thus alleviating human workers from even more complex responsibilities (Coombs et al., 2020).

The digital revolution comes with innovations that will change insurance processes significantly. Eling and Lehmann (2018) present an overview of emerging digital technologies for insurance companies. Their framework comprises a variety of technologies that enable IPA. It is relevant to note that these innovations rather aim at complementing and elevating current BPA technologies than replacing them.

A fundamental building block for the future of process automation, given by the paper, is data acquisition and analysis technology. Relevant emerging technologies in that field encompass artificial intelligence (AI), big data, and the internet of things (IoT). These fields are highly intertwined and related, as AI is commonly used as a tool for big data analysis and IoT enables the acquisition of big data.

These building blocks for data acquisition and analysis are going to be vital for the future of process automation by generating and utilizing high volumes of data. One example of an application that involves all three technologies in an insurance process is given by Małek (2020): Customer data that is captured by a customer's smartwatch can be automatically transferred to an insurance company, which uses the data to calculate more accurate underwriting premiums. The possibilities for integrating these technologies are ample and will later be discussed when looking at the insurance value chain.

Next to AI, IoT, and big data, blockchain is a promising technology for the future of process automation. Blockchain can aid insurance companies, for example, by enabling smart contracts (Gatteschi et al., 2018). These could be implemented in various processes. For instance, an automated transfer of money may only be triggered when a customer repairs their car at a certified dealership; the dealership could then verify its identity using the smart contract.

These innovations are fundamental for technological change and for process automation to become more intelligent. To understand BPA and digital transformation within a specific sector, it is necessary to look at the value chain and specific processes. Insurance companies generally have a wide range of core tasks that vary in suitability for automation technologies. The previous part gave an overview of process automation and emerging technologies that may impact the industry in the future. To gain a better understanding, the following part will delve into primary processes within the insurance sector and use cases of automation technologies in this context.

2.2 Streamlining the Insurance Value Chain

One of the primary applications of process automation today is in claim management. This involves handling all tasks from the moment a policyholder submits a claim until it's resolved. The main aim of automating claim processing is to achieve what is called "straight-through processing" (STP), which means automating the process to the point where no human intervention is required (Erk et al., 2020). This is where RPA bots come into play, streamlining

the entire process from the initial claim notification to the final settlement, especially for high-volume standardized claims. Implementations of automation have already shown impressive results, reducing processing times by up to 90% and significantly cutting down on the need for human staff (Lamberton et al., 2017). Most insurance companies already have digital and automated systems for tasks like document uploads and automated bank transactions (Oza et al., 2020). RPA bots follow predefined rules and algorithms to automate these processes, ensuring data lands in the right system and is attached to the correct claim. They can also assist in maintaining regular customer contact through standardized notifications during the claims process. To enhance these automated systems further, AI can be integrated. Features such as intelligent workflows, natural language processing, and data extraction help minimize human intervention, especially in less standardized claims (Kholiya et al., 2021).
For instance, Oza et al. (2020) introduced a deep learning module in a claim-processing chatbot. This module can analyze photos of a damaged car and determine the severity, aiding in claim categorization. Another example is given by the Japanese insurer Fukoku Mutual Life, which uses Watson Explorer from IBM to calculate automated payouts (the payouts are still subject to human approval) (Eling and Lehmann, 2018).

A second significant application in the insurance industry is process automation in pricing and underwriting. Underwriting involves assessing the risk of insuring individuals or properties, taking into account factors like age, lifestyle, or property value. Erk et al. (2020) estimate that by 2030, more than 90% of pricing for simpler insurance products like auto or home insurance will be fully automated, thanks to investments in machine learning models and analytics that leverage customer data.

Maier et al. (2019) introduced an example of such an automation tool: A predictive underwriting model that outperforms traditional methods by combining machine learning with historical data. Lissy et al. (2023) analyze in line that machine learning tools can identify patterns and analyze trends that are not visible to human underwriters, leading to better performance. Automated underwriting costs significantly less than traditional underwriting, yet no industry-wide automation is observable, applications are currently mostly used as decision-support tools. (Erk et al., 2020; Huberty et al., 2023).

Process automation also has a substantial impact on customer service. A digital pricing and underwriting process automatically triggers policy issuance. While communication increasingly shifts to digital channels, more self-service options for insurance customers become available (Erk et al., 2020). Fast-learning chatbots are contributing to this trend, shifting human customer support to rather exceptional cases.

Another technology that becomes increasingly relevant in this domain is cloud computing (Eling and Lehmann, 2018). Customer data and contract information can be digitally stored, accessed, and changed. As self-service options grow, it allows companies to automate changes in data. In terms of customer service, AI and big data can also create value through automated insurance advice. For instance, Allianz has invested in Moneyfarm to explore the possibilities of robo-advisors in the digital distribution of insurance (Marano and Li, 2023).

2.3 Technologies and Processes Overview

The previous chapter outlines ample innovations that can be used to streamline insurance processes. Table 1 summarizes these technologies and their possible applications in the insurance value chain. Providing a structured overview of the digital transformation this sector might face, the table gives a basis for the following research endeavor.

Table 1: **Emerging BPA-technology in the Insurance Sector**

Process	**Technology**	**Applications**	**Literature**
Claim Handling	• AI • Big Data • Blockchain • IoT • Cloud-Computing	• Integration of AI in RPA-bots • Natural language processing in claim acceptance • Optical character recognition in claim management • Automatic payout calculation • Automatic claim notification • Smart-Contracts (Automated claim validation)	• Eling and Lehmann (2018) • Berruti et al. (2017) • Oza et al. (2020) • Erk et al. (2020) • Kholiya et al. (2021)
Underwriting	• AI • Big Data • Block-Chain • IoT • Cloud-Computing	• Automated risk calculation using machine learning • Telematics device collects customer data automatically • Information storage via Cloud or Blockchain	• Erk et al. (2020) • Eling and Lehmann (2018) • Maier et al. (2019) • Lissy et al. (2023)

Customer-Contact	• AI • Big Data • Cloud-Computing	• Chatbot (Automated Sales/Service) • Digital contract information can automatically be changed • Smart-Contracts (Automated policy issuance) • Robo-Advisors (automated insurance advice)	• Erk et al. (2020) • Eling and Lehmann (2018) • Marano and Li (2023)

2.4 Barriers to Digital Transformation: A Systems Perspective

The review shows that, in theory, a wide range of automation technologies and complementary core processes exist in the insurance sector. Further, improving the level of automation and implementing intelligent tools is important to remain competitive for the companies (Erk et al., 2020). However, digital transformation proves to be a difficult task for practitioners in the insurance industry (Lissy et al., 2023). Many automation projects are delayed, and the level of fully automated insurance processes remains low (Lazareva et al., 2022; Huberty et al., 2023).

To understand the difficulties insurance companies face, it is necessary to unveil the barriers to digital transformation. The subsequent section aims to present the reasons, why insurance carriers have trouble implementing BPA technologies.

In order to understand the difficulties in process automation for insurance companies, a systems approach is necessary. A systems approach refers to investigating technology not in isolation but rather from a holistic perspective. It involves examining how the technology interacts with its context, including people, processes, the organization, and the environment (Bergek et al., 2015). To develop a comprehensive systems perspective, it's helpful to identify the key entities involved in the successful implementation of digital automation tools for insurance processes.

Holland and Kavuri (2021) propose a systems framework for digital tools in insurance processes, consisting of the following components: TECHNICAL; DIGITAL; BUSINESS; ETHICAL, REGULATORY, AND LEGAL. To illustrate how these concepts relate to BPA within the insurance realm, an example provided in the literature will be used in the following.

Oza et al. (2020) introduced a chatbot that helps with claim management. Implementing this chatbot enables users to upload pictures of a car crash into the application, which determines, based on machine learning capabilities, the severity of the claim. By using this example, the following part will elaborate on the individual components of the technological system and analyze related literature.

TECHNICAL COMPONENTS: Insurers must know the technologies and access the required data. Many emerging applications require an understanding of interrelated technologies. For instance, when implementing the chatbot, the company needs to be able to train a machine learning tool but also have access to a data set with previous car crashes to train the algorithm. Catlin et al. (2016) observed that, at the time of the report, the insurance industry lagged in digital sophistication, hindering its ability to fully exploit the value of digital advancements.

DIGITAL CONTEXT: Many incumbents saw digitalization for years rather as a threat than an opportunity, limiting their internal efforts. Inflexible and outdated IT infrastructure is slowing the implementation of technological advancements (Dirnberger et al., 2018). Novel technologies must either be implemented alongside outdated systems or companies must undergo exhaustive restructuring projects. Looking at the example: A chatbot that is integrated into the claims-handling process requires access to customer data. Such data might be stored on outdated systems, hindering seamless access to the application.

BUSINESS CONTEXT: To successfully implement BPA technologies, business processes must be suitable for a digital transformation. An insurer's service structure and product portfolio play pivotal roles. These are currently too complex for automation. Simplifying the product offerings by introducing tiers or packages (e.g., gold, silver, and bronze plans) rather than maintaining 50 or 100 distinct products can facilitate streamlined processes (Erk et al., 2020). However, this approach counters the prevailing trend of offering more personalized and individualized insurance products (Catlin et al., 2016). Additionally, the impact of an automated process should be evaluated, since it may also hinder process automation. For instance, there is a significant contrast in customer satisfaction and service quality resulting from an automated claims process for medical malpractice insurance versus workers' compensation insurance (Berruti et al., 2017). Going back to the example: When implementing the above-described chatbot, insurers may have a process structure that is too complex for the machine learning tool. For instance, categorizing a crash by severity may only be accurate with a total of 3 severity classes, but the insurer requires 5 categories by policy.

Ethical, regulatory, and legal environment: The insurance sector is heavily regulated to protect customers and stakeholders in general. Especially topics such as AI and big data are increasingly monitored, and regulatory bodies set the restrictions tighter, for instance, through the GDPR. Key components are to maintain transparency, data privacy, and alignment with ethical norms (Holland and Kavuri, 2021). Referring to the example, practitioners training an algorithm for the chatbot would need to adhere to privacy regulations when using historical crash data.

2.5 Findings of the Review and Research Opportunities

New technologies often get a lot of attention for their potential business value, but it's important to look at them from a practical perspective. Authors like Oza et al. (2020) and Lissy et al. (2023) mention AI and machine learning tools that can help with tasks like handling insurance claims or assessing risk. Even though these tools can, in theory, outperform humans, it is necessary to evaluate how they fit into the business context. Besides the pure technical feasibility of the innovation, factors such as implementation potential, legal framework, or ethical considerations are important to keep in mind (Holland and Kavuri, 2021).

Papers like Erk et al. (2020) or Dirnberger et al. (2018) present a variety of factors to consider when implementing BPA technologies and certain barriers that insurance companies face.

Especially when applying a systems approach, it is observable that scholars have identified multiple building blocks for insurance carriers to successfully create digital change. Still, the body of literature misses an internal stakeholder perspective. For instance, the framework given by Holland and Kavuri (2021) encompasses a variety of components that need to be considered for a successful implementation, but doesn't mention employees that have to work alongside new technologies. Other authors, such as Pramod (2021) emphasize that future research should be done from the human perspective on automation technologies, including operational efficiency and reskilling.

Implementing BPA technologies can have a severe impact on how the workforce needs to interact within a process. Digital tools can also create new workflows within a firm and necessitate a restructuring of tasks (Kirchmer and Franz, 2019). For instance, when considering the chatbot example from the literature review: Not every claim can be handled within such an application, some cases might be special and need human guidance. To create a customer-centric service, the insurer needs to present an omnichannel approach, where a human assistant and the chatbot create an integrated process. Employees therefore need to know how to use and interact with the new technologies.

The importance of the people perspective becomes especially evident when looking at the Human@Center study conducted by EY and Oxford University. They found that digital transformation initiatives are 2.6 times more likely to be successful if the employees stand at the center of the implementation plan (Sandford, 2022).

One crucial component is whether a technology is accepted by its users. A framework that is used in the literature to assess this is the Technology Acceptance Model (TAM). The TAM describes that the use of a technological system is based on people's motivation, which is influenced by perceived usefulness, perceived ease of use, and their attitude towards using it (Marangunić and Granić, 2015).

The original formulation of the TAM is already over 30 years old; still, academics extended and revised the model over the years, creating versions that are still applied today. The TAM does not incorporate social or control factors; thus, extensions provided in the literature such as the

TAM2, the Unified Theory of Acceptance and Use (UTAUT), or the UTAUT2 include more variables to improve the model (Williams et al., 2015). The incorporation of different factors varies, thereby depending on the application of the model and the context. For instance, some researchers incorporate contextual factors (e.g., job relevance or image), while others exclude these in their formulations (Ghazizadeh et al., 2012).

One extension with additional factors that appears to be relevant in this context is introduced by Ghazizadeh et al. (2012). Their approach complements the traditional model by adding factors for automation technologies. For users to accept automation technologies, the variables trust and compatibility of task and technology are relevant (see Figure 1).

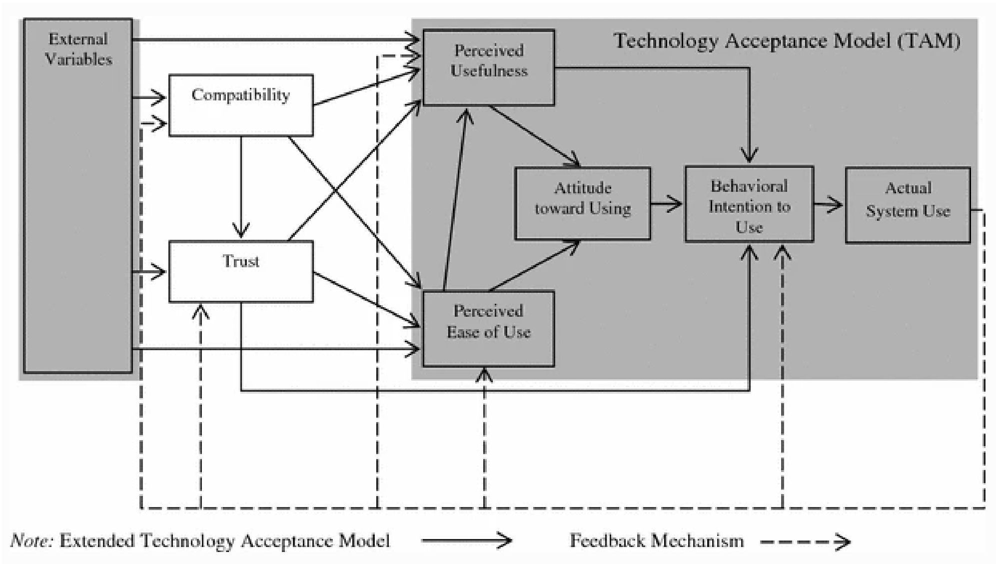

Figure 1: TAM with additional factors relevant for automation technologies (Ghazizadeh et al., 2012, p. 45)

It is to be mentioned that automation tools for business processes in insurance companies are usually mandated. Thus, employees have less freedom in choosing the technology, regardless of their attitude. Still, the employees' acceptance of automation tools is key to their success, since even in forced use, individuals may decide to delay, obstruct, or underutilize systems (Ghazizadeh et al., 2012).

To investigate the acceptance of BPA within insurance companies, it is vital to elaborate on the most common extensions of the TAM, the different components, and their applicability. Most commonly accepted and compulsive extensions are TAM2, UTAUT and UTAUT2 (Tamilmani et al., 2017; Marangunić and Granić, 2015)

The UTAUTs variables make it tailored to understand technology adoption among employees in structured environments. The model's core constructs, including Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC), directly resonate with the considerations of professionals in a work environment (see Figure 2) (Williams et al., 2015). For instance, insurance employees have a perception of how BPA can enhance their job performance (Performance Expectancy) and the ease of integrating these automated tools into their workflow (Effort Expectancy). UTAUT also builds on variables that are incorporated in the TAM2, such as the social context, which is relevant in a work environment (e.g., the influence of co-workers). The UTAUT formulation integrates 8 different influential acceptance models, which makes it a widely accepted and comprehensive framework (Nordhoff et al., 2020).

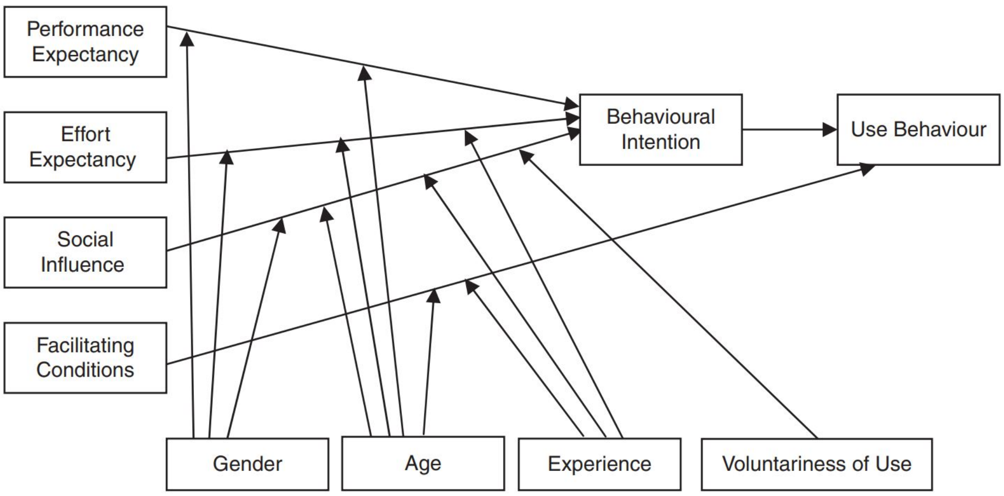

Figure 2: UTAUT with relevant influencing factors (Williams et al., 2015, p. 444)

While UTAUT2 offers an extended perspective by incorporating constructs like Hedonic Motivation, Price Value, and Habit, these are more consumer-centric and may not be as relevant when assessing technology acceptance in an organizational context (Venkatesh et al., 2012).

It is also worth mentioning that other models explain technology adoption from different perspectives. For instance, the Technology-Organisation-Environment (TOE) model describes how innovations are adopted within companies from an organizational point-of-view (Aligarh et al., 2023). To research employee perception and operational implications, the TAM and its extensions seem particularly suitable, perspective-wise.

BPA stands to add value by increasing employee productivity, thus, it paves the way for an interesting investigation of whether the believed and theoretical benefits of emerging BPA technologies can be realized in insurance companies. It is relevant to investigate if the new technologies fit into the operational environment and how well they can be integrated with the workforce.

3 Research Questions, Objectives, and Approach

3.1 Research Objective

The objective of the research is to explore and analyze the integration of emerging technologies that can streamline insurance processes. Particular interest lies in investigating the implementation from an employee perspective, understanding acceptance, and deriving operational barriers and opportunities. As a vital component for a successful digital transformation, the thesis will propose workforce integration strategies that can increase workforce acceptance of innovations in this realm.

3.2 Research Questions

To meet the objective of the study, the following main and sub-research questions are addressed:

"What are key influencing factors for employees' behavioral intention to use digital innovations in insurance companies and how can adoption be improved?"

1. What emerging process automation technologies, relevant to the insurance sector, can be identified in the literature?

2. What factors influence the behavioral intention of employees in the insurance sector to use digital innovations?

3. How does the behavioral intention to use innovations vary across different technologies and process applications in the insurance sector?

4. What implementation strategies regarding workforce integration can insurance companies adopt to successfully utilize emerging automation technologies?

3.3 Research Approach

The following passage describes the approach used to answer the research questions. The strategy is to follow a mixed-methods approach, which should offer a thorough knowledge of the complexities brought on by digital breakthroughs in process automation within the insurance industry.

For Research Question 1, an analysis of the literature is used to find developing BPA technologies relevant to the insurance industry. Table 1 of Section 2.3 provides a structured list of technologies and complementing processes. This list constitutes the basis for answering the subsequent research questions.

In order to investigate the impact digital developments in process automation will have in terms of acceptance, surveying employees of different insurance companies will be done to address Research Question 2. This will grant insights into the behavioral intention to use technologies on an operational level. The study aims to investigate the socio-technological context of the phenomenon; therefore, the survey questions will be guided by frameworks identified in the literature within that realm. The UTAUT and TAM will be used as a basis for formulating the survey questions. This includes extensions, such as described by Ghazizadeh et al. (2012), to fit the context of BPA. The theoretical framework derived for this study can be found in Section 4.

The approach is to quantify the relevant variables. For example, relevant factors, such as the perceived ease of use of BPA technologies, shall be answered on a Likert- scale. This will allow improved data analysis, generalizability, and comparability. Analyzing the findings of the survey will help in answering Research Question 3. The survey results can be found under Section 6.1.

Next to the survey, expert interviews (semi-structured) will be conducted. Firstly, the interviews will be used to validate the survey by allowing data triangulation. Experts will be asked about the contents of the survey to provide a sense of validity. However, other factors, such as face and construct validity, may be determined through the expert interviews. Furthermore, the interviews will help with identifying strategies to cope with the barriers, exploit opportunities in the future, and answer RQ4. The findings of the expert interviews can be found under Section 6.2.

4 Theoretical Framework

The following section aims to deliver a framework for behavioral intention to use emerging automation technologies within insurance companies and hypotheses on the relationships among relevant factors. The literature shows that behavioral intention directly relates to actual usage and in the context of automation technologies, does usage intention influence workforce productivity (Williams et al., 2015; Ghazizadeh et al., 2012).

4.0.1 Model for Behavioral Intention to Use Technology

As stated in the literature review, the Unified Theory of Acceptance and Use of Technology (UTAUT) builds a promising basis to investigate relevant acceptance factors. Therefore, it constitutes the basis for the theoretical framework of this research. The model respects all factors that are primarily influencing the behavioral intention to use technologies given in the UTAUT, and in order to fit the context, additional variables and dependencies are incorporated. Other variables, such as voluntariness of use, are excluded since they are believed to be not applicable in this context (e.g., employees are assumed to have no significant freedom in choosing technologies). Some relationships, such as the moderating role of age on the influence of performance expectancy on behavioral intention, are excluded to reduce complexity and to meet the extent of a master thesis. Figure 3 shows the proposed framework.

4.0.2 Hypotheses

Fundamental to investigating behavioral intention are the primary influencing factors that are given by the UTAUT: Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions. The definitions and nuances of the individual factors are adapted to fit the specific context.

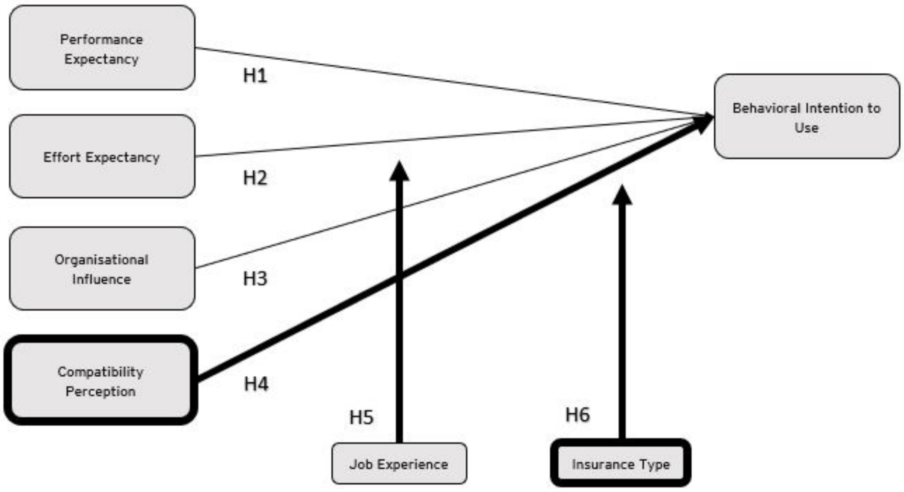

Figure 3: Theoretical framework to assess "Behavioral Intention to Use" emerging automation technologies within the insurance sector. The factors and relationships that are added to the traditional UTAUT model are bold.

In technology acceptance models, performance expectancy, or perceived usefulness, plays a pivotal role in influencing the behavioral intention to use technology. This seems to apply to automation tools in organizational settings as well. Perceived usefulness touches on how digital tools can enhance the efficiency and accuracy of employees' work. Integrating new automation technology means breaking up existing processes. If the proposed changes are not delivering the expected performance, it can lead to even more work (or re-work) for employees. Premature implementation of technologies is not uncommon during digital transformation initiatives and previous studies showed that performance expectancy can be a primary influencing factor on behavioral intention to use technology in a work setting (Ebertz et al., 2018; Alraja et al., 2016). Therefore, the first hypothesis is:

H_1: The behavioral intention of employees in insurance companies to use emerging automation technologies is positively influenced by the performance expectancy of the application.

The second construct of the UTAUT model is also believed to be relevant when applied in this context: *Effort Expectancy*. Understanding workflows in an organizational setting requires effort, repetition, and time. Consequentially, digital transformation comes with continuous learning, training, and restructuring of roles. As these imply effort from the employee side, it might influence the attitude towards new technologies. Additionally, it is not given that even with training and (re-)learning, the new processes will be easier than before. Such expectations likely influence the willingness to adapt to new implementations. Further, other scholars, such as Wang (2016), show that effort expectancy can have a significant influence on the behavioral intention to use technology in an organizational setting. Hence:

H_2: The behavioral intention of employees in insurance companies to use emerging automation technologies is negatively influenced by the effort expectancy of integrating the application.

In UTAUT, the constructs *Social Influence* and *Facilitating Conditions* are primary influencing factors. These variables are also believed to be significant determinants in this context. Still, social influence and facilitating conditions have different meanings and different implications in organizational environments. These aspects are important to consider: Support from peers and support from supervisors. Support from peers is here defined as a general organizational attitude towards digital change; hence, social influence. Innovations are easier to accept in an organizational culture that is open to change and in companies that have already seen successful implementations. While such social influence can stem from everyone within the company, it is crucial to also consider top-down social influence. Creating a positive attitude towards digital tools can be significantly influenced by management support (Venkatesh and Bala, 2008). It encompasses relevant training and role restructuring, which are often missing in the digital transformation of organizations (Gupta, 2018). It also treats the fear of being replaced by an automation tool, which is known to be influential in technology acceptance amongst employees (Bajer, 2017). *Facilitating Conditions* and *Social Influence* are believed to be correlated in this context. Hence, a strong relationship between a positive culture regarding digital transformation and management support regarding new technologies is assumed. As Allam et al. (2020) describes, highly correlated variables may be aggregated to avoid multicollinearity in data analysis. Therefore, the variable *Organizational Influence* is used to cover both constructs. The third hypothesis follows, therefore:

H_3: The behavioral intention of employees in insurance companies to use emerging automation technologies is positively related to organizational support and social influence.

The first three hypotheses are rather straightforward applications of the primary variables of the UTAUT model. The following ones include either additional factors or relationships that are believed to be relevant in this context.

Guided by the insides from Ghazizadeh et al. (2012) it becomes apparent that the perceived compatibility of tasks and technology is an influencing factor in the acceptance of automation technologies. Compatibility comes in diverse dimensions. However, this research specifically centers on the alignment between values and technology, as articulated by Karahanna et al. (2006). When looking at different insurance processes, this seems to be especially relevant. Emerging technologies, such as AI or blockchain, can be integrated into various processes. Using technologies for different tasks comes with different implications, which might be influential on the acceptance of their users. For instance, implementing AI within underwriting to assess the risk of insuring a person may be perceived as less suitable than when it is utilized in customer service. It appears consequentially necessary to investigate the role of perceived compatibility on behavioral intention within that context. Hereby, it is also useful to make a clear distinction between "Performance Expectancy" (PE) and "Compatibility Perception" (CP). While PE touches on whether users believe the technology can perform a certain task, compatibility measures whether users believe a certain task should be performed by an automation tool. The fourth hypothesis follows:

H_4: The perceived compatibility of technology and process positively influences the intention of employees to use emerging automation technologies in insurance companies.

Experience acts as a moderator in the UTAUT model. Hereby, it is important to define the concept of experience. In UTAUT, experience concerns the prior experience with a certain technology, which moderates the behavioral intention to use it. In light of innovations regarding BPA, the concept of experience has a slightly different meaning.

In the context of the digital transformation of workplaces and the integration of automation tools, experience refers to knowledge about the processes. The factor *Job Experience* measures the time employees are working with insurance workflows, hence their process experience.

Scholkmann (2021) shows that individuals tend to resist digital change. As discussed previously, *Effort Expectancy* is an important factor regarding digital change and the tendency to resist. Experience with the current workflows might have a significant influence on the role effort expectancy plays in technology acceptance. People who are more used to existing workflows are believed to place a higher value on effort expectancy than colleagues who joined the sector more recently. This comes from the assumption that previous training and learning might appear obsolete, and re-training could be more difficult for these employees. The fifth hypothesis therefore follows:

H_5: Job experience strengthens the influence effort expectancy takes on the behavioral intention to use emerging automation technologies of employees in insurance companies.

Another insight, given by the literature, is that the type of insurance sold is a crucial factor when looking at BPA. Berruti et al. (2017) emphasize that customers experience a different level of value when processes are automated, depending on the insurance product. This might be the same for stakeholders within a company.
Various insurance products, such as life, health, or property, possess inherent complexities and differences. These differences might alter the way automation technologies are perceived and subsequently adopted. For instance, a life insurance provider may offer personally tailored insurance products, while a liability insurance carrier only provides predefined packages. As described by Wellmann et al. (2020), variance in complexity makes automation technology significantly more or less suitable for certain processes.
Very important in this context is also the need for subjective judgment, which is necessary for the trend of automating an ever-growing number of processes. As described earlier, the concept of *Compatibility Perceptions* captures whether employees believe a certain task “should” be automated by technology. Hereby, it seems that the type of insurance could play a pivotal role in the strength of its influence on BI. For instance: Utilizing AI to assess the risk of insuring a car might be perceived as more suitable than when used to assess the risk of insuring a person. The last hypothesis follows consequentially:

H_6: The type of insurance influences the impact task compatibility has on the intention to use emerging automation technologies.

5 Methodology

5.1 Survey

5.1.1 Data Collection and Management

As stated in the Research Strategy section, a survey is used to unveil the behavioral intention to use emerging automation technologies within the insurance sector. To answer RQ2 and RQ3, the survey questions will be guided by the technologies identified in the literature and the acceptance model proposed previously. Hereby, questions will also concern the implementation of the same technology at different points in the insurance value chain. To meet the extent of a thesis, questions will focus on technologies and processes that are believed to have the most impact on employees. The technologies used to draft the question are listed in Table 1. Included in the survey questions are *Artificial Intelligence*, *Blockchain*, and *Internet-of-Things*.

To allow quantitative data analysis of the opinions and beliefs, the survey will ask for ordinal perceptions of the concepts on a Likert- scale. Respondents will be asked to select their corresponding year-span for the factor experience.

The factor *Type of Insurance* will be dichotomous. Employees will select whether they fall into the categories of *Life Insurance* or *General Insurance*. Life insurance includes all risks related to life, where the insurance carrier provides financial protection for the policyholder and their beneficiaries in the event of death or survival to a certain age. General insurance encompasses various types of insurance that protect against property loss and liability, covering risks such as damage to property, accidents, and legal liabilities. It includes car insurance, homeowners insurance, renters insurance, business insurance, and more.

As the target group of the survey, employees of insurance companies will be asked to participate. The survey aims to investigate the technology acceptance of individuals who would be directly involved with the tools if they were implemented. This study has a rather wide scope within the insurance sector; it doesn't focus on a single process or technology but rather aims to compare the acceptance of different technologies and use cases. Processes within the following three fields are included: *Underwriting/Pricing*; *Claims handling*; *Customer Service*.

To gain a nuanced understanding of the concepts, the survey will be spread amongst different insurance companies. Including a wide spectrum of insurance types and sizes among the companies.

The responses on the Likert scale are transformed into numerical values. The following transformation is used: 1 = "Strongly Disagree"; 2 = "Disagree"; 3 = "Somewhat Disagree"; 4 = "Neutral" 5 = "Somewhat Agree"; 6 = "Agree"; and 7 = "Strongly Agree". In descriptive statistics, missing values are replaced by "Neutral". For statistical analysis, hypotheses are tested both ways: By replacing NA data with "neutral" and by omitting NA data. The data is also managed according to the participants' occupations. Questions that ask about the application of an innovation to a certain process shall not be answered by participants who work in a different field. For instance, the answers of participants who work in customer service may not be used to assess processes in underwriting. All items in the survey that capture the same factor are aggregated by building a composite score. The composite score is the average of all answers given to questions that capture a single latent factor (Boone Jr and Boone, 2012).

Regarding data quality, it is important to establish validity. Important measures are criterion validity, content validity, and construct validity. Construct validity concerning convergent as well as discriminant validity. Criteria and content validity describe how well the tool captures what it intends to do. Construct validity is given when the items of the survey are well suited to the theoretical framework. Validity shall be determined by statistical analysis and expert interviews.

All data management is done in R-Studio and Excel. Data analysis is conducted in SPSS, R-Studio, and Excel.

5.1.2 Statistical Analysis

In order to prove the alternative hypotheses, or accept the null hypotheses, statistical data analysis is done. Williams et al. (2015) state in a literature review of UTAUT research that a variety of analysis methods are used by scholars to prove their hypotheses in this context. Most prominently used and relevant for this context are correlation analysis, regression analysis, and structural equation modeling.

While there are many different analysis approaches, it is crucial to keep in mind the hypotheses postulated and the data acquired when choosing the method(s). The survey asks respondents to provide their insights on a Likert scale. Answers will therefore be ordinal. Many statistical approaches, such as ANOVA, t-test, or Pearson's correlation coefficient, are parametric methods. Parametric tests are suited for data that meets certain assumptions, such as an underlying normal distribution. Parametric assumptions might be violated when dealing with ordinal data. For instance, parametric tests assume equal intervals. This may not be true when dealing with Likert-type data. The interval between "Strongly Disagree" and "Disagree" is not necessarily the same as between "Neutral" and "Agree". When analyzing ordinal data, these requirements can sometimes be met. For example, by providing theoretical grounds for why certain assumptions hold, or managing the data accordingly. For instance: Increasing the number of points on the Likert scale to allow more options can be used to converge towards equal intervals (Awang et al., 2016). Alternatively, non-parametric methods can be applied that do not build on these assumptions. The proposed theoretical framework contains two types of hypotheses. Firstly, directly influencing factors, and secondly, moderating effects.

H_{1-4} regard direct effects and can be (dis-)proven by correlation analysis. Non-parametric tests that are suitable for these hypotheses are Spearman's ρ and Kendall's τ.

These two tests can be used to assess bivariate correlations between factors. Both methods give insights into the direction and strength of the association between two variables (Akoglu, 2018). The output of the two methods is a correlation coefficient between -1 (perfect negative correlation) and $+1$ (perfect positive correlation). Hypotheses can be accepted or rejected based on the strength of the relationship and its significance. Typical values for statistical significance in a correlation analysis are values of $p < 0.05$ (White et al., 2022). H_{1-4} are all one-sided. This means the hypothesis implies a direction of influence. Hence, there is either a positive or negative relationship. Therefore, the correlation analysis can be one-tailed.

H_{5-6} cannot be tested by simple correlation analysis, as these hypothesize an influence on the relationship between two variables. Such a moderating effect can be tested in regression analysis by using interaction terms (Sarstedt et al., 2019). Such interaction terms are modeled as multiplications of the independent variables. For instance, H_5 is modeled as: $(X_i \times M_j)$ with i = *Effort Expectancy* and j = *Job Experience*. To test a moderating variable, the regression analysis should include the direct influence of the independent variable, the direct influence of the moderating factor, and the influence of the interaction term (Baron and Kenny, 1986). The effect of the moderator can be tested by conducting a hierarchical moderated regression, with the factors added in a subsequent order to the model (Arshadi and Damiri, 2013). The hypothesis of the moderation effect can be accepted if the integration term is significant and the moderation effect improves the predictive power of the model. An improvement in the predictive power can be observed if the value of R^2 is increasing when adding the interaction term to the model.

Next to testing H_{1-6}, it is a substantial part of the statistical analysis to answer RQ3, whether technology acceptance varies across technologies and process applications. Therefore, further data analysis of the survey results shall determine whether the observations of *Behavioral Intention to Use* a technology vary amongst insurance processes and innovations.

The same implications about parametric and non-parametric tests are relevant for this analysis. Many tests that compare groups and determine whether they are significantly different, such as the t-test, build on parametric assumptions. One non-parametric method that is commonly used in statistical analysis is the Mann-Whitney U (Wilcoxon rank) test. It is an alternative to the t-test when the assumptions of normality and homogeneity of variance are not met (Dexter, 2013). An extension of the Mann-Whitney U test, the Kruskal-Wallis test, can be used if more than two groups shall be compared (McKight and Najab, 2010). As this research treats ordinal data and compares more than two technologies and processes, the Kruskal-Wallis test appears suitable.

Statistical testing can also be used to create validity. In particular, conducting a confirmatory factor analysis (CFA) helps with creating construct validity (DiStefano and Hess, 2005). This test aims to confirm the hypothesized structure of a set of variables. In psychological and sociological studies, as well as this thesis, a set of observations is used to explain a latent factor. In this case, the set of observations consists of the individual statements of the survey. The latent variables are the factors of the theoretical framework. The confirmatory factor analysis can evaluate how well the observed variables correlate to the latent variable. This is done by establishing factor loadings of the latent variables and the observed variables (Yong et al., 2013). Similar to correlation analysis, a score close to 1 describes a high correlation and a good fit. A score close to 0 indicates lower suitability for identifying the latent variable correctly. In addition to the factor loadings, indices, such as the comparative fit index (CFI) or Tucker-Lewis index (TLI), can be used to show how well all of the questions are suited to explain the latent factors.

5.2 Interviews

As an additional data source, expert interviews will be conducted. These interviews serve a dual purpose: Firstly, to validate the findings obtained through the survey, ensuring the credibility and reliability of the gathered data. Secondly, these expert insights will help in deriving effective strategies to navigate future implementations of technology in insurance companies and aim at answering Research Question 5.

The interviews will be conducted with individuals who have a background in the insurance industry or change management for technology implementations. The intention is to create an interview pool with experts from various fields and professions to create a nuanced understanding. Interview partners will be professionals on a managerial level. The interviews are semi-structured, and the questions will fall into the following categories:

1. Validity
   (a) Technologies and Process Changes
      - Interviewees will be asked to give their opinions and beliefs regarding emerging technologies in the insurance industry. The findings will be used to evaluate how well the survey questions match potential future implementations.

   (b) Factors for Technology Acceptance
      - Interviewees will be asked what they believe are important influencing factors regarding the behavioral intention to use technologies in this context. This aims at validating the theoretical framework and the findings of the survey.

2. Strategies

   - Interviewees will be asked about strategies to influence the determining factors of the behavioral intention to use technology. The questions will depend on the survey findings, hence which factors turned out to be significantly influencing.

Sui Pheng et al. (2019) give a guide on how to use expert interviews to validate research findings. Their paper presents an approach where all interview partners are asked a set of structured or semi-structured questions, which have the intention to conclude the following three results for each of the respondents: *1. Confirmation of Findings*, *2. Disagreement*, or *3. Further Insights*.

Questions regarding validity will be informed by the technologies identified in the literature and influencing factors determined through the survey, to conclude one of the 3 results. Experts will be asked specifically about emerging technologies in the insurance sector, the theoretical framework, and the outcome of the survey. To possibly arrive at further insights, open questions will be asked that depend on the expertise of the interview partner.

In order to analyze for validity, a qualitative content analysis is conducted, as outlined by Mayring (2015). Content analysis will be done by interview coding and text reduction. For each of the interviews, a summary is composed. These summaries will be used to determine if the interviewee confirms the findings, disagrees or presents further insights.

To derive strategies, a flexible coding approach for the interviews will be applied, as introduced by Deterding and Waters (2021). The questions regarding the strategies are open-ended and can evolve throughout the interview. Coding will be based on the literature and is done through induction of the interview contents. Therefore, no predefined code list is drafted. The goal is to arrive at overlapping concepts and ideas that the experts have to increase the behavioral intention to use technologies in the context of insurance companies. The analysis is done in ATLAS.ti.

6 Results

6.1 Survey

6.1.1 Descriptive Results

In total, 21 participants filled out the survey. The survey population encompasses employees from insurance companies that work with lines in life insurance as well as property and casualty insurance. Respondents are spread across different insurance operations, and the companies range from larger multinationals to smaller and specialized insurers. 6 respondents work for MNCs and 15 for SMEs. Figure 4 gives the frequencies of the variables.

InsuranceType

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	General Insurance (P&C)	11	55,0	55,0	55,0
	Life Insurance	9	45,0	45,0	100,0
	Total	20	100,0	100,0	

Experience

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0-2 years	4	20,0	20,0	20,0
	3-5 years	1	5,0	5,0	25,0
	6-8 years	3	15,0	15,0	40,0
	9+ years	12	60,0	60,0	100,0
	Total	20	100,0	100,0	

Role

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Claim Handling	5	25,0	25,0	25,0
	Customer Service	5	25,0	25,0	50,0
	Other	2	10,0	10,0	60,0
	Underwriting	8	40,0	40,0	100,0
	Total	20	100,0	100,0	

Figure 4: Frequencies of *Insurance type*, *Experience*, and *Role* (excuding 1 NA respondent)

Figure 5 gives the descriptive statistics of the latent factors. All ordinal Likert-type values are transformed to numerical values, ranging from 1 = “Strongly Disagree” to 7 = “Strongly Agree” (A full list of Likert-scale codes can be found under the methodology section (5.1.1)).

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Performance_Expectancy	21	1,00	7,00	4,3810	1,35927
Effort_Expectancy	21	2,00	6,00	4,3333	1,19722
Organisational_Influence	21	3,00	6,00	4,1905	,74960
Compatibility_Perception	21	1,00	6,00	4,0952	1,22085
Behavioral_Intention	21	1,00	6,00	4,1905	1,36452
Valid N (listwise)	21				

Figure 5: Descriptive statistics of the latent factors

Figure 6 shows the behavioral intention to use technology across different innovations. Figure 7 shows the behavioral intention to use technology across different process applications.

It can be observed that employees are more inclined to use AI than blockchain or IoT in their work, with a slightly higher average answer. The median answer for the behavioral intention to use AI is “Somewhat Agree”, while it is “Neutral” for blockchain and IoT.

Regarding processes, it can be observed that employees are more inclined to accept innovations in claims management and underwriting to automate processes than in customer service. The median answer for claims handling and underwriting is “Somewhat Agree”, while it is “Neutral” for customer service.

It is also notable that the answers range from “Strongly Disagree” to “Agree”, while none of the participants strongly agreed with a behavioral intention to use technology.

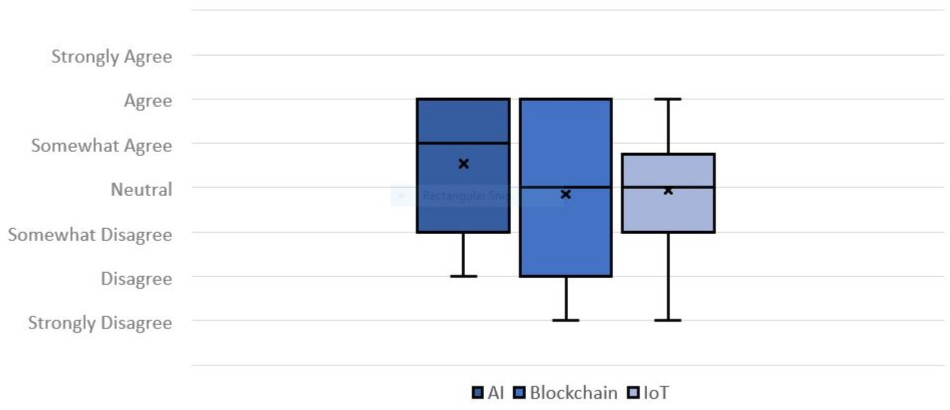

Figure 6: Behavioral intention to use innovations across different technologies

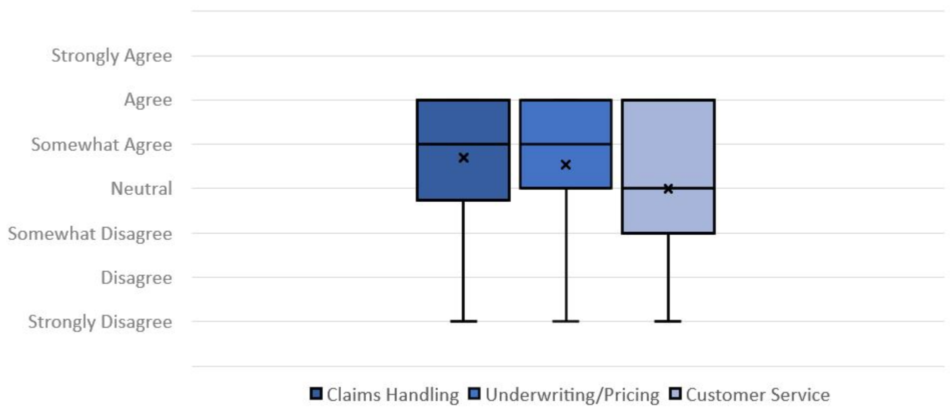

Figure 7: Behavioral intention to use innovations across different processes

6.1.2 Confirmatory Factor Analysis

The confirmatory factor analysis (CFA) was executed in R Studio using the *lavaan* package. Factor loadings for individual questions were examined to assess their appropriateness in representing the latent factors, as outlined by Yong et al. (2013). Similar to a correlation analysis, this process helps determine the direction and strength of relationships among survey items. Appendix A provides a comprehensive list of all survey questions, while Appendix B gives the factor loadings of the relevant latent factors.

Out of the 28 questions analyzed, 6 showed a strong fit with their respective latent factors (factor loading > 0.7), 18 showed a moderate fit (factor loading > 0.4), and 4 demonstrated a poor fit (factor loading < 0.4). Factor loadings exceeding 0.5 are commonly deemed sufficient (Leonnard, 2017; Martin-Harris et al., 2008). Consequently, 15 of the 28 questions exhibited satisfactory construct validity.

It's important to note that confirmatory factor analysis (CFA) typically employs indices such as CFI or TFL for evaluation, which could not be calculated due to the small sample size of participants (21 participants with 28 survey items). Despite this limitation, the factor loadings remain a valuable tool for evaluating the CFA.

The outcomes of the confirmatory factor analysis fell short of complete satisfaction. This stems notably from the questions that should capture the latent factor *Compatibility Perception*, where all items have a factor loading value that is not sufficient.

These findings can have multiple origins, such as the small sample size, poor convergent validity, insufficient discriminant validity, or other factors of the survey design. The discussion section delves into potential reasons for the findings and elaborates on how these challenges can be addressed.

When disregarding the items capturing the latent factor of *Compatibility Perception*, we receive rather satisfactory results for the CFA. For each of the other latent factors, more than half of the questions show satisfactory values. Of these factors, 15 of the 22 observed variables have sufficient factor loadings.

6.1.3 Technology Acceptance across Innovations and Processes

Research Question 3 aims to develop an understanding of differences in technological acceptance or rejection between different innovations in the insurance sector or applications in the value chain. The box plots in Section 6.1.1 already suggest that there is seemingly no difference. To establish a sense of confidence, a Kruskal-Wallis test is used to determine whether there is a significant difference observable within the groups. Figure 8 shows the results of the

Kruskal-Wallis test comparing the observations of different technologies. Figure 9 shows the results of comparing the application of innovations at different processes.

Both tests result in a significance level of $p > 0.05$. This means there is no difference in behavioral intention that is observable, and we assume there is no difference in technology acceptance.

Hypothesis Test Summary

	Null Hypothesis	Test	Sig.[a,b]	Decision
1	The distribution of Bahvioral_Intention is the same across categories of Technologies.	Independent-Samples Kruskal-Wallis Test	,389	Retain the null hypothesis.

a. The significance level is ,050.

b. Asymptotic significance is displayed.

Figure 8: Kruskal-Wallis test to compare the behavioral intention to use technology across different innovations

Hypothesis Test Summary

	Null Hypothesis	Test	Sig.[a,b]	Decision
1	The distribution of Behavioral_Intention is the same across categories of Processes.	Independent-Samples Kruskal-Wallis Test	,228	Retain the null hypothesis.

a. The significance level is ,050.

b. Asymptotic significance is displayed.

Figure 9: Kruskal-Wallis test to compare the behavioral intention to use technology across different processes

6.1.4 Testing Hypotheses 1-4

In order to test H_{1-4}, a correlation analysis with Spearman's ρ is conducted. Figure 8 shows the corresponding correlation matrix. To assess the correlation matrix, it is necessary to keep in mind the values of the correlation coefficient and the level of significance between behavioral intention to use and all other variables.

Akoglu (2018) gives a guide to the interpretation of correlation analysis, which is used in the following. Their paper states that, in psychology, relationships are titled strong if the coefficient lies between 0.9 and 0.7, moderate if it lies between 0.6 and 0.4, and weak if it lies between 0.3 and 0.1. 1 is a perfect relationship, and 0 shows no relationship. The categories count for positive as well as negative dependencies.

Consequentially, the following significant relationships can be observed [1]:

1. Strong positive relationship between Performance Expectancy and Behavioral Intention to Use.
2. Strong positive relationship between Organisational Influence and Behavioral Intention to Use.

Correlations

			Performance_ Expectancy	Effort_Expecta ncy	Organisational _Influence	Compatibility_ Perception	Behavioral_Int ention
Spearman's rho	Performance_Expectancy	Correlation Coefficient	--				
		Sig. (1-tailed)	.				
		N	21				
	Effort_Expectancy	Correlation Coefficient	-,262	--			
		Sig. (1-tailed)	,125	.			
		N	21	21			
	Organisational_Influence	Correlation Coefficient	,803**	-,378*	--		
		Sig. (1-tailed)	<,001	,046	.		
		N	21	21	21		
	Compatibility_Perception	Correlation Coefficient	,387*	-,077	,318	--	
		Sig. (1-tailed)	,042	,370	,080	.	
		N	21	21	21	21	
	Behavioral_Intention	Correlation Coefficient	,818**	-,212	,835**	,248	--
		Sig. (1-tailed)	<,001	,179	<,001	,139	.
		N	21	21	21	21	21

**. Correlation is significant at the 0.01 level (1-tailed).
*. Correlation is significant at the 0.05 level (1-tailed).

Figure 10: Spearman's ρ correlation matrix

[1] These relationships count for treating NA data as "Neutral". Appendix C shows the correlation table for omitting all NA data. Both relationships can be proven by the second analysis. Additionally, this test shows a positive moderate correlation between *Compatibility Perception* and *Behavioral Intention to Use* with significance ($p < 0.05$). This relationship will not be assumed to be true but will be considered in the following analysis.

6.1.5 Testing Hypothesis 5 and 6

As stated in the methodology section, moderation interaction can not be tested by simple correlation analysis. To test hypotheses 5 and 6 a hierarchical regression is conducted, where first a regression is done without an interaction term, and as a second step, an interaction term is included to account for the moderating effect. In general, the alternative hypothesis can be accepted if the interaction term is significant and R^2 is increasing with the interaction term.

Figure 11 shows the model results for testing H_5. It shows that the interaction term of *Job experience* and *Effort Expectancy* has no significance with a value of $p = 0.21$. H_5 must in consequence be rejected.

To test H_6 the same procedure is applied. Figure 12 shows the model results. It can be observed that the interaction term has a p value of 0.46, which lies above the commonly accepted threshold. Therefore, H_6 must be rejected.

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	8,329	2,584		3,224	,005
	Effort_Expectancy	-,811	,433	-,741	-1,875	,078
	Experience	-,479	,703	-,477	-,682	,504
	EE_x_Exp	,153	,117	1,036	1,305	,209

a. Dependent Variable: Behavioral_Intention

Figure 11: Regression analysis to test the moderating effect of *Job experience* on *Effort Expectancy*

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	3,775	1,787		2,112	,050
	Insurance_Type	-,178	,127	-,307	-1,402	,179
	Compatibility_Perception	,298	,268	,242	1,113	,281
	CP_x_Comp	,025	,032	,166	,763	,456

a. Dependent Variable: Behavioral_Intention

Figure 12: Regression analysis to test the moderating effect of *Insurance Type* on *Compatibility Perception*

6.1.6 Survey Summary

Figure 13 shows the proposed framework and the relationships that are supported by the statistical analysis.

Following the statistical analysis of the survey, two main takeaways can be drawn:

1. Insurance companies that want to have implementations of emerging technologies accepted by their workforce, have to emphasize the operational value that the changes entail. Hence, undermining the productivity and efficiency gains, or other added value the tools bring, is crucial.

2. Insurers should foster a positive organizational influence around technological implementations. This includes co-workers and peers, but also top-down management and facilitating conditions.

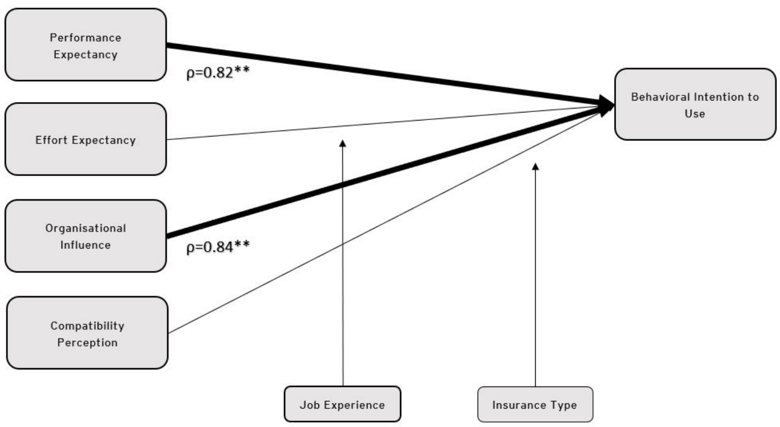

Figure 13: Theoretical framework for technology acceptance in insurance companies. Relationships that are supported by the analysis are bold. ρ gives the correlation coefficient. (** indicates significance with $p < 0.01$)

6.2 Interviews

6.2.1 Interview Partners

Table 2 gives the list of interview partners, their experience, and description of expertise.

Table 2: Expert Interview Partners

Interview Partner	**Experience (Years)**	**Description**
Person 1	40+ (Insurance)	Multiple (Manager / Director) roles at Dutch insurance companies
Person 2	5+ (Consulting)	Senior Manager in consulting with a focus on people management for technology implementations
Person 3	6+ (Insurance) / 1+ (Consulting)	Managerial role in the IT department of a Dutch insurance company / Technology consulting for financial services
Person 4	25+ (Insurance)	Director for IT-Operations at a German insurance company

6.2.2 Expert Interviews for Validity

The following section gives concise summaries of all interviews and a description of whether the expert confirms the findings, disagrees or provides further insights. This section focuses on validating the results. Questions regarding strategies are discussed in the subsequent section.

Person 1: Confirmation of Findings / Further Insights

As Person 1 is an insurance expert, the interview focused on emerging technologies and their applications in this sector. Person 1 agreed that the chosen technologies of artificial intelligence, blockchain, and the Internet of Things are relevant for the future of insurers. Person 1 noted that they have no personal experience with blockchain implementations but knowledge about other insurance companies, that aim at utilizing the technology, and that they believe it is a promising tool. Still, the expert noted that artificial intelligence is in an early phase and the industry needs to make improvements in AI performance for widespread implementation. Person 1 believes that the insurance industry is currently on a positive trajectory of utilizing technologies for process automation in underwriting and pricing. Improvements need to be made in process automation for claims management. Further insights were gained: Person 1 believes crucial technologies for insurers are low-code and no-code platforms. Additionally, they emphasized the importance of open platforms. These technologies also show significant implications regarding technology acceptance and are therefore further discussed in the following section.

Person 2: Confirmation / Further Insights

Person 2 is a professional in people consulting, which is an advisory service that focuses on the people's perspective of change within an organization. While Person 2 has previously worked on projects regarding changes in insurance companies, they have no specific background in financial services. The interview therefore centered around the theoretical framework and technology acceptance rather than industry-specific technologies. The focus lies on the outcomes of the survey and influencing factors. Person 2 could undermine the notion that performance expectations and organizational influence are indeed important considerations when implementing new technologies in an organization. Regarding performance expectancy, Person 2 described the importance of clearly communicating the goals of a transformation and the benefits employees can expect. Regarding organizational influence, Person 2 emphasized the importance of understanding your stakeholders and being flexible in how to approach implementations. Different stakeholder groups need different approaches. Important further insights regarding organizational influence were gained. Person 2 stressed the importance of prior experiences with implementations. If a company has a history of unsuccessful technology implementations, they believe it will negatively influence the acceptance of further innovations.

Person 3: Confirmation / (Further insights beyond the scope of thesis)
Person 3 is an expert in technology for the insurance industry, with experience in technology implementations. The interview consequentially centered around emerging technologies and their possible impact on the insurance industry. As the most promising technology, Person 3 mentioned the use of artificial intelligence in customer service. They further noted the importance of AI in claims handling and underwriting. Still, automation of processes proves to be more difficult in these areas. Person 3 further mentioned the importance of the Internet of Things, emphasizing the role IoT can play in preventing insurance cases, rather than aiding the claims process. The interviewee explained that they see blockchain implementations currently only in the reinsurance industry to circumvent brokers rather than the normal insurance industry. Regarding technology acceptance, Person 3 gave insights on how important it is to create an understanding of the technology. Besides merely providing the performance provided, an organization must lay out precisely how it works. Person 3 gave an example of how their organization faced issues with the acceptance of a calculation tool implemented in their actuarial department. Even though it was working reliably and accurately, the employees did not trust the risk calculations. After elaborating on the single steps of the tool, acceptance increased among their employees.

Person 4: Partial Confirmation
Person 4 is a professional in the insurance industry with expertise in IT systems. The interview focused on emerging technologies as well as their experience with IT implementations. Person 4 confirmed their knowledge about AI initiatives and projects that enable straight-through processing of insurance tasks. Further, recent shifts toward cloud computing were emphasized. Person 4 could neither confirm nor deny the potential impact of blockchain, as they were not aware of any projects in that direction. Throughout the interview, the expert emphasized the importance of change management to gain technology acceptance. It is important to bridge the gap between IT-savvy workers and the end-user. Providing training or tutorials can help with understanding new technology and may prevent rejection. Person 4 noted that they experience quite an open atmosphere regarding technological change within

their company, but see the insurance industry as a rather conservative sector. Data protection is important for insurers, which may favor traditional process handling over emerging technologies in some cases.

6.2.3 Interviews for Strategies

As described in the methodology section, a semi-structured interview approach is used to unveil what experts believe is important to increase the acceptance of emerging technologies in their field. First, transcripts of the interviews were created and then used to code the interviews openly. Further, axial coding was conducted to identify and connect overlapping ideas and concepts. The interview analysis resulted in 7 distinct codes that fall under the themes of *Performance Expectancy* and *Organisational Influence*. The following section will provide these codes, their frequency in parentheses, an explanation, and examples of how to leverage these concepts for improved technology acceptance. Analyzing the 4 interviews resulted in a total code frequency of 60 occurrences. An occurrence table can be found in Appendix D.

Performance Expectancy

Awareness of Technology (8)

Analyzing the interviews made it apparent that the lack of awareness of the technology and its benefits may factor into performance expectancy. The experts mentioned that while the word of innovations often travels fast and people are generally well informed of technologies such as AI or blockchain, awareness of their benefits is sometimes lacking. (Note: This discrepancy can also be undermined by comparing the level of *Performance Expectancy* of employees on the operational level with that of experts; the survey results are noticeably lower.)

To counter this phenomenon, the use of product champions was mentioned. A product champion may advocate for a certain technology. In the case of a planned implementation, this could result in enhanced visibility of the benefits the technology comes with.

Knowledge of Technology (17)

The expert interviews suggest that even if employees are aware of the technology and the benefits digital change can bring, it may not be enough. Insurance processes are often complex, for instance, the risk calculations of actuaries. Usually, the consequences are also quite impactful, for instance, claim approval or denial of health insurance. Employees are therefore inclined to understand how certain tools work, rather than just being able to apply the technology. They want to ensure that if a process is automated, it doesn't influence the quality. This stems from the importance of the processes.

Complexity Reduction (7)

The idea of *Complexity Reduction* could be found across the interviews and may be a strategy to create awareness, as well as understanding of emerging technology.

On one hand, low-code or no-code technologies can be implemented in companies. Low-code refers to software development through graphical interfaces rather than coding. These can help bridge the gap between the IT side and the insurance process side through easy engagement with technology. This lowers the barrier to innovation and creates visibility for technology. On the other hand, *Complexity Reduction* can help with understanding innovations better and therefore improve acceptance. By providing training or breakdowns on how tools are built, further knowledge may be created and understanding improved.

Organisational Influence

Understanding Stakeholders (8)

As seen previously, it is crucial to bridge the gap between the IT side of the business and the insurance side. A deciding factor in whether this is successful appears to be stakeholder understanding. To undergo a successful transition, companies need to understand the values of different employees. This appears especially important when looking at the variety of insurance processes. Aspects that are considered to be important can vastly differ between an automated claims process and an underwriting process. In order to understand what is crucial to individuals, personas can be drafted or stakeholders can be mapped. Personas refer to fictional characters that could be involved in the process, which entails distinct and varying characteristics. Using personas can increase the likelihood that project or change management respects all views of employees. Utilizing this strategy, technology implementations can be tailored to the employees and increase acceptance.

Flexibility (8)

Flexibility in change or project management is a characteristic of an organization that follows up on the necessity of understanding the stakeholders. There is not one approach that fits all. As said above, the important points between an automation initiative in risk calculation and customer service may differ for employees, and the management approaches should consequentially do too. One example of a strategy that was named to create flexibility is agile. Agile has proven to be useful in a variety of other industries, and as it encourages close collaborations with the users, it can help with understanding the employees better.

Trust (4)
Trust is a concept that appeared throughout the interviews, but is also commonly found in the literature regarding organizational influence. Trust needs to be established in the technology, as well as the company. Employees could be negatively influenced by previous projects that left a negative mark on implementations. As Frei and Morriss (2020) describe, trust must be built through authenticity, logic, and empathy. If an organization can implement these values into their transformation projects, acceptance of the technologies will increase.

Communication (8)
When asking the experts how to create a positive environment around *Organisational Influence* and how that can be leveraged to improve acceptance of digital change, communication appears to be central. Whether it is understanding stakeholders or building trust, open communication between stakeholder groups helps with alignment and supports the behavioral intention to use technology.

7 Conclusion and Discussion

The following section delves into the key findings, limitations, and conclusions of the study. While certain limitations may challenge the findings, they undermine why conclusions were drawn and also open new paths for interesting future research.

7.1 Findings of the Research

The contributions of this study go in various directions, which can be undermined by emphasizing how the research questions were addressed and answered. Research Question 1 aims to identify relevant emerging process automation technologies for the insurance sector. This was answered by analyzing relevant papers in the literature review. The findings are summarized and presented in Table 1 under Section 2.3.

The literature comprises ample benefits of BPA technologies in the realm of insurance. Technologies such as AI, blockchain, IoT, or cloud computing can help reduce human intervention in insurance processes, such as claims handling or underwriting (Lissy et al., 2023; Oza et al., 2020). For instance, RPAs can be equipped with features such as natural language processing or optical character recognition to handle an ever-growing number of claims (Kholiya et al., 2021). Still, technology implementations always entail risk, as digital change faces certain barriers. The authors mention the prevalent legacy of IT systems in insurance companies, business operations that are unsuitable for automation, or legal issues (Erk et al., 2020; Holland and Kavuri, 2021).

One barrier to technology implementation is the lack of acceptance by its users. This evolved as the research scope and led to the second research question: "What factors influence the behavioral intention of employees in the insurance sector to use digital innovations?"

This research question is answered, by first deriving a theoretical framework for technology acceptance in this context. The framework and related hypotheses can be found under Section 4. The framework was tested by surveying employees of insurance companies, which revealed the importance of *Performance Expectancy* and *Organisational Influence* when aiming for high *Behavioral Intention to Use* innovations for insurance processes. Finding these dependencies also constitutes the answer to the first part of the main research question.

Confirming these relationships is in line with expectations and the connected hypotheses postulated in Section 5.1.2. Other relationships could not be verified with confidence in this study. That may have different origins, such as the limitations of the survey, which will be discussed in the following section, or a missing correlation.

For instance, *Effort Expectancy* was hypothesized as a directly influencing variable but turned out to be non-significant. The expert interviews, in line with this, reveal that the workforce at the operational level appears to be interested in and generally open to technology change. This indicates a reason for such a non-significant finding: If employees are endeavoring the digital transformation of a company, effort might be less important than expected.

The third research question aims to uncover how the behavioral intention to use innovations varies across technologies and insurance processes. This could be answered by assessing the behavioral intention to use technology between different innovations and how they can be used. A statistical analysis that compared the different groups led to the conclusion that acceptance does not differ between technologies and applications.

This finding is a surprise, as using the same technology to perform varying tasks comes with different implications. For instance, applying AI to automatically calculate a risk score is different from using it to copy and paste data from one file to another. While this indifference can have various roots, one explanation might be a finding discussed in the following: Lacking awareness and knowledge of the technology. Without understanding exactly how a tool works and what it can be used for, acceptance might be less dependent on the technology and the point of application in the value chain.

The fourth research question, and the second part of the main research question, treats how the survey findings can be leveraged: Strategies insurance companies should adopt when implementing technology. This centers again around improving acceptance, specifically the key determinants *Performance Expectancy* and *Organisational Influence*, and was answered by conducting and coding expert interviews to find overlapping concepts and ideas of the professionals. Summaries of the interviews can be found in Section 6.2.2.

One focus area, identified through the expert interviews, is bridging the gap between technology experts and the workforce. This gap may originate from the lack of visibility or the overcomplexity of the technology. While not just the sheer fact of potential performance enhancement is necessary, the understanding of technology appears crucial as well. In that regard, multiple approaches and strategies could be identified, such as implementing product champions, offering training, or implementing low-code or no-code technology.

Regarding the organizational influence of a successful technology implementation, it became apparent that project and change management need to be flexible. It is important to understand your employees and adapt your approach according to the project and stakeholder groups. Techniques such as Agile can be used to facilitate flexible project management. Central to positive organizational influence is open and clear communication between all stakeholder groups.

7.2 Further Insights and Deliverables

The previous section discusses some of the contributions this research makes, by answering the research questions. Still, there are additional findings that have managerial implications, as well as academic value. This section delves into additional findings of the research and how the findings contribute to academia as well as the professional world.

Comparing the beliefs of employees on an operational level and experts in that field reveals an interesting discrepancy. On average, employees are neutral or somewhat in agreement with the performance-enhancing potential of artificial intelligence, blockchain, or IoT. This is a rather moderate performance expectancy compared to the experts, who showed stronger positive beliefs about the potential these tools hold. This discrepancy between the beliefs of experts and employees could also be observed in *Organisational Influence*. For instance, the survey showed that the fear of being replaced by automation tools indeed exists amongst the participants; the experts, on the other hand, agreed that the implementation of these tools is on the macro-level, leading to restructuring of roles rather than replacement. As this fear is justified and rational, especially on an individual level, it is important to have an aligned view of digital change and how it will impact the organization.

As this directly relates to the strategies derived earlier, it is recommended for organizations to bridge the knowledge gap between experts and the workforce. Create an understanding of the employees that are supposed to work with the tools, unveil what is important to them, and communicate the benefits the implementation of a tool will bring.

Another finding that evolved throughout the research, although not central to the research question, is the understanding of performance expectancy. It became apparent that when researching technology acceptance in this context, it is not just relevant to create visibility of the performance, hence productivity or efficiency gains, but also an understanding of how these improvements are achieved. When automating complex and highly significant processes, such as underwriting, employees take pride in the accuracy, reliability, and justification of their work, as some level of autonomy and control is taken over by the tool.

Incorporating AI, machine learning, and big data analytics into automated workflows often results in a diminished understanding of underlying processes, despite being integral to BPA. It's not just about approving or denying coverage; there's a need to comprehend the reasoning behind these decisions.

This observation is likely applicable to similar situations. The findings suggest that when applying the UTAUT model to comparable automation contexts, it's not only the sheer *Performance Expectancy* that matters but also an understanding of how this performance is achieved. In essence, understanding how processes are automated is crucial.

7.3 Limitations

One limitation of this study stems from the number of participants in the survey and its potential impact on generalizability. The number of participants included in the study may raise concerns about the external validity of the findings. The sample size, while providing valuable insights, might not be representative of the broader population of insurance employees, thereby limiting the generalizability of the study's conclusions. Additionally, it is crucial to note that a majority of respondents in the study originate from small and medium enterprises (SMEs). This introduces a potential limitation, as in the context of technological change, employees of multinational corporations might be more actively involved earlier in the process. The skew towards SMEs in the participant pool may impact the generalizability of findings to larger organizations. Future research could consider expanding the participant pool to ensure a more diverse and inclusive representation, enhancing the external validity of the study, and strengthening the applicability of its outcomes to a wider range of contexts.

In addition, it is necessary to acknowledge that some relationships within the theoretical model, particularly those involving moderating effects, could not be statistically confirmed in this study. It is crucial to interpret these non-significant findings with caution, as they do not necessarily imply the absence of these relationships but could be due to the small sample size. The study's constraints may have impacted the ability to detect the dependencies. Thus, the unproven relationships underscore the need for further research with larger and more diverse samples to better understand the potential moderating influences within the proposed theoretical framework. Future research could expand the sample size to enhance statistical power and give a more comprehensive understanding.

The study encountered further challenges related to construct validity, as the results of the confirmatory factor analysis (CFA) were not entirely satisfactory. Several factors may contribute to this limitation. Firstly, the sample size also plays a crucial factor here, influencing the CFA outcomes. The second factor might be the broad nature of the survey questions, covering multiple technologies. The study aimed to discover the acceptance of emerging technologies. To avoid a bias towards a certain technology, multiple innovations were included in the survey. This inclusivity resulted in different technologies being used to measure the same latent factor, introducing variability in responses and potentially diminishing the expected high correlations between items.

Lastly, the issue of potential cross-loadings became evident, especially concerning the latent factor of *Compatibility Perception*. This factor was incorporated based on its significance in the technology acceptance literature when evaluating automation technologies (Ghazizadeh et al., 2012; Agarwal and Karahanna, 1998). The concept of compatibility in technology acceptance can go in various directions, while the focus of this research lies on the compatibility of values and technology, as defined by Karahanna et al. (2006). In essence, this factor describes whether a person believes a technology is appropriate to perform a certain task. While the belief in compatibility could be important, it may not have been sufficiently distinguished from other variables. Its conceptual overlap with *Behavioral Intention to Use* and *Performance Expectancy* may have introduced challenges in ensuring clear discriminant validity.

These complexities highlight the need for nuanced refinement in future studies, including the consideration of more specific survey items and a better examination of construct boundaries to enhance the overall validity of the measurement model.

Another limitation might be predictive validity. The assumption that current employees' views predict future workforce dynamics may be limited, given potential technological shifts leading to workforce restructuring or the need for specialized skills. The opinions of participants, if not directly engaged with future technologies, might lack relevance.

7.4 Further Research

Apart from further research that could cope with limitations, the study also opens interesting paths for additional investigations. One interesting endeavor could be the research of how the behavioral intention to use technology in insurance companies translates to actual usage behavior. The dependence of both factors can be expected in this context since multiple studies confirm the relationship between behavioral intention to use and actual usage (Kuo and Yen, 2009). Still, confirmatory research may strengthen this assumption. This investigation could especially prove valuable, as this study context describes a work setting, where the usage of technologies is usually mandated. As Ghazizadeh et al. (2012) describes, technology rejection in work environments translates to delay, under-utilization, or obstruction of implementations rather than deliberately not choosing an innovation. There are a variety of valuable papers on technology acceptance and organizational settings. For instance, Wang (2016) researched the acceptance of e-learning amongst an organization's employees. Still, these settings differ from a wide array of other research regarding the TAM or UTAUT. Additional investigations, therefore, seem valuable and relevant.

Another interesting future research direction appears to be fairness and trust regarding emerging technologies and automating certain insurance processes. This links to the findings discussed in the previous section: When researching technology acceptance regarding the automation of work processes, sheer knowledge of performance might not be enough. Technology must reliably create fair and trustable outcomes. This thesis aimed at capturing the values of employees and whether they think it is appropriate to automate certain processes by the latent factor *Compatibility Perception*. It could not be significantly proven by the survey (only when omitting NA data). Still, an example given by Person 3 during the interview showed that it may be relevant and influential. They gave an example of a tool that would automatically calculate risk scores. The employees did not trust the calculations until the process was broken down and they could understand how the tool worked. As this negatively influenced the technology acceptance, fairness and trust may therefore be relevant for the behavioral intention to use a tool.

This exceeds the technology acceptance of employees and extends to the customer. As artificial intelligence is used to decide whether to grant or deny insurance coverage, or houses are 24/7 under surveillance by IoT devices to prevent burglary, it may become relevant to investigate if customers accept this type of automation.

7.5 Conclusion

In summary, this research delved into the technology acceptance of employees within insurance companies, specifically exploring the realm of emerging technologies designed to automate processes. By identifying and analyzing the key influencing factors *Performance Expectancy* and *Organizational Influence*, this study aimed to enhance the understanding of the human-centric aspects of technology adoption in this context. The strategies proposed for improving future implementations emphasize the importance of aligning technological advancements with employees' performance expectations and considering the organizational context. This research not only contributes valuable insights into the current landscape but also sets the stage for further investigations within the insurance sector and other workplaces.

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A Questionnaire Items

1. **Performance Expectancy**

   (a) I believe that Artificial Intelligence and Big Data have the potential to significantly enhance my productivity in claim handling, through features such as Natural Language Processing or Optical Character Recognition (e.g., a picture of car damage can be uploaded and analyzed by software to automate a car insurance claim). (0=Strongly Disagree to 7=Strongly Agree)

   (b) I expect that IoT (Internet of Things) can streamline existing claim processes significantly (e.g., an insurance company gets automatically notified with relevant data after a car crash). (0=Strongly Disagree to 7=Strongly Agree)

   (c) I foresee that Artificial Intelligence and Big Data can enable an automated underwriting process and successfully assess the risk of insuring an object or person. (0=Strongly Disagree to 7=Strongly Agree)

   (d) I foresee that Blockchain will be a useful addition to further automate insurance processes (e.g., automated pricing decisions are calculated by using information stored on the Blockchain). (0=Strongly Disagree to 7=Strongly Agree)

   (e) I believe that IoT (Internet of Things) is useful for automated underwriting processes (e.g., a smartwatch collects customer data to automatically calculate the pricing of health insurance premiums). (0=Strongly Disagree to 7=Strongly Agree)

   (f) I am assured that Artificial Intelligence can greatly improve the customer service experience by automating routine inquiries and allowing human agents to focus on more complex customer needs (e.g., an AI system could instantly process and address common questions about policy details or claim status). (0=Strongly Disagree to 7=Strongly Agree)

2. **Effort Expectancy**

   (a) I believe that the integration of AI into my workflows will be difficult (e.g., working alongside an AI-based RPA that automates some tasks will prove difficult for me). (0=Strongly Disagree to 7=Strongly Agree)

   (b) I am of the view that incorporating Blockchain into our insurance processes will disturb established routines and will require significant adjustments (e.g., utilizing smart contracts for immediate verification and settlement of claims will not be easy to understand). (0=Strongly Disagree to 7=Strongly Agree)

(c) I think that the integration of IoT devices and the usage of data acquired through IoT devices will complicate our processes (e.g., using data from a smartwatch to calculate health insurance premiums). (0=Strongly Disagree to 7=Strongly Agree)

(d) I anticipate that integrating AI into the underwriting process will be challenging for me (e.g., working with AI systems that evaluate and score risk factors, thereby supporting the decision-making process for approving or denying coverage). (0=Strongly Disagree to 7=Strongly Agree)

(e) I believe working alongside Artificial Intelligence for automated customer contact, like chat-bots, will be difficult for me (e.g., taking over a service process that is already partly managed by a chat-bot). (0=Strongly Disagree to 7=Strongly Agree)

3. **Organizational Influence**

(a) I feel supported to work with emerging technologies in my role (e.g., receiving relevant training to get to know digital tools). (0=Strongly Disagree to 7=Strongly Agree)

(b) The work atmosphere in our organization fosters a sense of reassurance that the adoption of Artificial Intelligence is intended to complement and enrich our tasks, rather than being a replacement for our roles. (0=Strongly Disagree to 7=Strongly Agree)

(c) My colleagues believe that integrating Artificial Intelligence into insurance processes is a good practice. (0=Strongly Disagree to 7=Strongly Agree)

(d) My peers encourage the implementation of Blockchain within our organization. (0=Strongly Disagree to 7=Strongly Agree)

(e) My work environment feels positive about utilizing IoT (Internet of Things) for insurance tasks. (0=Strongly Disagree to 7=Strongly Agree)

4. **Compatibility Perception**

(a) I think Artificial Intelligence and Big Data should be used to streamline claim handling processes (e.g., extracting customer information and inserting it into the right forms). (0=Strongly Disagree to 7=Strongly Agree)

(b) I believe Blockchain should be implemented in insurance processes (e.g., storing and validating necessary customer data on the Blockchain). (0=Strongly Disagree to 7=Strongly Agree)

(c) I believe that IoT (Internet of Things) devices should be used to enhance the automation of claim management (e.g., employing IoT sensors in vehicles to automatically alert insurers in the event of an accident, thereby initiating the claim process more efficiently). (0=Strongly Disagree to 7=Strongly Agree)

(d) I think using Artificial Intelligence is appropriate for automating the underwriting process, particularly in evaluating the risks associated with insuring individuals or objects (e.g., leveraging AI algorithms and big data analytics to accurately determine risk profiles, thereby streamlining the underwriting decision-making process). (0=Strongly Disagree to 7=Strongly Agree)

(e) I feel that IoT devices should be used for underwriting purposes (e.g., using data from smartwatches to assess individual health risks for insurance premium calculations). (0=Strongly Disagree to 7=Strongly Agree)

(f) Artificial Intelligence should be used for customer contact (e.g., utilizing AI systems to offer advice in choosing insurance products or chatbots for customer service). (0=Strongly Disagree to 7=Strongly Agree)

5. **Behavioral Intention to Use**

(a) If given the choice, I'd like to work with Artificial Intelligence to further automate claim-handling processes in the future. (0=Strongly Disagree to 7=Strongly Agree)

(b) Given the option, I would choose to integrate Blockchain technology into our processes. (0=Strongly Disagree to 7=Strongly Agree)

(c) I am in favor of adopting IoT (Internet of Things) devices in claim handling to streamline the process (e.g., through an automated claim notification in case of a car incident). (0=Strongly Disagree to 7=Strongly Agree)

(d) I am looking forward to the possibility of automating underwriting processes by leveraging Artificial Intelligence and would like to integrate it into my work (e.g., using Artificial Intelligence to assess the risk of insuring a person or object). (0=Strongly Disagree to 7=Strongly Agree)

(e) If given the choice, I'd choose to implement IoT (Internet of Things) devices to support automated underwriting (e.g., using data from a smartwatch to calculate health insurance pricing) (0=Strongly Disagree to 7=Strongly Agree)

(f) I am in favor of working with Artificial Intelligence to enhance customer interactions (For example, automated insurance advise via Chat-bot) (0=Strongly Disagree to 7=Strongly Agree)

B Factor Loadings

Table 3: Standardized Factor Loadings

Question	PE	EE	OI	CP	BI
1a	0.64	0	0	0	0
1b	0.70	0	0	0	0
1c	0.40	0	0	0	0
1d	0.44	0	0	0	0
1e	0.54	0	0	0	0
1f	0.80	0	0	0	0
2a	0	0.50	0	0	0
2b	0	0.76	0	0	0
2c	0	0.56	0	0	0
2d	0	0.26	0	0	0
2e	0	0.64	0	0	0
3a	0	0	0.57	0	0
3b	0	0	0.83	0	0
3c	0	0	0.43	0	0
3d	0	0	0.34	0	0
3e	0	0	0.51	0	0
4a	0	0	0	0.23	0
4b	0	0	0	0.32	0
4c	0	0	0	0.14	0
4d	0	0	0	0.18	0
4e	0	0	0	0.38	0
4f	0	0	0	0.42	0
5a	0	0	0	0	0.67
5b	0	0	0	0	0.80
5c	0	0	0	0	0.20
5d	0	0	0	0	0.63
5e	0	0	0	0	0.45
5f	0	0	0	0	0.44

C Correlation Matrix

Correlations

			Performance_Expectancy	Effort_Expectancy	Organisational_Influence	Compatibility_Perception	Behavioral_Intention
Spearman's rho	Performance_Expectancy	Correlation Coefficient	--				
		Sig. (1-tailed)	.				
		N	16				
	Effort_Expectancy	Correlation Coefficient	-,392	--			
		Sig. (1-tailed)	,066	.			
		N	16	16			
	Organisational_Influence	Correlation Coefficient	,686**	-,436*	--		
		Sig. (1-tailed)	,002	,046	.		
		N	16	16	16		
	Compatibility_Perception	Correlation Coefficient	,682**	-,051	,675**	--	
		Sig. (1-tailed)	,002	,426	,002	.	
		N	16	16	16	16	
	Behavioral_Intention	Correlation Coefficient	,746**	-,146	,731**	,561*	--
		Sig. (1-tailed)	<,001	,294	<,001	,012	.
		N	16	16	16	16	16

**. Correlation is significant at the 0.01 level (1-tailed).

*. Correlation is significant at the 0.05 level (1-tailed).

Figure 14: Spearman's ρ correlation matrix (omitting all participants that have one or more NA data entries)

D Code Occurrence Table

	3: Person 2 20	4: Person 1 14	5: Person 3 14	6: Person 4 11	Totals
Awareness 8	3	3	1	1	8
Communi... 8	5	1	1	1	8
Complexit... 7		2	2	3	7
Flexibility 8	4	2	1	1	8
Knowledg... 17	6	6	2	3	17
Trust 4			2	2	4
Understan... 8	7		1		8
Totals	25	14	10	11	60

Figure 15: Code Occurance Table of the Interviews