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How do Customers of Financial Institutions Perceive the (potential) use of Conversational Agents in Customer Service, and how does this affect their trust in the Company?

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Abstract

This thesis examines how customers of financial institutions perceive the (potential) use of conversational agents in customer service, as well as how its use affects their trust in the company and their willingness to adopt such technologies.

Conversational agents are increasingly being implemented in the banking sector. For this reason, there is an increasing understanding of what motivates customers to accept these technologies, particularly as banks are in a trust-sensitive industry. Much of the exisiting literature has mainly focused on technology acceptance in an overall context. However, a lack of examination exists within this topic in the banking sector, especially regarding psychological and relational factors such as trust.

For this reason, a quantitative survey with 228 participants was conducted, with the majority being from Germany and the United States. Results of the survey were analyzed using descriptive statistics, correlation analysis, simple linear regression, and independent-samples t-tests.

The conclusion showed moderate overall willingness to use conversational agents in banks, while hybrid service models combining these tools with human agents ended up with the highest approval. On the other hand, psychological variables, such as general attitudes toward AI and perceived empathy, had a notable influence upon the intention to use conversational agents. Certain demographic variables, such as nationality, seemed to have a limited impact on willingness to use conversational agents. Age however, did show impact.

The findings indicate that a successful implementation of conversational agents depends primarily on customer trust and emotional responsiveness, while technological efficiency alone not being a strong motivator. Future research should focus on real-life behavioral data and a broader sample to further validate these findings.

Key words: Conversational Agents, Trust, Financial Institution, Artificial Intelligence, Banking Industry, Customer Relationship Management

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List of Abbreviations

CRM: Customer Relationship Management

AI: Artificial Intelligence

CA:	Conversational Agent
MIS:	Management Information Systems
RPA:	Robotic Process Automation
VA:	Voice assistant/ Voice agent
TAM:	Technology Acceptance Model
UTAUT:	Unified Theory of Acceptance and Use of Technology

1. Introduction

1.1 Background

Customer Relationship Management (CRM) is an approach by companies or organizations in which they strategically focus on collecting, managing, and intelligently using its customer data. In addition, technology will help with building long-term relationships and further improve customer experience (Ledro, Nosella & Pozza, 2023, p.1). This in turn can lead to gaining a competitive advantage (Ledro, Nosella & Vinellin, 2022, p.48). CRM can be divided into three different areas: Marketing, Sales and Service/Support (Woo, Yoo & Park, 2024, p.4).

This also applies to Banks, as according to Singh (2022, p.179), CRM is a vital part for focusing "in their banking practices, strategy mechanisms and the relevant suitable technologies adopted to control and manage data for different customers with a view to improve the overall business relationships with customers through meeting the requirements of the customers for better operational efficiency". In the end, when done properly CRM in banks should lead to a notable affect and long-term benefits in the bank's performance and operational efficiency.

As technology advances and other non-bank players, such as FinTech firms, are entering the market, the banking industry sees the need to evolve its strategic approach, letting go of traditional approaches (Singh, 2022, p.184). In addition, Banks have faced significant operational costs and challenges, due to human error and large volumes of paperwork (Singh, 2022, p.192). Now, artificial intelligence (AI) technologies are being used by traditional banks, resulting in improvements, such as better customer engagement, accelerating innovations and improved business intelligence, resulting in massive cost reductions (Singh, 2022, p.179). Through the use of digital platforms and severe competition, banks aim to give customers efficient and qualitative services, becoming a top priority in the everyday business. Also, by using automated assistants, banks can move their workers on to higher-value activities (Singh, 2022, p.193).

This includes the use of AI conversational agents (CA), as seen with the Bank of America. In 2018, the bank launched its AI-driven virtual assistant Erica, helping its customers "with money transfers, bill payments and other mobile operations" (Reuters, 2024). As of April 2024, over 42 million customers have used the assistant 2 billion times. In Germany, the Commerzbank launched its virtual-assistant Ava in 2025 (Commerzbank, 2025). Conversational agents are digital systems that interact with users via graphical or voice-based interfaces (Prinz, 2022, p.21).

There are different categories of conversational agents for companies to choose from. In customer service, chatbots are the most prevalent agents for organizations. A chatbot can be described as "an artificially intelligent chat agent that simulates human-like conversation, for example, by allowing users to type questions and, in return, generating meaningful answers to those questions (Prinz, 2022, p. 2)", helping companies with tasks regarding communication, such as service requests. Then there are voice agents, which are being used most commonly by smartphones and other smart devices, such as Siri by Apple or Amazon's Alexa (Prinz, 2022, p.20). Lastly, there are virtual avatar assistants, like the one Microsoft is planning to launch, which is an AI assistant with a virtual body or face that their users can interact with (Windows Central, 2025).

Due to all these options in technology, customers of banks have the increased potential of having a pleasant experience with regard to to customer service, such as 24/7 service or not having to experience long wait times, or be on hold as employees of the bank manually look up information while trying to resolve many of the client's needs. Now, customer service can be simplified and automated to solve the needs of the bank's clients.

For clarification, this paper focuses on conversational agents in general and not only the one powered by AI (artificial intelligence), as many companies still use rule-based virtual assistants (AI vs rule-based will be explained later).

1.2 Relevance

A bank can only succeed in business, if it takes customer relationship management seriously and ensures clients an excellent experience, which in turn will create customer loyalty (Singh, 2022, p.197). Unlike in many other industries, banks rely on long lasting relationships with their clients. With the availability of AI, banks can make better decisions while also strengthening their behavior analysis of customers. Simultaneously, AI is able to provide clients access to core banking systems, while responding at a faster pace, without the need of an actual bank representative (Singh, 2022, p.190). According to a study by

Kim, Jindabot & Yeo in 2024 (p.10), trust significantly influenced bank customer loyalty so much so that by achieving certain levels of trust, customers are willing to invest their money even with some risk involved. Trust is the primary basis for establishing a relationship between clients and banks, hence it is vital to increase customer trust to promote high customer loyalty. In addition, technology in customer service can positively influence customer loyalty, if the technology being used is considered useful (Kim, Jindabot & Yeo, 2024, p.11). The purpose of this paper is to determine, how customers of banks will perceive the implementation of conversational agents, especially as many regard AI in general with concern (Kennedy, Yam, Kikuchi, Pula & Fuentes, 2025). This is especially true in a time, in which conversational agents are being implemented in the service sector more than ever. For example, already in 2017, there were 34,000 chatbots alone active on Facebook, "increasing to more than 300,000 one year later in 2018" (Prinz, 2022, p.2).

How will implementing conversational agents affect the clients' trust in a bank? How will it affect loyalty? How does it affect the perceived empathy towards those agents and do customers feel that their privacy is being respected?

1.3 Research Problem

The rise in use of CAs in the customer service is undeniable, including in the banking sector. However, it still remains unclear how customers truly perceive the use of these specific technologies regarding customer service. As for now, banks are trying to present the implementation of CAs (conversational agents) as an innovational support tool that is efficient for customers and company (see chapter 1.1). Meanwhile, the perspective of the client is rather absent, especially regarding the usage of CAs in the banking sector. Customers may have expectations that go beyond speed and availability. As mentioned above, trust is a key factor for customer service, while simultaneously, the use of AI (plays major role with CAs) is slanted more in a negative light. Maybe customers would be content with a balance between streamlined innovation and human contact, who is able to give emotional reassurance, a perceived competence, and the feeling of being understood. Clients could possibly prefer human agents dealing with their important and sensitive issues compared to a CA.

Therefore, it is still unknown how customers of banks feel about conversational agents, even if they have the capacity to provide the same level of quality or empathy compared to their human counterpart. The main questions are, if these digital agents are able to fulfill the requirements regarding satisfaction, trust, and perceived security, will customers remain loyal to their bank, although the traditional way of interacting with humans has diminished or been eliminated. Looking at the perspective of the customer becomes an important topic, because their view may determine whether these CAs will become a relevant addition of customer relationship management or a factor for dissatisfaction.

1.4 Gap in Literature

While literature on CAs and especially AI is expanding, information on the usage of these digitized agents in the banking system is scarce. There is a large variety on the general use of CAs, even CRM included. But these studies are either too general or focus on different industries. While some information from these other industries is comparable, the banking system is unique in having to maintain trust from the customer and handling sensitive financial information (Ali, Murray, Al-Ahmad, Jeon and Dwivedi, 2025, p.9). On the other hand, other industries with a good amount of information, such as retail or e-commerce, are too general. In conclusion, the literature on other sectors cannot be applied directly to the banking sector.

Worth mentioning is that there is information on CRM in the banking system, but mainly without the focus on the usage of CAs. There is literature on the implementation of AI in CRM in banks, however, they seem to generalize the use of these technologies without a focus on CAs. There is no information on the perspective of customers in regards to empathy, trust, usefulness, satisfaction, and safety relating to the use of CAs by banks. In addition, this literature seems to promote the usage of AI in a very positive light without looking at potential drawbacks.

Lastly, there is an absence of the perspective by gender, age or culture and nationality. The possibility of these factors changing the viewpoint on CAs is not insignificant. Therefore, there is a chance that existing literature is overlooking relevant aspects of customers' attitudes.

1.5 Research Objective

The main objective of this paper is to determine how customers perceive conversational agents, especially regarding to customer service, and specifically, in the banking sector. As financial institutions heavily depend on trust, reliability and personal reassurance by the client, it is important to understand how customers evaluate the increased implementation of automated systems such as chatbots, voice-assistants or virtual avatars. Therefore, this study does not only focus on the general outlook on CAs, but how the perceptions will influence factors such as reassurance, perceived safety, trust, satisfaction and the choice to continue interacting with these technologies and companies employing them.

Another goal of this research is to investigate, if perceptions differ between specific demographic groups since this kind of information seems to be lacking in current literature. The survey asks participants about their age, gender and nationality, as these factors could possibly shape a different view on conversational agents. By implementing a cross-demographic comparison, this study will be able to analyze the potential differences between the groups, regarding CAs in the banking industry. In regards to nationality, I will mainly focus on the differences between Germany and the United States of America, as I am a citizen of both these nations and this is where I am conducting my survey.

The aim of this paper is to find answers that could possibly support banks in evaluating and improving their CRM strategies. By analyzing clients expectations, concerns, and acceptance levels, the answers of this study could give insights on conversational agents and whether they are tools that banks can complement traditional human service. As a result, the goal is to examine if CAs are efficiency-enhancing tools for routine tasks, while also maintaining or even improving customer trust and loyalty

1.6 Research Questions & Hypotheses

As mentioned above, this study is based on customers' perspective on conversational agents, especially in regards to their usage in customer relationship management in the banking sector in combination with the relevance of trust in their bank. Furthermore, an additional goal is to address gaps in the current literature. The main research question of this investigation is described and broken down below.

Main Question

How do customers of financial institutions perceive the (potential) use of conversational agents in customer service, and how does this perception affect their trust in the company?

To answer this question fully, ten hypotheses were formulated by extracting information from existing literature on customer experience, technology acceptance, trust, AI-communication tools and conversational agents.

The hypotheses can be grouped into four categories:

Experience-Based and Attitudinal Predictors of Conversational Agent Acceptance

H1: Customers with previous experience using conversational agents in other industries show higher intention to use conversational agents in banking.

H2: Respondents who feel indifferently towards interacting with AI will show a higher willingness to use conversational agents in banking.

H3: Respondents with higher empathy-based trust in conversational agents will show a greater willingness to use them for complex or sensitive banking issues.

Demographic Differences in Conversational Agent Perception

H4: Younger respondents (<30) will perceive conversational agents as more useful than older respondents.

H5: Males will perceive conversational agents as being more useful than females.

H6: Older respondents (>50) will express stronger privacy and security concerns regarding conversational agents in banking compared to younger respondents.

H7: German respondents will exhibit stronger privacy and security concerns toward conversational agents in banking than US respondents.

H8: Customers in the United States will demonstrate a higher willingness to adopt conversational agents in banking than customers in Germany.

Interaction Preferences and Conversational Agent Type

H9: Most customers will prefer a combination of Conversational Agents and human interaction in the banking industry.

H10: Customers will show different levels of preference among conversational agent types (chatbots, voice assistants, and virtual agents), with voice assistants expected to score highest in perceived naturalness.

Trust, Satisfaction, and Loyalty Outcomes

H11: Dissatisfaction with conversational agents will not significantly reduce overall customer loyalty toward their bank.

H12: Respondents who perceive conversational agents as more empathetic will report higher levels of customer service satisfaction.

With these hypotheses, we will be able to analyze the relationships between behavioral intentions, customer perceptions, demographics, emotional factors, privacy concerns and trust. This will provide us a full understanding of the factors, regarding customer acceptance of CAs in banking and insights for implementing effective CRM strategies.

1.7 Structure of the Thesis

This thesis is structured into 6 chapters.

After the Introduction, Chapter 2 focuses on the theoretical backround and literature review, such as exisiting studies. It presents the definition and evolution of Customer Relationship Management, as well as the integration of artificial intelligence into CRM systems, including the benefits, risks, and challenges that come with it. In addition, a thorough analysis of conversational agents is provided, along with an introduction to technology acceptance models. These topics are also then looked at from the perspective of the banking industry. Furthermore, trust formation, privacy concerns, and customer experience outcomes are also discussed.

The focal point of chapter 3 is the methodology used for this study. It goes into detail of research design, literature review method, conceptual framework and hypothesis development, survey design and measurement, sample and data collection, data analysis method as well as ethical considerations.

Next, chapter 4 dives into the results of the survey, presenting sample characteristics, descriptive statistics of the sample and hypothesis testing, which used correlation analyses that are applied, regression analysis, and group comparisons.

Chapter 5 discusses the results in combination with the theoretical background and literature review, followed by theoretical and practical implications. Finally, limitations of the study and suggestions for future research are discussed.

Lastly, Chapter 6 provides conclusive statements, which summarize the main findings of the study and provides an overall assessment of conversational agent adoption in the banking context.

2 Literature Review/ Theoretical Framework

In this chapter, we will go through all the relevant theoretical background materials of this study. The insights from this chapter are the foundation for the hypotheses that will be presented in chapter 3.

2.1 Customer Relationship Management (CRM)

2.1.1 Definition and Historical Developement

Customer Relationship Management is a system that is technology-supported and simultaneously customer-oriented. The main goal is to balance the satisfaction of the customer needs and the company's investments in the relationship between the organization and the client. Customer loyalty programs, customer service and customer information management are all examples that can be used in CRM (Swoboda & Schramm-Klein, 2025, p.191). Generally, CRM "can be considered as the improvement, innovation, or transformation measures taken by enterprises to enhance their core competitiveness in areas such as marketing, sales, services, channels, and customer management" (Yang, 2025, p.vii). With CRM, a better understanding of customers, their lifestyles and their needs can be developed. In recent years, CRM has progressed from being predominantly a data collection tool to becoming an organization-wide, process- integrated framework, supporting all stages of the customer relationship process. The focus on sustaining customer relationships, has been relevant for years, especially due to the digital and personalized targeting of customers (Swoboda & Schramm-Klein, 2025, p.187).

This is seen more in terms of retention, as opposed to acquiring new customers, due to the fact it has been known from findings in the 1990s that long-term customer relationships are more profitable than short-term ones. Increased purchase frequency and higher revenues are a result from customer loyalty, stemming from lower operating costs, referrals and price premiums (Swoboda & Schramm-Klein, 2025, p.189). As a consequence of this theory, companies started using CRM in the late 1990s and early 2000s to achieve a competitive advantage (Singh, 2022, p.56), part of an overall strategy to acknowledge the changing desires of customers, with the purpose to reduce the market cost by enhancing revenues and improving customer retention. By 2003, 78 percent of respondents of a study claimed to be employing CRM systems, a 43% increase from the year 2000 (Rigby, 2003, p.6-7), highlighting an apparent trend of companies relying on these systems.

The evolution of what CRM has become today is based upon the emergence of management information systems (MIS), a development that has taken decades to occur (Rajola, 2013, p.29). Initially, MIS began to provide internal data for planning and control, followed by Decision Support Systems and Executive Information Systems to support increasingly complex decision-making. However, issues started to arise, as these early tools were not optimally integrated with the operational systems, causing data alignment issues, and making analysis unreliable (Rajola, 2013, p.30). However, technological advancements were made, as client/server architecture, data warehouses and data mining leading to stronger integration and more automated decision support (Rajola, 2013, p.30-31). Finally, the growth of internet usage and increased competition, organizations started focusing on having a solution that could manage and automate interactions with clients efficiently, creating a base for modern CRM (Rajola, 2013, p.32).

All this considered, CRM has also developed from being purely a collection point for customer data to a company-wide and process-integrated support for the whole customer relationship process (Auge-Dickhut, Koye and Liebetrau, 2016, p.xvi). In addition, CRM systems have the ability to "enable communication across channels and the management of the preferences, behavior and interactions of customers (Auge-Dickhut, Koye and Liebetrau, 2016, p.80)," creating the concept of omnichannels. Omnichannel service is a business strategy, providing customers the optimal experience with a company across all channels, including in store, mobile and online (Oracle, 2025), giving companies the option to connect with customers in new ways (Singh, 2022, p.57).

With the occurrence of the pandemic and the establishment in general of digital age, the need for companies to engage with customers in new ways and to better understand their needs and desires became more important (Singh, 2022, p.56). In this new age, CRM is expected to evolve from reactive problem-solving in sales and services toward proactive prevention and real-time correction (Yang, 2025, p.16). To enable this, CRM systems progressively integrate modern technologies such as AI, the Internet of Things, edge computing and cloud computing.

In summary, over time, CRM moved from purely managing customers towards establishing long-term customer relationships were retaining existing clients has become ever more important (Swoboda & Schramm-Klein, 2025, p.187). CRM then began to go beyond standardized approaches and moved toward a targeted customer interaction (Swoboda & Schramm-Klein, 2025, p.187), while simultaneously driving innovation across marketing, sales, services, channels, and customer management (Yang, 2025, p.vii). Long-term loyalty being a value for a company, Customer Lifetime Value (CLV) has become a major metric guiding CRM strategies (Swoboda & Schramm-Klein, 2025, p.189). As a result, modern CRM focuses on maintaining long-term customer relationships, since it generates higher profitability than short-term ones (Swoboda & Schramm-Klein, 2025, p.187).

2.1.2 CRM in the Banking Sector

CRM is a crucial tool in the banking industry, since financial services need to be trust-based (Kim, Jindabot & Yeo, 2024, p.10), while at the same time their services are less tangible than more typical products and services. (Auge-Dickhut, Koye and Liebetrau, 2016, p.57). Simultaneously, new digital competitors are entering the market, offering more user-friendly services and increasing market competition (Auge-Dickhut, Koye and Liebetrau, 2016, p.21). The sector is expecially competitive since customers can easily switch providers when not satisfied with a current service. Additionally, due to the availability of the internet, clients have the opportunity to better inform themselves when select the best providers (Auge-Dickhut, Koye and Liebetrau, 2016, p.112).

Since customers require personal guidance, banks must solve the complexity of supporting the customers intensive need for advice and integration (Auge-Dickhut, Koye and Liebetrau, 2016, p.58), proving once again the importance of a trust-based relationship between a bank and its customers. Furthermore, another reason why CRM is so critical in the banking sector is that most profits come from a relatively small share of loyal customers (Rajola, 2013, pp.40–41). Acquiring new clients is up to five times more expensive compared to servicing existing customers. As a result, banks must build customer-centered models to survive in an evolving market (Auge-Dickhut, Koye and Liebetrau, 2016, p.xi).

As mentioned before, financial services are segmented as a trust-dependent industry. Creating long-term value for customers is a must, as this is what they will be measured by accordingly (Auge-Dickhut, Koye and Liebetrau, 2016, p.113). Consequently, customer loyalty directly influences profitability, as long-term clients increase the Customer Lifetime Value over time, making the company more profitable (Swoboda & Schramm-Klein, 2025, p.189). In combination with new forms of competition giving customers more options, CRM is important for maintaining long-term relationships (Rajola, 2013, p.41). For this to be achieved, banks need to support customers continuously across all communication channels, to make services more predictable and efficient. (Rajola, 2013, p.42). For CRM to function, it is essential for banks to centralize all customer data, such as past transactions. In addition, external information needs an integration with the internal data, through a "centralized archive". This data is being extracted by interacting with customers through communication channels. The enhanced data analysis should be distributed throughout the organization and customer profile information other core systems. As a result, banks are able to make sophisticated analysis, with a greater chance of fulfilling their goal in increasing a loyal client base. This demonstrates that banks personalizing their communication is essential for the course of the relationship with the customer. The touchpoints between a bank and customer can be through mobile apps, call centers, branch systems or online platforms, promising consistent service quality.

Recently, there has been a major development in the overall evolution of the digital economy. Now, AI tools such as intelligent interaction, machine learning and data-driven learning can improve customer response times and personalized support (Yang, 2025, p.103-104). This evolution of AI-enhanced CRM sets the stage for the use of conversational agents that automate common service requests and provide instant support. These solutions are integrated with CRM data and processes, making CRM the basis of these new interfaces.

2.2 Artificial Intelligence in CRM

2.2.1 Integration of Artificial Intelligence in CRM

Artificial Intelligence can be summarized as “a system’s ability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaption” (Kaplan & Haenlein, 2019, p.15), which can be used as a major technological component of CRM. AI has become the solution of solving business problems, such as relying on automated systems of various business processes, produce valuable insights by analyzing data and improving service processes by engaging with customers and employees (Singh, 2022, p.59). In the chapter above, we already see the reasons for companies to invest into CRM, as it focuses on vast volumes of data, while collecting customer information and gather analytical insights, enabling companies to predict behavior. Meanwhile, AI is a technology tool that is able to complement CRM. According to Singh, adding AI to CRM delivers “more predictive and customized information in all fields of business” (2022, p.72), optimizing the interaction with customers, while gathering customer insights. Helping with analytical insights, AI also enables companies to predict behavior, segment customer groups and optimize overall marketing actions (Singh, 2022, p.72-73).

Another aspect of AI technology being used in CRM, is the extensive support of process automation in day-to-day routine tasks (Singh, 2022, p.70), also known as robotic process automation (RPA) (Singh, 2022, p.145). These RPAs were developed to deal with repetitive manual activities (Harwardt & Köhler 2023, p.41), such as data entry, data verification, report generation and email processing. The combination of AI and RPA significantly increases process efficiency, lowers error rates and accelerates response times, resulting in a company’s improvement in overall service performance and enhancement of the customer experience. In addition, bots are also able to automate more complex processes like “customer segmentation, predictive lead scoring and sales forecasting” (Singh, 2022, p.145). Due to the automation in CRM processes, sales, service, and marketing personnel have greater availability for more valuable tasks, like improving the customer experience.

In addition, hyper-personalization plays a central role in CRM, since these capabilities use real-time data to analyze behavior patterns of customers. This enhances customer satisfaction, as these insights are used to tailor content, recommendations, and communications towards clients. As a result, hyper-personalization improves customer engagement and loyalty (Singh, 2022, p.42). Finally, the use of AI technologies is crucial for extracting and integrating every increasing amounts of data (Singh, 2022, p.43).

2.2.2 Benefits of AI for CRM

Over time, AI is becoming more influential and is now a major component of modern CRM systems. As mentioned in the previous section, the efficient interaction between a business and customers is one of the main reasons that AI is gaining in popularity. The availability and potential efficiencies of conversational agents, such as AI-powered chatbots, are reasons for the spread of these tools in customer service functions (Prinz, 2022, p.6). In theory, customers have the benefit of having access to information and customer service at a much higher speed, while with a lower price (Barone & Stagno, 2023, p.38), especially because CAs, such as chatbots, have the ability to handle large quantities of client requests through automation in a short period of time (Barone & Stagno, 2023, p.40-41). Consequently, customer experience improves, as clients are managed more efficiently. Theoretically, companies are then able to delegate human agents to more important tasks.

Furthermore, AI is able to support reliable service performance through different touchpoints, creating a smoother flow of information through different channels (Singh, 2022, p.208), such as the previously mentioned AI-powered chatbots. In this digital system, omni-channel interaction, machine learning and experience accumulation, voice, and image AI applications and IoT application technologies can be integrated into this process (Yang, 2025, p.103). The retail industry in particular can gain strategic advantages, by analyzing customer behavior and predicting what customers intend to purchase. (Singh, 2022, p.209). This data can be collected through various touchpoints, including websites, physical stores, mobile applications and social media platforms, providing a clearer picture about the needs and demands of shoppers and enabling the hyper-personalization that is needed for modern CRM. This is crucial for improving customer engagement and loyalty (Singh, 2022, p.42).

AI powered conversational agents are not the only reason that human actors can be used in a more productive matter. An additional benefit of AI technologies in CRM systems is the usage of robotic process automation, resulting in reduced costs, lower error rates and more operational efficiency

(Harwardt & Köhler 2023, p.41). Also, in this case employees can be directed to more complex tasks, as routine jobs and tasks are being automated.

In summary, it can be said that AI can contribute to faster response times to customers, which can play a major role in improving positive service satisfaction ratings. Machine-learning models are increasingly able to rapidly process customer requests and significantly accelerate resolution times by reducing human interventions for day-to-day tasks. Because of this, customer wait-times can be reduced, while simultaneously providing a smoother service experience. In combination with time benefits, AI increases efficiency and tailors the needs to the unique client, illustrating the benefits artificial intelligence can provide. These advantages will continue to shape customer expectations and redefine the standards of high-quality CRM, as companies increasingly adopt AI in their service processes.

2.2.3 Risks and Challenges of AI in Customer Service

As seen in the last chapter, AI technology brings many benefits for CRM, however their implementation also adds a certain risk level that can influence a client's perspective on a company. According to M. Alawamleh, Shammas, K. Alawamleh and Bani Ismail (2024, p.1-2), overall business performance can be negatively impacted, if a business relies on "AI largely for some important tasks that need human intervention". This can adversely affect customer satisfaction as well as overall business value and effectiveness resulting in lower sales and profits. For instance, the perceived lack of empathy and emotional intelligence of an AI-driven communication system can bring challenges to organizations. Authentic emotions in service encounters can influence the effects on customer service (Prinz, 2022, p.41). While human-to-machine communication might be the future, human touch cannot be replaced by machine interactions (Balakrishnan & Dwivedi, 2021, p.648). For this reason, customers could feel hesitant interacting with AI-agents as they are perceived as artificial and emotionally unintelligent, while also having privacy-related fears (Barone & Stagno, 2023, p.41), an issue that can influence overall customer satisfaction.

Another challenge that can arise with the use of AI, is the risk of errors and service failures due to the technology itself, especially when algorithms are no longer monitored by humans and learning fully autonomously and without monitoring. After a failure, it becomes complicated to trace back if the mistake originated from faulty programming or from the learning process itself (Harwardt and Köhler, 2023, p.44–45). In combination with AI systems having limited abilities to adapt to a fast paced and unpredictable world, a risk persists that predictive algorithms can overestimate expectations and reduce organizational flexibility when an unforeseen event occurs (M. Alawamleh, Shammas, K. Alawamleh and Bani Ismail, 2024, p.6–7).

Finally, companies are faced with major privacy concerns, especially regarding the use of AI by businesses (M. Alawamleh, Shammas, K. Alawamleh and Bani Ismail, 2024, p.6). For AI to be used productively in the CRM context, it will have to rely on large-scale collection of personal and behavioral data, which leads to sensitive customer information being stored and shared, creating the fear of surveillance and misuse of third-party access. On top of this are hacking and cybersecurity risks that contribute to the undermining of customer trust.

In general, people with negative attitudes towards the use of AI technologies may also accociate seeing AI as a threat to their own job security or privacy (Daly, Wiewiora and Hearn, 2025, p.6). Trust plays a major role in customer acceptance of artificial intelligence since it is the basis of transparency, long-term customer relationships and positive business outcomes (M. Alawamleh, Shammas, K. Alawamleh and Bani Ismail, 2024, p.3). People who have difficulties with change in general are also likely to have negative attitudes towards the use of AI (Daly, Wiewiora and Hearn, 2025, p.6). Transparency is intertwined with trust, as limited transparency and user comprehension of AI can lead to mistrust and reservations about AI in general (M. Alawamleh, Shammas, K. Alawamleh and Bani Ismail, 2024, p.5). A lack of understanding about AI and how it works can lead to a perceived „black box“ problem, which results in a sense of mistrust by some people. Either way, evidence suggests that users can change their attitudes towards AI when experiencing a personal benefit (Daly, Wiewiora and Hearn, 2025, p.7).

In summary, even though AI provides efficiency and scalability, organizations adopting AI in CRM, need to address these shortcomings in order to provide the customer a sense of transparency that will reduce trust barriers and foster a positive customer experience. These risks highlight the necessity of combining automation with human oversight, creating a balanced system of automation and human judgment.

2.3 AI in the Banking Industry

Not surprisingly, artificial intelligence also has become a key driver of digital transformation in the banking industry. Especially since traditional banks "face increasing pressure to innovate and compete with FinTechs" (Felipe, Torres de Oliveira, Toth-Peter, Mathews and Dulleck, 2025, p.2), at the same time that customers are increasingly comfortable with and even expecting to leverage digital services.

2.3.1 Digital Transformation and Industry Trends

The banking industry is faced with a digital transformation, as competition is growing and evolving from FinTech companies, while technological innovations and changing customer expectations become a force factor too (Felipe, Torres de Oliveira, Toth-Peter, Mathews and Dulleck, 2025, p.2). Banks are increasingly required to adapt their business model to remain competitive, in a world in which the financial ecosystem is rapidly digitalizing, while simultaneously having to deal with the challenges of complex organizational structures and regulations. This makes technological integration crucial. As a result, traditional banks have the goal to enhance the customer experience through digital transactions and personalized services (Felipe, Torres de Oliveira, Toth-Peter, Mathews and Dulleck, 2025, p.3).

Consequently, banks are becoming more accessible, providing an omnichannel experience, that offers customers more flexibility, agility and innovation (Singh, 2022, p.193-194). The idea behind this is that clients want a seamless, convenient banking experience, giving them the option of multiple channels, resulting in better customer service. Until recently, those omnichannels offered customers different touchpoints, such as online, mobile, call centers and physical branches, with banks trying to maintain a consistent, cohesive and informed experience. Now banks have and will rely more on an digital "central hub for data exchange, enabling different systems and applications in a bank to communicate" with each other (Steele, 2025), with the help of new omnichannels, chatbots, emails, websites and social media platforms, extracting this valuable data (Singh, 2022, p.181). A central hub drives "common processes and communications, routes work appropriately, and provides consistent guardrails (Steele, 2025)," thereby managing the flow of business processes and communication. At the end, these tools allow banks to efficiently gather data and obtain data-driven insights. This kind of digitalization can also be enabled by AI (IBM Consulting, 2025). The benefits of AI to banking are not only helpful for communicating with the customer, but also for risk analysis, fraud management, credit reporting and audit trails, and therefore simplifying work processes inside a bank (Singh, 2022, p.71). Interestingly enough, after a trend of declining bank branch numbers in the US, hitting a decade low at the end of 2022, the country saw an increase in branch openings (Steele, 2025), suggesting that these new AI-tools can also support traditional banking operations.

In addition, AI is increasingly assisting with repetitive, rule-based processes that have so far been done by people (Ali, Murray, Al-Ahmad, Jeon and Dwivedi, 2025, p.3). This development is also known as Robotics Process Automation (RPA). RPA is especially used in areas such as account management, data entry and verification, claims processing, fraud detection, and customer service operations, which end up leading to lower operating costs, improved efficiency, reduced human error and improved customer service.

2.3.2 Conversational AI Use Cases in Banking

Conversational artificial intelligence has become one of the most visible AI tools that customers interact directly. This is also true in the banking industry. These automated assistants give banks the option to move shift workers to higher-value tasks (Singh, 2022, p.193). Chatbots are the most common conversational agents, simulating conversations with customers via websites, text messages and messaging apps as well as over the phone in a human and natural way (Singh, 2022, p.146). Being able to respond faster than a human worker while working around the clock, conversational agents (CAs) can follow-up with past communications, offer support and collect feedback.

Bank of America's virtual assistant "Erica" is a notable example of AI-driven CA in banking. As of August of 2025, nearly 50 million users have used Erica since its launch in 2018, averaging more than 58 million interactions per month (Bank of America, 2025a). Some examples of personalized insights that Erica provides clients are cash-back opportunities and balance forecasting, while proactively informing clients about rewards eligibility and relevant banking benefits. It also assists customers with investment-related guidance and enables seamless transitions to human advisors by scheduling appointments, thereby combining automated self-service with high-touch customer support. With Erica and other implemented AI tools, Bank of America is able to collect and process large volumes of data, resulting in faster access to insights, enhanced decision making and more efficient workflow (Bank of

America, 2025b). This helps the bank to enhance employee productivity, while contributing to overall business growth by leveraging data-driven support for customers.

In Germany, the Commerzbank has launched its virtual-assistant Ava in 2025. Eva is an AI-powered avatar implemented into their banking app (Commerzbank, 2025). Ava helps customers with service requests, account management and product-related questions. The avatar is available 24/7 and combines generative AI technology with a human-like avatar, resulting in an improved experience for clients. In addition, customers are able to carry out selected banking transactions directly, such as managing credit cards or adjusting limits, while for more complex issues, clients are transferred to human customer service agents. This provides a balance between automation and personal support. Ava enables all these capabilities while also complying with strict security and regulatory standards.

An additional example of the growing use of AI-driven conversational agents can be seen in other banks too. For example, in the US, Capital One's Eno, is available on multiple channels and contributes to overall security by protecting credit card accounts and assisting with the tracking of customer spending (Capital One, 2025). It is also worth mentioning that there are banks that use video chats, informing customers about complex financial products, while also getting help in live discussions with experts (Singh, 2022, p.222).

In conclusion, there is increasing evidence regarding how AI-driven CAs are becoming a strategic component of modern banking operations. On one hand, there are conversational agents primarily improving service availability, speed, and personalization. On the other hand, they assist the company's overall business efficiency by automating routine interactions, while also helping to extract large volumes of data, which in the end improve the organization's ability to obtain superior insights.

2.3.3 Customer Expectations and Challenges

The banking industry deals with a high degree of complexity, mainly due to their institutional structures, regulatory constraints, and keeping up with evolving customer needs (Felipe, Torres de Oliveira, Toth-Peter, Mathews and Dulleck, 2025, p.2). Traditionally, banks had a vertical and integrated organizational structure, which made and provided products and services internally (Auge-Dickhut, Koye and Liebetrau, 2016, p.77). Customer interaction was centered mainly on basic services such as holding accounts and deposits, while the client usually selected only one main bank as their primary advisor. For clients this complexity could have undermined perceived transparency, causing in difficulties to fully comprehend financial products. Since the arrival of the internet, clients have the opportunity to better inform themselves to choose their preferred provider (Auge-Dickhut, Koye and Liebetrau, 2016, p.112). As a result, traditional, provider-centric banking models are not sufficient anymore, since increasing transparency and choice forces banks to interact with its customers as equals (Auge-Dickhut, Koye and Liebetrau, 2016, p.111).

Before the start of the digital era, banks focused on isolated account relationships, forcing clients to inform themselves about multiple banks and services if they decided to use multiple providers (Auge-Dickhut, Koye and Liebetrau, 2016, p.77). This structure highlighted confidentiality and privacy but also limited flexibility and transparency, giving clients fewer options to combine products or services across the industry. Due to the evolving industry situation, banks have needed to adopt new models, like implementing AI-driven CRM, and addressing new privacy concerns arising from the large volumes of data needed for their algorithms and enhancing performance (Ali, Murray, Al-Ahmad, Jeon and Dwivedi, 2025, p.9). Banks therefore need to find a balance between automation and human oversight. As mentioned in earlier sections, trust is fundamentally necessary in a successful relationship between banks and customers. Data sensitivity is linked closely to trust and where in an AI-supported service environment, transparency becomes particularly relevant. This is more so true for banks, as banking is associated with greater sensitivities compared to many other industries. Failures in this industry can result in financial losses and everlasting damage between bank and client.

2.4 Conversational Agents (CAs)

Conversational agents “are software systems that mimic interactions with real people by means of conversation through written and spoken natural language as well as gestures and other body expressions” (Mariani, Hashemi and Wirtz, 2023, p.1). These agents are the most common type of AI that most people will get in contact with (Prinz, 2022, p.20). Conversational agents only exist digitally and do not have any physical appearance, although able to interact with users through different communication channels (Prinz, 2022, p.21). CAs are widely being adopted across various industries, such as banking, retail, healthcare, education, and hospitality, where they assist organizations, enhance customer experience and provide important data insights. This data is then being processed to support marketing, sales, and service activities. Due to CAs, companies can gain valuable market insights and are able to enhance customer service. Conversational agents hold many benefits for companies, such as enabling cost savings, while attempting to engage in a natural, human-like way in a 24 by 7 manner with customers (Rzepka, Berger and Hess, 2022, p.839). Some of the well-known and recognizable CAs are Google's Assistant, Apple's Siri, or Amazon's Alexa (Kabel, 2020, p.1). There are three categories of conversational agents for organizations to choose from. Chatbots, voice agents and virtual avatar assistants.

2.4.1 Types of Conversational Agents

- *Chatbots (rule-based vs AI-based)*

Chatbots are now the most used CA in customer service. In the past, this tool was mainly utilized for low-complexity customer service tasks, however they now make up approximately 80% of customer queries (Barone, Stagno, 2023, p.39). A chatbot, can be described as "an artificially intelligent chat agent that simulates human-like conversation, for example, by allowing users to type questions and, in return, generating meaningful answers to those questions (Prinz, 2022, p.2)". This helps companies with tasks regarding communication, such as service requests. This specific agent is text-based and responds to humans via text (Barone & Stagno, 2023, p.39). Chatbots can be used on websites or on apps, such as Facebook Messenger (Kabel, 2020, p.20). Chatbots can take on different roles along the customer journey, as they can range from being an assistant that support tasks without influencing decisions, to being a coach that actively guides decision-making and to even being a co-worker that interacts in a human-like manner (Barone & Stagno, 2023, p.40).

It is worth mentioning that not all conversational agents are AI-driven. This is especially evident with chatbots, as they can be divided into two sets: scripted (rule-based) and AI-based (Singh, 2022, p.130). Scripted chatbots follow a set of predetermined rules that are only able to answer questions they are preprogramed for. AI-driven chatbots on the other hand can interpret the human language and are able to come up with answers that have not been pre-programed. The combination of computer science and linguistics is known as Natural Language Processing (NLP) (Harwardt and Köhler, 2023, p.27). Computers are able to understand, interpret, and generate human language due to the enabling of NLP.

- *Voice assistants*

Voice assistants are “conversational agents that communicate with humans through a voice interface and that are commonly used by consumers in their household” (Barone & Stagno, 2023, p.55). Voice agents are being used most commonly with smartphones and other smart devices, most famously, Apple’s Siri or Amazon’s Alexa (Prinz, 2022, p.20). Voice agents can also be used on websites to complete customer inquiries (Kurpicz-Briki, 2024, p.99). Like chatbots, voice assistants (VAs) are CAs that also “use NLP to respond automatically using human language” (Barone & Stagno, 2023, p.56). Compared to chatbots, individuals do not have to physically interact with VAs with an interface, as spoken commands are the main feature of this technology (Barone & Stagno, 2023, p.57). Since there is only a minimal use of a standard physical technological interface, VAs must simulate human language very well, in order to achieve the required level of social interaction.

- *Virtual agent avatars*

The third and final group of conversational agents is the virtual agent avatar. Also called the multimedia (embodied) conversational agent, this CA extends text and speech agents by incorporating graphical avatars that display human-like behaviours such as gestures and facial expressions (Prinz, 2022, p.22-23). According to past studies, the visuals and behavioral cues used by a virtual avatar enhances social presence, leading customers to perceive these CAs as being more human-like rather than a purely technical system. Like with the other conversational agents, virtual agent avatars complement services well by using AI to manage customer queries in real-time (Gillain, 2024, p.12).

2.4.2 Human-Like Features & Anthropomorphism

Banks need to determine how to effectively create a successful customer experience, especially regarding the client’s acceptance of conversational agents, “as well as to map the cognitive, affective and behavioral consequences that interacting with these AI-agents can have from a consumer point of view” (Barone & Stagno, 2023, p.38). By either using natural language processing (NLP) for chatbots and voice assistants or human-like behavior by virtual agent avatars, these agents have the potential to replicate human interaction in a realistic manner, due to anthropomorphism. Anthropomorphism refers to the extent to which conversational agents “are imbued with human-like characteristics and qualities” (Barone & Stagno, 2023, p.43). By doing so, CAs with human-like characteristics represent a significant development, as these AI-powered agents give a customer the perception that the technology is friendly and sociable. This can greatly influence how consumers will evaluate a conversational agent (Barone & Stagno, 2023, p.44). As a result, there is potential for customers to experience a benefit in interacting with a perceived social actor, which can increase engagement and satisfaction.

2.4.3 Empathy, Personalization & Customer Expectations

Empathy can be described “as a person’s attempt to understand another person’s experience, whether positive or negative” (Prinz, 2022, p.45). A certain amount of effort and consciousness is also attributed to empathy. Research has found that in a traditional sense, empathy has been a crucial aspect in strengthening service relationships between an organization and a customer (Prinz, 2022, p.7). In this context the combination of empathy and conversational agents, can lead to customers feeling of sense connection with a CA, this being considered a kind of anthropomorphism. However, even with its potential in delivering higher quality service than humans, a lack of empathy in customer could limit the possibility of fully replacing humans, as these automated systems are preprogrammed responses and algorithms (Ferraro, Demsar, Sands, Restrepo and Campbell, 2024, p. 554). This is especially true when human agents are able to interpret nuance, tone, and context while replying with empathetic and personalized responses.

However, if CAs are able to display reinforcing emotions, chatbots may motivate customers to respond positively in return, which then increases satisfaction in service evaluations and supports anthropomorphism at a conscious level (Prinz, 2022, p.124). To trigger this anthropomorphic response, graphical avatars, or virtual agent avatars, are increasingly being used (Prinz, 2022, p.125).

Besides empathy, competence plays a significant role in trust-building and the adoption of technology (Daly, Wiewiora and Hearn, 2025, p.2). Especially regarding customers who initially approach technology with scepticism, it is important that AI (and therefore CAs) is able to exhibit consistent and reliable outcomes (Daly, Wiewiora and Hearn, 2025, p.9). This is especially when CAs can perform competently, leading to anthropomorphism and achieving a higher customer satisfaction level (Ferraro, Demsar, Sands, Restrepo and Campbell, 2024, p. 551). In a worst-case scenario, unsatisfactory behaviour on the part of conversational agents can negatively reflect on a company’s reliability and competence (Ranieri, Di Bernardo and Mele, 2024, p.203).

Complementary to empathy and competence, customers have strong expectations regarding privacy when communicating with conversational agents. As CAs personalize services towards customers based on past interactions, large amount of data that agents collect and analyse can raise privacy concerns (Ferraro, Demsar, Sands, Restrepo and Campbell, 2024, p.555-556). This is even more true in the banking industry, as customers are sharing highly sensitive information. Data misuse can lead to serious risks, such as identity theft or fraud, that in turn undermine customer trust. However, banks have a few options as to how to tackle this problem. Organizations have to be transparent about data collection, provide customers with options on how to deal with their data, and tailor privacy policies to different customer preferences regarding data sharing. The tension between efficiency and emotional reassurance marks a key challenge in designing a CA.

In general, conversational agents present a paradox: on the one hand they outperform humans by gaining valuable market insights, are available around the clock, and can help reduce operational costs. At the same time, they can be perceived as being cold and incapable of genuine human interaction (Barone & Stagno, 2023, p.41). Firms must solve this dilemma by designing a CA feature that make the bot human-like to foster positive customer perceptions and motivate them to interact with these tools, while also ensuring competence and upholding strong standards of privacy and transparency. Finding the perfect mix between these aspects will ensure that customers expectations are met or exceeded.

2.5 Acceptance and Adoption of Conversational Agents

With conversational agents now being more widely implemented into organizational processes, it is important to evaluate user acceptance of these tools. In particular, it is critical to identify the drivers of customers relative to their acceptance of CAs, "as well as to map the cognitive, affective, and behavioural consequences that interacting with these AI-agents can have from a consumer point of view" (Barone & Stagno, 2023, p.38). While CAs can bring many benefits to the table, for example efficiency and availability, the adoption of these agents ultimately depends on how users will perceive them. Therefore, acceptance models provide a valuable theoretical framework for understanding what makes a person willing to engage with CAs and which factors influence them, especially as it relates to financial services and trust-sensitive information of customers collected and used in the banking industry.

2.5.1 Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) is one of the most widely used frameworks that "explains the acceptance of information systems by individuals" (Marikyan & Papagiannidis, 2024, p.1). The primary objective of TAM is to explain and forecast if individuals will accept the use of a specific information system by identifying the psychological mechanism underlying technology-related behaviour. The practical perspective "of TAM was to inform practitioners about measures that they might take prior to the implementation of systems" (Marikyan & Papagiannidis, 2024, p.2-3). TAM is based on the Theory of Reasoned Action, explaining a human behaviour from a psychological perspective, which before had been underrepresented in information systems research. Davis, the creator of the model, introduced a stronger focus on the behavior of people using information systems research. Fundamental technology acceptance is a process in which system characteristics effect how users think and feel about a technology, which will then determine, if they actually use it. A key step in the model's development, was the identification of measurable factors that are closely linked to system usage. Davis defined perceived usefulness and perceived ease of use as the two central factors determining whether users accept a technology.

Perceived usefulness refers the degree to which an individual believes that a system enhances his/her performance. Perceived ease of use on the other hand describes the extent to which an individual believes that the system is perceived as easy to use. The latter is based on self-efficacy theory and innovation diffusion research, which demonstrates how complex technologies are less likely to be adopted. Both of these constructs were confirmed by empirical studies and reliably measured and therefore realistically explains technology use in organizational settings.

There is a three-stage process for acceptance according to TAM: the system features influence cognitive beliefs, these thoughts shape their attitude or intention to use the system, which then finally leads to the actual use. Perceived usefulness can directly affect whether a system is used. Perceived usefulness can directly affect whether a system is used. Perceived ease of use, meanwhile, influences usage indirectly by making the system perceived as more useful, thereby emphasizing the central role of perceived usefulness in predicting acceptance.

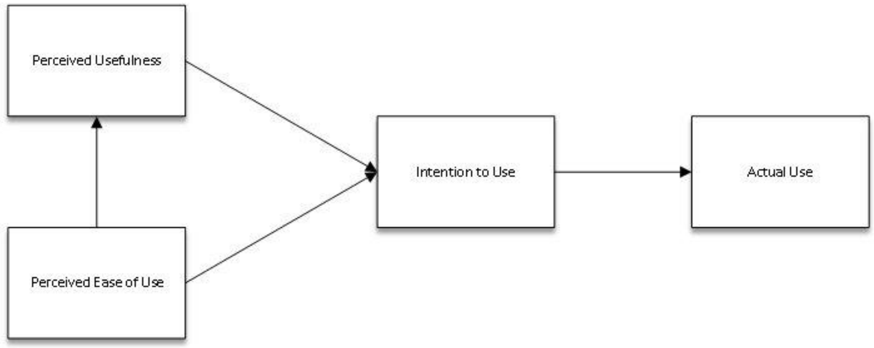

Figure 1 Technology Acceptance Model (TAM)

Source: **Marikyan & Papagiannidis (2024, p. 3).**

In general, TAM makes an important contribution to information systems research, by providing an analysis of user motivation across technologies and contexts and an improved understanding of how system characteristics translate into adoption behaviour.

2.5.2 Extended Acceptance Models

After the development of the original Technology Acceptance Model, researchers continued to study technology acceptance, as it has a strong link to organizational productivity (Marikyan & Papagiannidis, 2024, p.4). While technology acceptance is explained well by TAM, the authors of the model wanted to improve its predictive power, particularly by better understanding what shapes perceived usefulness, the strongest predictor of intention to use. This led to further research on the factors that shape usefulness perceptions in organizational contexts.

TAM 2 extends the original model by adding social influence and cognitive instrumental factors: subjective norm, image, job relevance, output quality, result demonstrability, experience and voluntariness (Marikyan & Papagiannidis, 2024, p.4-5). Both the social influence and cognitive instrumental factors help explain why users perceive a technology as useful, compared to to the earlier model, when only usefulness predicted acceptance.

TAM 3 was created by combining the two older models of both perceived usefulness and perceived ease of use into one updated model, with a focus on behavioral intention (Marikyan & Papagiannidis, 2024, p.6-7). Unlike earlier versions, TAM 3 differs by further integrating “the direct predictors of perceived ease of use, which include computer self-efficacy, perception of external control, computer anxiety, computer playfulness, perceived enjoyment and objective usability" (Marikyan & Papagiannidis, 2024, p.6).

Eventually the Unified Theory of Acceptance and Use of Technology (UTAUT) was developed to address limitations in earlier acceptance models (Marikyan & Papagiannidis, 2023, p.3). Based on former models, UTAUT identifies performance expectancy, effort expectancy, social influence, and facilitating conditions. As UTAUT was rather focused on organisational settings, UTAUT 2 was developed as a more general framework by increasing its explanatory power and adapting it to consumer technology use (Marikyan & Papagiannidis, 2023, p.6). Three additional constructs were added: hedonic move, cost/perceived value and habit, moderated by age, gender and experience.

In conclusion, these extended acceptance models provide more context into frameworks, helping to analyze user acceptance and adoption of conversational agents and other AI-driven systems.

2.5.3 Acceptance of Conversational Agents in Service and Banking Contexts

Conversational agents, such as chatbots and voice assistants, are already being extensively used by companies in the customer service sector, providing clients with instant responses, automated routine inquiries, and support across different channels, giving the impression that the acceptance rate of CAs is satisfactory. TAM is one of the most used models to investigate conversational agents adoption (Mariani, Hashemi and Wirtz, 2023, p.5). Moriuchi for instance used TAM to study consumer engagement and loyalty (Moriuchi, 2019). Pillai & Sivathanu analyzed customers behavioral intention and actual usage of AI-powered chatbots, regarding the Indian hospitality and tourism industry while using an extended TAM model with context-specific variables (Pillai & Sivathanu, 2020). Similar to TAM, UTAUT is also a broadly used theoretical framework to explore customers willingness to adopt to a new technology (Mariani, Hashemi and Wirtz, 2023, p.6). Moriuchi also examined how anthropomorphism and user engagement influences customer intentions and actual behaviour to reuse voice assistants (Moriuchi, 2021) while Melian-Gonzalez used the UTAUT model to test usage intention of chatbots in the tourism sector (Melián-González, Gutiérrez-Taño & Bulchand-Gidumal, 2019).

Literature shows that CA adoption specifically is driven by a few factors, such as design features, the users perception and contextual and environmental influences (Mariani, Hashemi and Wirtz, 2023, p.8).

When looking at the design-related influences, anthropomorphism and personalization generally enhances engagement and adoption, even though a few studies "showed under certain circumstances anthropomorphic design could be unfavorable in terms of the negative impact on the behavioral intentions" (Mariani, Hashemi and Wirtz, 2023, p.9). The second category, user-related aspects, has five factors that drive increased adoption intentions. These are: 1) usage convenience; 2) perceived usefulness; 3) trust; 4) enjoyment; 5) attitude toward technology. Here, privacy risks and inconvenience can reduce usage (Mariani, Hashemi and Wirtz, 2023, p.10). Finally, contextual and environmental factors influence the acceptance and continued use of CAs, as different industry settings and usage situations affect the viewpoints of users (Mariani, Hashemi and Wirtz, 2023, p.11).

In the banking context, services are characterized by strict regulatory requirements and the handling of sensitive personal and financial data. Therefore, privacy concerns could be elevated related to the financial sector (Ali, Murray, Al-Ahmad, Jeon and Dwivedi, 2025, p.9), and therefore influencing the acceptance of CAs regarding customer service at banks. This raises the question of how perceived usefulness and efficiency compare to a bank's ability to protect confidential information and comply with regulatory standards. A study based on the banking industry in Vietnam revealed "that bank customers tend to continue using chatbot services only if they are trustworthy and useful, and customers needs are satisfied" (Nguyen, Chiu & Le, 2021, p. 16).

Overall, the acceptance of CAs in service and banking contexts may be influenced by additional factors beyond traditional technology acceptance constructs. While usefulness and the fulfilment of customer needs are factors of acceptance of conversational agents, trust-related aspects play a decisive role as well. This highlights that context-related models regarding acceptance and adoption towards technology usage in highly regulated and trust-dependent industries is needed, rather than exclusively relying on traditional models, such as TAM or UTAUT.

2.6 Trust, Risk, and Transparency in AI-Based Systems

The increasing integration of AI-based systems into organizational processes and customer-facing services has brought major privacy concerns with it, as these tools rely on the large-scale collection of personal and behavioral data. Hence, the use of AI being used productively in the CRM context will end up with sensitive customer information being stored and shared, creating the fear of surveillance and misuse from third-party access. The risk factor of hacking and cybersecurity add to the undermining of customer trust.

2.6.1 Trust Formation in AI-Based Systems

Trust is a crucial aspect of AI adoption, as it determines if individuals are willing to rely and depend upon AI technologies (Daly, Wiewiora and Hearn, 2025, p.1). Studies show that trust plays an essential role in the perception of user's attitudes toward AI. Privacy violations, the loss of autonomy and other negative perceptions hinder trust, while positive views, such as reliability, performance and user-centered designs enhance it. Trust can be defined as "willfully placing confidence in a party while providing personal information" (Hasan, Shams, & Rahman, 2021, p.592). Unlike with previous technologies, AI deals with other complexities regarding trust, such as with automation, anthropomorphism, transparency, accuracy, and mass data extraction (Daly, Wiewiora and Hearn, 2025, p.2). In the financial sector, trust is particularly important, as in this industry "heightened regulatory scrutiny, poor data collection practices and hidden consent agreements can erode consumer trust" (Ali, Murray, Al-Ahmad, Jeon and Dwivedi, 2025, p.9). Without sufficient trust, the use of AI could be met with resistance or be restricted to limited usage.

2.6.2 Algorithmic Transparency & Explainability

A key trust factor for individuals relating to AI systems should be transparency (Gillain, 2024, p.395). AI interactions will have to explain why a certain algorithmic decision was made and should therefore be interpretable, and consequently underscore accountability for AI-driven outcomes. Transparency is crucial as users are not able to rely on AI decisions unless they comprehend how the system operates (M. Alawamleh, Shammas, K. Alawamleh and Bani Ismail, 2024, p.5). However, studies show that AI algorithms lack transparency, causing customers to not fully understand how decisions are made. One challenge is the limited understanding of individuals regarding the generation of answers of artificial intelligence, also commonly known as the black box problem. As a result, the lack of explainability can lead to mistrust and hesitation to use AI. Research therefore highlights the importance of making AI algorithms more transparent and understandable to build user trust.

2.6.3 Privacy Risks and Ethical Concerns

With the adoption of AI across various sectors, companies are able to automate processes, improve decision-making, while gaining better customer insights (Gillain, 2024, p.11), making AI essential for economic survival and competitiveness. However, implementing these tools brings its challenges, adding ethical risks for the safety of clients and the rights of citizens (Gillain, 2024, p.13). These ethical challenges are due to inherent limitations, as AI makes decisions that affect sensitive outcomes such as hiring, credit approval, or customer treatment, making fairness and transparency critical requirements (Gillain, 2024, p.14).

One of the more crucial ethical concerns is data collection, "related to ownership, security, privacy, and possibly undesirable biases in the data" (Gillain, 2024, p.250). Academic researchers are increasingly focusing on privacy concerns, as consumers perceive the use of personal data by algorithms as one of the most critical risks in digital environments, as AI analyzes massive amounts of sensitive information (M. Alawamleh, Shammas, K. Alawamleh and Bani Ismail, 2024, p.6). In the context of customer relationship management, sophisticated AI has the possibility to exploit customer vulnerability and create information asymmetries, adding to the potential distrust, especially if an organization were to prioritize the benefits of targeted advertisement over customer privacy and fairness (Singh, 2022, p.58).

In conclusion, even though AI can assist companies in increasing efficiencies, decision-making, and customer insights, its reliance of massive amount of data and customer adoption also presents significant ethical and privacy related risks. Concerns regarding AI, such as data ownership, privacy, and information asymmetries, highlights the importance of transparency, accountability, trustworthiness and reliability, fairness and removing biases (Gillain, 2024, p.427).

2.6.4. Banking-Specific Regulatory Expectations

Similar to traditional banking, clients using AI-driven platforms will prefer products and services which offer clear financial benefits, including effective services in all aspects of safety and security (Singh, 2022, p.195). However, many concerns persist regarding fraud and transaction failures, especially for high-value transactions. For this reason, many clients still prefer conventional modes of transactions, highlighting the need of CRM approaches maintaining trust and meeting customer expectations around security and reliability.

In addition, due to banking's highly regulated nature, "poor data collection practices and hidden consent agreements can erode consumer trust" (Ali, Murray, Al-Ahmad, Jeon and Dwivedi, 2025, p.9). AI systems rely on large volumes of sensitive personal data, such that privacy and security concerns are elevated. Consequently, solutions are needed, for example financial institutions using federated learning and increased security protocols to reduce fraud and data misuse. Overall, banks should strengthen ethical strategies, in which they prioritize transparency, simplify consent processes, and educate both customers and employees about AI-driven data use.

2.7 Customer Experience and Service Outcomes

Customer service is based on the idea that a company provides assistance and support to customers before, during, and after the purchase or use of a product or service in order to meet customer needs and expectations (Institute of Customer Service, 2014). Until recently, this was performed almost exclusively by frontline employees who traditionally played a central role in customer service by acting as a link between a company and its customers and by delivering value through information provision, assistance, and recommendations (Ruan and Mezei, 2022, p.1). However, as conversational agents are increasingly being adopted by many companies throughout different industries (Mariani, Hashemi and Wirtz, 2023, p.1), the question persists as to how these AI-tools influence the customer experience and key service outcomes.

The end result of customer expectation confirmation is customer satisfaction (Ruan and Mezei, 2022, p. 2). Customers motivated by hedonic or experiential goals seek positive emotions such as pleasure and excitement during the purchase or consumption process, whereas customers driven by utilitarian or functional goals aim to make informed choices that meet practical needs. Therefore, product attributes can be divided into functional and experiential attributes. Functional attributes adress tangible performance-related needs, such as materials of clothing or performance of a cell phone, while experiential attributes influence sensory perceptions, emotions, and aesthetic pleasure (Ruan and Mezei, 2022, p.3). Regarding conversational agents, studies show that AI-bots achieve higher levels of customer satisfaction when AI communication focuses upon product functional attributes, while human support receives a higher rate of customer satisfaction when the communication is focused on product experiential attributes. Considering that CAs are able to offer immediate and tailored responses at any time and all times, there could be a possibility of them improving customer satisfaction. Nevertheless, clients will reject technology, if it fails to meet their cognitive or emotional goals, which can lead to frustration, disappointment, stress, dissatisfaction and uncertainty (Ranieri, Di Bernardo and Mele, 2024, p.194). These negative experiences, also called technostress, are caused by unawareness of how to use the technology or the lack of trust in it. According to a recent study (Ranieri, Di Bernardo and Mele, 2024, p.203), if chatbots are not able to reassure customers or provide accurate and timely responses, the dissatisfaction rate increases and trust declines. In addition, consumers would prefer direct human interaction, if CAs are unhelpful or provide inconsistent information and generate misunderstandings. Therefore, CAs could complement human actors, which may lead to more effective outcomes regarding customer satisfaction, instead of replacing human support completely.

Historically, customer loyalty has been a central aspect of marketing and been considered to be the most valuable asset a company can possess (Kim, Jindabot & Yeo, 2024, p.2). Loyal customers demonstrate a commitment and attachment to a current provider, as well as to express a greater willingness to pay for products or services while being less likely to switch to a competitor. In addition, loyal customers also tend to make repeat purchases and to remain with the same brand or service over time. This is why companies place a premium value in retaining loyal customers. On top of that, "customer loyalty increases intent to return which improves financial results" (Singh, 2022, p.28). Such loyal customers will then also give positive recommendations to their acquaintances. Also, as mentioned in the chapter "CRM in the Banking Sector", most profits, at least in the banking industry, come from a minority of loyal customers, with new client acquisition proving to be substantially more expensive. Therefore, CAs must deliver consistent, useful, and trustworthy service, which can then contribute to keeping customers content and loyal to the organization. For this reason, bots need to be geared towards building loyalty and bolstering the customer experience (Ranieri, Di Bernardo and Mele, 2024, p.192).

Conversational agents also have the potential to significantly affect organizational customer relationship management (CRM), helping to make the jobs of employees "easier and improving their productivity and effectiveness" (Singh, 2022, p.146). These AI-driven agents can assist workers by providing real-time insights, prompts, alerts, recommendations, and decision recommendations. During live interactions, CAs are able to anticipate probable follow-up questions, recommend resolutions, and support employees to strike the right conversational tone. In addition, servers are able to store previous customer chat and purchase history due to CAs, which can make the complaint resolution faster and more convenient (Singh, 2022, p.208). Due to the fact that AI agents can replace or assist human customer service, companies have the possibility to delegate their human resources to more important and high value tasks. For CRM to achieve its full potential, it will need to be fed with large amounts of consumer data. CAs can be trained to collect and control this data to generate market intelligence (Mariani, Hashemi and Wirtz, 2023, p.1).

3 Methodolgy

3.1 Research Design

The objective of this paper is to examine the relationship between customer perception of conversational agents, specifically in traditional banking, and how they relate to certain variables, such as trust, satisfaction, perceived empathy, perceived security, and customer loyalty. To achieve this objective, this study follows a quantitative research design using a cross-sectional survey approach.

Using a quantitative approach is particularly suitable for this study, as this method "is a means for testing objective theories by examining the relationship among variables" (Creswell, 2009, pp. 22–23), which, in this paper's case, has to do with consumer perceptions about conversational agents. Consequently, variables can be measured the quantitative data analyzed. Prior studies on AI, conversational agents or general technology acceptance have predominantly made use of quantitative research design, allowing for comparisons with past results. In addition, the existing research assisted with the creation of the hypotheses of this study.

"Cross-sectional studies are carried out at one time point or over a short period" (Levin, 2006, p. 24), capturing consumers current perceptions of CAs in banking. As this approach provides a snapshot of the outcome, the cross-sectional study will focus on the current acceptance and evaluation of the rapid adoption of AI-driven customer service technologies by companies, rather than a behavioral change over a longer period of time. Data was collected on individual characteristics (in this study's case, online), which provides a collection of results, giving the opportunity for a statistical analysis.

In summary, the combination of quantative research design with a cross-sectional survey align with the study's aim to empirically test theory-driven hypotheses, which are derived from acceptance models and existing literature. This will help to get a better understanding of customer perceptions of conversational agents in the banking context.

3.2 Literature Review Method

The theoretical foundation and hypothesis development of this study are based on a structured literature review that follows the approach proposed by Webster and Watson (2022). In this approach, emphasis is set on a conceptual and theory-driven synthesis of past literature rather than a purely chronological summary of prior studies (Webster, Watson, 2022, p.xiv). In following this approach, appropriate academic literature needed to be identified using various databases, such as the one at the university, ScienceDirect, ProQuest or Semantic Scholar. Various sources were also found from previous studies, in order to help gather more insights from additional literature. Keywords, used respectively in English and German, were identified to help identify further existing literature. The terms included words such as “conversational agents”, “chatbots”, “voice-assistant”, “AI”, “customer relationship management (CRM)”, “technology acceptance”, “trust” and “banking”. To establish a comprehensive theoretical grounding, it was important to get a combination of foundational and recent studies. As Webster and Watson recommend, the literature review was performed by using a structured and systematic approach rather than using a limited set of studies conducted by individual authors. The hypotheses of this study, to a certain extent, are grounded in the Technology Acceptance Model (TAM) as well as its variations (such as TAM2 or UTAUT), in which they characterize the user perceptions, beliefs, and behavioral intentions regarding a certain technology. In this study, the main focus has been on perceived usefulness, trust, experience, and willingness to use CAs, while also incorporating context-specific factors relevant to the banking sector, such as privacy concerns, empathy, demographic differences, and preferences of customer service interactions. Some of these factors have been identified in prior studies to play a major role relating to AI-driven customer service. As this study uses the Webster and Watson approach, it ensures that the development of hypotheses is systematically based on prior literature and clearly traceable for readers.

3.3 Conceptual Framework & Hypothesis Development

As stated in the chapter above, this study was created on established theories of technology acceptance and prior literature and studies, which explains how customers perceive and evaluate the use of conversational agents in banking and its customer service. For this reason, the conceptual framework combines both general acceptance factors and context-specific elements relevant to the banking industry.

<u>Experience-Based and Attitudinal Predictors of conversational agent acceptance</u>

H1: *Customers with previous experience using conversational agents in other industries show higher intention to use conversational agents in banking.*

Prior research finds that positive user experience with conversational agents can increase satisfaction, intentions of continuance as well as recommendations to others. This is specifically the case, when the technology is perceived as enjoyable and compatible with users' habits (Lee, Sheehan, Lee and Chang, 2021). Balakrishnan and Dwivedi (2021) also created a study, in which the two authors investigated the relationship between user experience and technology continuation intention, and where the results showed a significant positive relationship between the two factors. Other findings indicate that positive interactions with a conversational agent such as responsive and friendly conversations, especially outside of business hours, can enrich consumer experience (Ranieri, Di Bernardo and Mele, 2024, p.205). In conclusion, positive prior experiences with CAs brings favorable attitudes, satisfaction, and continued use intentions. These previous experiences should affect receptiveness towards CA usage in the banking sector, supporting the basis of Hypotheses 1. It should be noted that this hypothesis is grounded in the belief that the majority of prior interactions with conversational agents were associated with favorable customer experiences.

H2: *Respondents who feel indifferently towards interacting with AI will show a higher willingness to use conversational agents in banking.*

H2 is partly based of the Technology Acceptance Model, suggesting that an individual's attitude toward a technology strongly influences their behavioral intention to use it. Neutral or positive views on a technology can therefore be interpreted as the absence of a strongly negative attitude. For that reason, this hypothesis predicts consumers who feel indifferently towards interacting with AI in general will therefore have a higher willingness to use conversational agents in the banking context as well, compared to individuals who view AI with pessimism.

H3: *Respondents with higher empathy-based trust in conversational agents will show a greater willingness to use them for complex or sensitive banking issues.*

H3 is grounded in existing literature, which identifies trust as one of the most influential factors in predicting users' intentions to use conversational agents in banking contexts (Nguyen, Chiu & Le, 2021, p. 15). As banking services are highly trust-dependent and complex or sensitive issues involve increased perceived risk, it can be assumed that higher trust levels in conversational agents are associated with greater willingness to use them for such matters. In this study, trust is operationalized as empathy-based trust.

Demographic Differences in conversational agent Perception

H4: *Younger respondents (<30) will perceive conversational agents as more useful than older respondents.*

The theoretical model of UTAUT identifies age as one of the key aspects for adopting a certain technology (Marikyan & Papagiannidis, 2023, p.3). It is also commonly known that older individuals are more resisitant to adopting technologies compared to their younger counterpart (Moxley, Sharit and Czaja, 2022, p. 2).

H5: *Males will perceive conversational agents as being more useful than females.*

UTAUT also cites gender as a key factor influencing how users evaluate and adopt technology (Marikyan & Papagiannidis, 2023, p.3). One study shows that "males showed more favorable attitudes toward technology use than females, especially on the dimensions of belief (e.g., believing in the societal usefulness of technology) and self-efficacy (e.g., self-confidence in one's ability to learn and use technology effectively) (Cai, Fan and Du, 2017). Based on this theoretical background, this study hypothesizes that males will perceive conversational agents to be more useful than females do.

H6: *Older respondents (>50) will express stronger privacy and security concerns regarding conversational agents in banking compared to younger respondents.*

Hypotheses 6 is based in existing literature on age-related differences in privacy perceptions. A study based on the influence of age and (non-) participation on Facebook and drawing on data from 2011 (Steijn, Schouten and Vedder, 2016, p.8), came to the conclusion that older individuals associated situations related to personal information with privacy, reporting more concern regarding privacy (Steijn, Schouten and Vedder, 2016, p.1). Drawing on this finding, H6 hypothesizes that older respondents (>50) will hold stronger privacy and security concerns regarding CAs in banking compared to younger users.

H7: *German respondents will exhibit stronger privacy and security concerns toward conversational agents in banking than US respondents.*

This hypothesis is grounded on the differences in data protection cultures between Germany and the United States. The European-Union has many high-profile enforcement regulations, such as General Data Protection Regulation fines against major tech companies, which demonstrates the EU's robust regulatory stance on personal data protection (Chee, 2025). Germany is part of the EU, therefore these strict regulatory practices may increase public awareness of privacy risks and strengthen privacy sensitivity feelings among German consumers compared to their US counterparts.

H8: *Customers in the United States will demonstrate a higher willingness to adopt conversational agents in banking than customers in Germany.*

Hypotheses 8 is based on the idea that technology adoption differs between countries and cultures. The Technology Acceptance Model (TAM) and its extensions claim that the strength of acceptance factors varies depending on several variables (Marikyan & Papagiannidis, 2024, p.9-10). As mentioned in H7, a culture of increased awareness of privacy risks, for example in Germany, might limit the acceptance of new technologies. Simultaneously, countries with a strong culture of innovation and high exposure to digital services tend to foster a greater openness toward new technologies. The rapid and wide-spread deployment of recent emerging technologies, such as digitalization, have tended to lag in Germany when compared to the United States (Martinez, 2025). These differences may contribute to a higher willingness of U.S. customers to adopt and accept conversational agents when interacting with their bank.

Interaction Preferences and conversational agent Type

H9: *Most customers will prefer a combination of Conversational Agents and human interaction in the banking industry.*

H9 is grounded on the idea that banks should offer a hybrid customer service, allowing for the inclusion of human agents if necessary, giving customers a choice. While customers will appreciate the efficiency and benefits of conversational agents, chatbots are missing the human touch, which cannot be replaced by machine interactions (Balakrishnan & Dwivedi, 2021, p.648). Authentic emotions in service-encounters can influence the effects on customer service (Prinz, 2022, p.41) and customers might feel hesitatingly interacting with conversational agents as they are perceived as artificial and emotionally unintelligent, while also having privacy-related fears (Barone & Stagno, 2023, p.41). Therefore, a combination of human and AI-driven agents may improve customer needs in the banking sector.

H10: *Customers will show different levels of preference among conversational agent types (chatbots, voice assistants, and virtual agents), with voice assistants expected to score highest in perceived naturalness.*

Hypotheses 10 is based on prior research, indicating that speech exhibitions "higher perceived efficiency, lower cognitive effort, higher enjoyment, and higher service satisfaction than text-based interaction" (Rzepka, Berger and Hess, 2022, p.839). These factors can be attributed to a stronger perception of naturalness and therefore making voice-assistants more popular than chatbots. Meanwhile, human-like graphical representation of chatbots, or virtual agents, had a negative effect on individuals (Prinz, 2022, p.54-55), as human-like avatars did not increase perceived naturalness. In conclusion, it is expected that voice assistants will be perceived as the most natural among conversational agents in this study.

Trust, Satisfaction, and Loyalty Outcomes

H11: *Dissatisfaction with conversational agents will not significantly reduce overall customer loyalty toward their bank.*

H11 is difficult to predict, as recent literature suggests that the impact of conversational agents on customer loyalty is inconsistent and depends on multiple factors. For example, some firms, such as Klarna, have placed greater emphasis on redeploying workers back to customer service after encountering quality problems with AI-based systems (Mann, 2025). In the case of the fintech company Klarna, this development suggests that dissatisfaction with AI-based services may negatively influence customer perceptions of a company and potentially affect customer loyalty.

On the other hand, Bank of America's virtual assistant Erica is a success story, in which the company demonstrates that a well-designed conversation agent can deepen relationships with its customers while also improving service efficiency (Bank of America, 2025a). According to Technology Acceptance Model, high perceived usefulness and ease of use will increase continued usage intention (Marikyan & Papagiannidis, 2024, p.2-3), which could indicate that the frequent usage of Erica gives customers of the Bank of America a strong functional benefit. The growing number of users interacting with Erica, accompanying decreasing call-center requests, suggests that successful implementations of AI systems can enhance customer engagement and loyalty.

As in the case with Erica, conversational agents have personalized insights and offer other features, such as accessibility and interactivity, which can influence customer experience and continuance intention (Li, Fang and Chiang, 2023, pp. 6–7).

H12: *Respondents who perceive conversational agents as more empathetic will report higher levels of customer service satisfaction.*

This hypothesis is grounded in existing literature that long-term success of conversational agents-customer relationships depends on the quality of the interaction. Human-like features, such as emojis and responsive and friendly communication can strengthen customer connection and enhance user experience, even with the awareness of the CAs artificial nature (Ranieri, Di Bernardo and Mele, 2024, p.205). In conclusion, these human-like attributes contribute to perceptions of empathy and emotional responsiveness, enhancing customer satisfaction.

3.4 Survey Design & Measurement

Survey design

Data was collected via an online questionnaire using Google Forms. This ensured that the survey was easily and efficiently distributed via the internet (vast majority on Reddit), and readily available to respondents from different countries (mainly Germany and the United States). One aim of this study was to compare US-American attitudes with those of German participants. Therefore, two Google Forms were created, in which English and German surveys were created. Both versions having identical information in their respective languages to ensure a consistent interpretation independent of the language used. The goal was to create a survey design, in which the questionnaire would be short enough to maintain interest while covering all constructs required for the testing of the various hypotheses. The survey was designed to be completed within 5 minutes. Prior to data collection, the survey was reviewed by a few individuals to ensure clarity and comprehensibility.

Questionnaire structure

The survey is organized in several sections:

1. *Demographics (About you)*

   In this section, respondents give information regarding their age, gender and nationality (US, Germany and other).

2. *General experience with conversational agents*

   Respondents are asked if they have ever interacted with an conversational agent before (in a customer service setting, in what specific industries, including banking), with which specific types of agents (chatbot, voice-assistant, virtual assistant), resulting in what kind of experience and finally, which CA they found to be most human-like.

3. *Conversational agents in banking*

   Here, respondents evaluate their general attitudes, acceptance, and behavioral intentions regarding conversational agents used by in banks. Participants answered questions measuring perceived usefulness, intention to use, preferences for human interaction and hybrid service options, perceived security of personal data, general attitudes toward artificial intelligence, institutional trust, switching intention, and customer satisfaction.

   In addition, this section has included items capturing technology acceptance–related constructs, such as perceived usefulness and openness to using conversational agents for banking services in the future. The participants are also asked if they would use CAs for complex and sensitive issues versus simple use cases or even not at all. Finally, perceived empathy is evaluated through the lens of trust and satisfaction. In conclusion, this part of the survey looks into key factors shaping customer evaluations of conversational agents in banking.

Measurement and scaling

The items in the questionnaire were measured using standardized self-report scales, in which many questions were measured with five-point Likert scales ranging from 1 (strongly disagree) to 5 (strongly agree). Developed by Rensis Likert, a Likert scale is used for measuring attitudes by asking respondents to indicate their level of agreement with a statement (Sullivan and Artino, 2013, p. 541). With this format, clarity is ensured too respondents and comparability across items. Besides five-point Likert scales, there are other variations that were used in the survey, such as measured using closed-ended multiple-choice question (e.g., “Have you ever used a conversational agent in your bank’s customer service before?”), mixed-format multiple-choice question with an open-ended option (e.g., “In which industries have you used conversational agents?” with an “Other” field) and a semantic differential question (e.g., rating conversational agents on a scale very negative-very positive).

It should be noted that the developed questions in this study were created specifically for this questionnaire and not derived from prior studies, as existing literature has mainly focused on conversational agents in general than on their application and in the banks context.

Most key constructs were measured using single-item Likert-scale questions. Given the exploratory nature of the study and the context-specific focus on conversational agents in banking, this approach was considered appropriate for capturing respondents’ perceptions efficiently.

3.5 Sample & Data Collection

The data was collected via the internet on Google Forms. The survey was first shared with a few personal contacts in Germany and the United States and afterwards over Reddit, in which many other nationalities outside the US and Germany also answered. In order to improve the likelihood of reaching the relevant target group, German and US-American participants over the age of 17, the survey was posted multiple times in German subreddits and for specific time-zones that would also ensure that many US-Americans would respond.

Individuals taking part in this survey were voluntary and anonymous. As banks typically only offer customer accounts to persons over the age of 18 (PNC Insights, 2024), respondents were required to be at least 18 year old. It was not essential for respondents to have basic experience with digital banking services or conversational agents, however it was preferred.

The sampling method entailed an approach in which participants were recruited based on accessibility and willingness to participate, meaning this study did not use the average sampling size of the population. Therefore, the sample may not be fully representative of the overall population of bank customers, which limits the generalizability of the findings. The goal was to get the participant number at least into the triple digits. After data cleaning, 138 respondents answered in the English survey while 90 completed the German survey, resulting in 228 overall valid answers. The data collection started in November 2025 and ended in January 2026.

These are the key variable combinations. User experience measured respondents overall evaluation of their interaction with conversational agents. Perceived usefulness reflects the practical value of these systems in banking contexts. Intention describes respondents willingness to use conversational agents in the future. Human and hybrid preference reflected preferred service formats in customer service interactions. Privacy and AI attitude measured concerns and general perceptions regarding artificial intelligence. Institutional trust and switching intention assessed trust in banks and potential switching behavior. Empathy (trust) and empathy (satisfaction) captured the perceived emotional responsiveness of conversational agents in relation to customers trust and service satisfaction.

3.6 Data Analysis Methods

After collecting the data, the results were examined using quantitative statistical techniques. The dataset was inspected for consistency, while incomplete or invalid responses were deleted from the set. All statistical analyses were conducted using Microsoft Excel.

Descriptive Statistics

Descriptive statistics were used to calculate frequencies and percentages to describe demographic variables and central study variables. Likert-scale questions of the survey were analyzed using means (M) and standard deviations (SD), giving an overall perspective and variability across groups.

Correlation Analysis

Relationships between key factors, such as perceived usefulness, trust, empathy, satisfaction, privacy concerns, and intention to use, were calculated with Pearson correlation coefficients. This method helped identify the strength of correlation between constructs.

Regression Analysis

Simple linear regression analysis was conducted, which helped examine whether specific variables predicted intention to use conversational agents and a willingness to adopt these tools for complex or sensitive banking customer service.

Group Comparisons

Independent-samples t-tests were used to compare mean differences between different groups, such as gender, nationality, and age categories. The statistical significance was set at $p < .05$.

3.7 Ethical Consideration

Participation in this survey was voluntary, and before answering the questionnaire, respondents were made aware that the submissions are to be kept anonymous, and only being used for academic purposes. Respondents had to consent to participate in this anonymous survey and were also able to stop the survey at any time without any consequences. Overall, no personally identifiable information and sensitive banking information was collected. Lastly, the collected data was not shared with third parties.

4 Results

This section provides an overview of the descriptive statistics of the participants and the main study variables, by showing demographic characteristics, usage patterns of conversational agents, and general attitudes towards their use in banking.

4.1: Sample Characteristics (N=228)

Variables	*Categories*	*N*	*%*
Age	**18-29**	**131**	**57.46**
	30-49	**33**	**14.47**
	50+	**64**	**28.07**
Gender	**Male**	**107**	**46.98**
	Female	**119**	**52.93**
	Diverse / Non-binary	**2**	**0.88**
Nationality	**German**	**93**	**40.79**
	US-American	**92**	**40.35**
	Other	**43**	**18.86**

Table 1: Sample Characteristics (N=228)

Table 4.1 shows the demographics of the 228 pariticipants of the survey. 18-29 year olds accounted for the largest demographic, with 57,46% (n = 131) of participants being in the specific age range. 50+ year olds followed with 28.07% (n = 64) of total respondents, while the 30-49 age-group had the lowest participation rate of 14.47% (n = 33).

Regarding gender, females constituded a small majority in this study, as 52.93% (n = 119) identified as female, while 46.98% (n = 107) as male, and 0.88% (n = 2) as diverse or non-binary.

In terms of nationality, Germans formed the slight majority, with 40.79% (n = 93) respondents, accounting for 40.79% (n = 93) of the respondents, while 40.35% (n = 92) identified themselves as US-Americans. 18.86% (n = 43) came from 24 other nationalities, of which India had the highest representation with 8 participants. One respondent did not disclose where they were from, which led to them being to the "Other" nationality variable. One respondent reported as dual British/German nationality. This subject was assigned into the German group.

4.2. Descriptive Statistics

Table 2: Descriptive Statistics by Nationality

Variable	Combined (N=228)	USA (N=92)	Germany (N=93)
	M (SD)	M (SD)	M (SD)
User Experience	3.24 (0.95)	3.16 (0.89)	3.30 (0.98)
Usefulness	3.20 (1.07)	3.10 (1.00)	3.29 (1.19)
Intention	2.80 (1.20)	2.89 (1.10)	2.69 (1.35)
Human Preference	4.11 (1.10)	4.11 (1.09)	4.11 (1.13)
Hybrid Preference	4.60 (0.80)	4.75 (0.59)	4.46 (1.01)
Privacy	2.75 (1.20)	2.77 (1.12)	2.75 (1.35)
AI Attitude	2.47 (1.18)	2.58 (1.04)	2.24 (1.32)
Institutional Trust	3.14 (1.32)	2.98 (1.23)	3.46 (1.32)

Switching	**3.68 (1.28)**	**3.70 (1.26)**	**3.67 (1.38)**
Empathy (Trust)	**2.75 (1.30)**	**3.11 (1.18)**	**2.19 (1.27)**
Empathy (Satisfaction)	**2.85 (1.32)**	**3.09 (1.23)**	**2.33 (1.33)**

Note. M = Mean, SD = Standard Deviation.

Table 2 displays descriptive statistics regarding the origins of the respondents, which are the United States (N = 92) and Germany (93 = N), as well as total respondents combined (N = 228), including the participants from other countries. The statistics in this table are reported using means (M), or avergares, and standard deviations (SD), to summarize the average value and the degree of dispersion in the data.

Respondents of all nationality groups show some similarities, such as having neutral levels of user experience and percieving conversational agents as useful. Simultaneously, hybrid service models involving CAs and human agents had the highest average ratings, indicating the preference to have the flexibility of communicating with either type of agent. While all nationalities showed high means, amongst US-Americans there is an especially strong consesus. Human preference had the exact same mean result (M = 4.11) in all three groups, showing a preference for a human touch when interacting with customer service. All groups also have similar positive mean rate with regards to switching providers, if their bank were to replace all human agents with conversational agents. This also includes a high to very high variability with polarized opinions in the responses.

Empathy-related variables had higher mean values in the USA sample compared to that of German participants. While US-Americans had moderate views about conversational agents being empathatic, Germans had negative tendencies about this. Regarding institutional-trust, Germans agreed on the notion that banks using conversational agents are less trustworthy compared to banks leveraging using human agents. US-Americans on the other hand had neutral views concering institutional trust. All survey questions regarding the topic of trust received polarizing responses. While all groups had negative opinions about the application of AI in banking, US-Americans demonstrated somewhat more positive attitudes toward artificial intelligence.

Overall, the results indicate that attitudes towards conversational agents are similar across countries, while notable differences are seen in trust and empathy-related perceptions.

Table 3: Descriptive Statistics by Age Group

Variable	*18-29 (N=131)*	*30-49 (N=33)*	*50+ (N=64)*
	M (SD)	M (SD)	M (SD)
User Experience	3.45 (0.91)	3.21 (0.89)	2.79 (0.93)
Usefulness	3.43 (1.01)	3.18 (0.98)	2.73 (1.10)
Intention	2.96 (1.21)	2.94 (1.20)	2.39 (1.09)
Human Preference	4.05 (1.08)	4.27 (1.07)	4.17 (1.15)
Hybrid Preference	4.59 (0.75)	4.61 (0.90)	4.63 (0.85)
Privacy	2.81 (1.13)	2.76 (1.28)	2.61 (1.30)
AI Attitude	2.71 (1.17)	2.58 (1.28)	1.94 (1.10)
Institutional Trust	3.11 (1.35)	3.09 (1.23)	3.23 (1.33)
Switching	3.57 (1.28)	3.64 (1.34)	3.91 (1.23)
Empathy (Trust)	2.95 (1.33)	2.70 (1.21)	2.39 (1.24)
Empathy (Satisfaction)	3.11 (1.28)	2.85 (1.25)	2.33 (1.29)

Note. M = Mean, SD = Standard Deviation.

Table 3 shows the results of descriptive statistics regarding the different age groups (18-29, 30-49, and 50+). 131 were between 18-29 years old, 33 30-49, and 64 were 50 and older. Regarding user experience and usefulness of conversational agents, younger respondents reported more positive compared to their older counterparts, in which they view these variables more neutralyl. In general, participants 50 and older consistently had more negative views regarding conversational agents compared to the youngest respondents. Respondents from the 50+ group especially had negative views on using conversational agents and interacting with AI with regards to customer service in banking, for example in regards of empathy related questions.

The preference for using hybrid service models were viewed positively in all three age groups, coming in a 4.60 median range. The preference for human agent-only interaction also had a positive mean. Similarities existed regarding the use of personal data when using conversational agents (privacy), as all age groups had neutral feelings about it while there was some variability in the responses.

Overall, the survey shows that the younger the participants are, the more they percieve conversational agents in a positive light compared to older respondents, especially in terms of usefulness, attitudes towards AI and empathy.

Table 4: Descriptive Statistics by Gender

Variable	***Male (N=107)***	***Female (N=119)***
	M (SD)	**M (SD)**
User Experience	**3.40 (0.88)**	**3.08 (0.98)**
Usefulness	**3.39 (0.96)**	**3.03 (1.15)**
Intention	**3.04 (1.24)**	**2.57 (1.13)**
Human Preference	**3.86 (1.19)**	**4.34 (0.95)**
Hybrid Preference	**4.58 (0.73)**	**4.63 (0.85)**
Privacy	**3.04 (1.16)**	**2.49 (1.19)**
AI Attitude	**2.77 (1.16)**	**2.22 (1.14)**
Institutional Trust	**2.92 (1.35)**	**3.34 (1.28)**
Switching	**3.45 (1.38)**	**3.87 (1.15)**

Empathy (Trust)	**2.87 (1.30)**	**2.64 (1.31)**
Empathy (Satisfaction)	**3.06 (1.29)**	**2.68 (1.33)**

Note. M = Mean, SD = Standard Deviation.

Table 4 shows descriptive statistics by gender, based upon 107 male and 119 female respondents. There were two people who identified being diverse / non-binary, but the number of participants was too low to be included in this section. In gerneral, males percieve their conversational agent experience and related usefulness more positively compared to their female counterparts, with the median for experience standing at 3.40 vs 3.08 and usefulness at 3.39 vs 2.92. In addition, males also have higher rates of intention use of conversational agents compared to females (M = 3.04 vs 2.57).

While both genders have a very positive view on having hybrid customer service options (M = 4.58 vs 4.63), females have also a more favorable stance towards exclusively having the option to interact with human agents compared to males (M= male 3.86 vs female 4.34). Going back to hybrid customer service, males had a low variability in their answers, showing a greater preference for wanting the option of both conversational bots and human agents (SD = male 0.73). Females also indicated higher willingness to switch bank providers if all human agents were replaced by bots (M = male 3.45 vs female 3.87).

Differences were also evident regarding the subjects‘ perceptions of relative safety and use of their personal data when interacting with conversational agents (privacy) and a general attitude toward artifical intelligence, with male participants leaning more positively on both points.

Overall, male respondents have more favorable opinions regarding conversational in general compared to female participants.

4.3 Hypothesis Testing

This section presents the results of the statistical analysis to test the proposed hypotheses. Depending on the hypothesis, independent-samples t-tests and correlation analyses were applied. Statistical significance was was established by using a significance level of $\alpha = 0.05$.

H1: *Customers with previous experience using conversational agents in other industries show higher intention to use conversational agents in banking.*

H1 was based on the idea that customers with previous experience with conversation agents in customer service will have a higher intention to use conversational agents in banking.

To test this hypothesis, an indipendent-sample t-test was conducted to compare participants who had previously interacted with conversational agents in customer service contexts beyond banking with those who had not.

The results show that respondents with prior experience stated slightly higher a intention to use conversational agents in banking ($M = 2.83$) than respondents who had no prior experience ($M = 2.53$). However, the difference was not statistically significant ($p = 0.17$, $N= 228$).

As a result, H1 is not supported. Previous experience with conversational agents in customer service does not significantly incline individuals to be more willing to use such agents in banking.

H2: *Respondents who feel indifferently towards interacting with AI will show a higher willingness to use conversational agents in banking.*

H2 was partly based of the Technology Acceptance Model, as it suggested that an individual's attitude toward a technology strongly influences their behavioral intention to use it.

To test H2, a correlation and a simple linear regression analysis were conducted to investigate the link between participant levels of indifference toward interacting with AI and their willingness to use conversational agents in banking.

The results show that there is a strong correlation between respondents feeling indifferently towards interacting with AI and willingness to use conversational agents in banking ($r= .62$, $p<. 001$, $N=228$). In addition, indifference significantly predicts willingness to use conversational agents ($ß= .63$, $R^2= .39$, $p<. 001$), explaining 39% of the variance in willingness.

The findings demonstrate that individuals who expressed greater levels of indifference regarding engaging with AI are considerably more inclined to use conversational agents in banking, supporting hypothesis H2.

H3: *Respondents with higher empathy-based trust in conversational agents will show a greater willingness to use them for complex or sensitive banking issues.*

H3 was grounded on the idea that individuals with higher empathy-based trust had a greater factor in predicitng user's willingness in interacting with conversational agents used by their bank.

For testing H3, the correlation between the respondents‘ percieved empathy-based trust in conversational agents and their willingness to use such systems for complex or sensitive banking issues was evaluated. Respondents who answered with "not sure" were not included.

As a result, it appears that there is a moderately positive correlation between empathy-based trust and willingness to interact with conversational agents for complex and sensitive issues ($r= .36$, $p< .001$, $N= 221$).

The results suggest that participants who percieved empathatic conversational agents being more trustworthy, also have a greater willingness to use them for complex or sensitive banking issues. Therefore, H3 is supported.

H4: *Younger respondents (<30) will perceive conversational agents as more useful than older respondents.*

H4 predicts that younger respondents (<30) would percieve conversational agents to be more useful than older respondents.

To test H4, an indipendent-sample t-test was conducted to compare participants‘ percieved usefulness scores across age groups. More importantly, participants in the age group 18-29 ($N= 131$) were compared with the 30-49 ($N= 33$) and 50+ ($N= 64$) age groups.

While there was no statistically significant difference in percieved usefulness between the 18-29 and 30-49 age groups ($p= 0.21$), however there was a significant difference between the 18-29 and 50+ groups ($p< .001$).

Therefore, younger individuals felt that conversational agents were more useful compared to the oldest age group.

As a result, H4 is partially supported.

H5: *Males will perceive conversational agents as being more useful than females.*

For H5, an indipendent-sample t-test was conducted to compare the differences of percieved usefulness of conversational agents by gender ($N= 226$). Since only two respondents identified as being diverse / non-binary, the male ($N= 107$) and female ($N= 119$) numbers were used for this test.

The result showed a statistically significant difference between the two genders ($p < .01$), as male respondents reported higher percieved usefulness of conversantional agents compared to female participants.

This concludes that gender may play a role in the perception of usefulness of conversational agents, which supports H5.

H6: *Older respondents (>50) will express stronger privacy and security concerns regarding conversational agents in banking compared to younger respondents.*

For H6, an indipendent-sample t-test was conducted to compare the relative differences between stronger privacy and security concerns as it relates to conversational agents across all age-groups ($N= 228$).

More importantly, participants in the age group 18-29 ($N= 131$) were compared with the 30-49 ($N= 33$) and 50+ ($N= 64$) age groups.

The results showed no statistically significant differences between the age groups, as the difference between young and middle-aged participants ($p= .83$) and young and older respondents ($p= .30$) was not noteworthy.

H6 was therefore not supported.

H7: *German respondents will exhibit stronger privacy and security concerns toward conversational agents in banking than US respondents.*

An independent-sample t-test was used to assess the differences between US-American and German participants ($N= 185$, German $N= 93$, US-American $N= 92$) regarding levels of privacy and security concerns relating to conversational agents in order to test H7.

The result showed no statistically significant difference between the two nationalities (p= .92). This suggests that such concerns about security and privacy when using conversational agents were similar. In summary, H7 was not validated.

H8: *Customers in the United States will demonstrate a higher willingness to adopt conversational agents in banking than customers in Germany.*

An independent-sample t-test was used to assess the differences between US-American and German participants (N= 185, German N= 93, US-American N= 92) regarding the willingness to adopt conversational agents in banking in order to test H8.

The analysis suggests no significant difference between the nationalities (p= .29), as participants of both groups showed similar attitudes regarding their willingness to adopt conversational agents in banking. As a result, H8 was not supported.

H9: *Most customers will prefer a combination of Conversational Agents and human interaction in the banking industry.*

H9 predicts that most individuals (N= 228) would approve of interacting with a combination of conversational bots and human agents in the banking industry.

The average shows a very high mean value for hybrid preference (M= 4.60, SD= 0.80), suggesting most participants strongly agreed with the preference for a combined service model.

Due to the results of descriptive statistics, H9 was supported.

H10: *Customers will show different levels of preference among conversational agent types (chatbots, voice assistants, and virtual agents), with voice assistants expected to score highest in perceived naturalness.*

H10 was tested with descreptive statistics to analyze respondents‘ perceptions of the naturalness of different conversational agents (N= 228) in the form of text-based chatbots, voice assistants, and virtual agents).

The results showed that text-based chatbots scored the highest, with 115 (50.88%) respondents percieving them as the most natural. Voice-assistants followed with 45 (19.91%) respondents, while virtual agents being last, with 13 participants (5.75%) percieving these agents as the most natural. 53 individuals (23.45%) were uncertain.

H10 was therefore not supported, as voice assistants received a lower perceived level of naturalness compared to text-based chatbots.

H11: *Dissatisfaction with conversational agents will not significantly reduce overall customer loyalty toward their bank.*

H11 predicts that dissatisfaction with conversational agents will not significantly reduce overall customer loyalty toward their bank.

To test this prediction, a correlation analysis was made that would examine the relationship between customer loyalty and participants who do not find conversational agents in general useful.

The results conclude that there was a statistically significant negative correlation between individuals not finding conversational agents useful and willingness to leave the bank provider, if only non-human agents existed ($r= -.28$, $p<.001$, $N= 228$). In conclusion, respondents who perceived conversational agents more negatively were more inclined to leave their bank.

H11 was therefore not supported.

H12: *Respondents who perceive conversational agents as more empathetic will report higher levels of customer service satisfaction.*

H12 predicts that respondents who perceive conversational agents as more empathetic will report higher levels of customer service satisfaction.

For this hypotheses, a correlation analysis was conducted to examine the relationship between the groups of respondents who are more likely to trust a conversational agent if it demonstrates empathy and responds to emotions as well as the group in which the participants were more likely to feel more content with the customer service experience if the agent demonstrated empathy.

Here, a strong positive correlation between empathy and satisfaction was revealed ($r= .73$, $p< .001$, $N= 228$). In addition, the coefficient of determination shows that percieved empathy accounts for a large proportion of the variance in customer satisfaction ($R^2 = .53$).

The finding is that participants who perceived conversational agents as being more trustworthy when also responding with empathy are substantially more content with the customer service experience compared to an absence of empathy.

H12 is therefore validated.

5 Discussion

5.1 Summary of Key Findings

The study has examined how customers of financial institutions percieve the potential use of conversational agents in customer service, and how this affects their overall trust in the company, as well as a willingness to adopt these technolgies. The goal was to costruct a quantitative survey to reach U.S.

and German participants. For this reason, a survey was created for each language, German and English, tailoring it to the needs of the respondents. 12 hypotheses were tested, to explore the relationships between general experience of conversational agents, demographic factors, and overall factors regarding CAs in banking, such as perceived uselfulness, trust, privacy concerns, switching intentions and usage intentions.

First, the intention, or willingness to use conversational agents in banking was moderate overall (M= 2.80, SD= 1.20). Out of all demographics though, females (M= 2.57) and the 50+ age group (M= 2.39) were the groups that showed low willingness in using these tools. However, while the other demographics have not shown strong rejection towards using conversational agents at their banks, none of them expressed high enthusiasm for fully automated service interactions either. Instead, hybrid service models combining conversational bots with human agents obtained the highest approval ratings and with generally consistent responses (M= 4.60, SD= 0.80). The preference of only having to interact with human agents was also in wide agreement, though with some variation in opinions (M= 4.11, SD=1.10). In conclusion, it indicates that individuals do not request a full replacement of human agents, but rather see the technology as a support alongside traditional interaction channels.

Regarding factors of adoption, a strong statistical relationship was identified between the individual's level of indifference toward interacting with AI and willingness to use conversational agents in banking ($r= .62, p<.001$), with a 39% variance in willingness ($R^2= .39$), suggesting that participants who feel indifferently towards AI technologies are significantly more likely to interact with conversational bots in banking.

The results also indicat that empathy-related variables also play a significant role, implying that respondents who perceived conversational agents as more empathetic, will also report higher levels of customer satisfaction ($r= .73, p< .001$), with empathy explaining 53% of the variance in satisfaction ($R^2= .53$). Regarding empathy, H3 was supported in which a correlation appeared between respondents with higher empathy-based trust in conversational agents and the individuals who showed a greater willingness to use them for complex and sensitive banking issues ($r= .36, p<.001$). In short, the results highlight that the perception of empathatic agents have a high impact regarding trust-building between the customers and AI-based banking services.

On the other hand, prior experience with CAs in other industries did not equate to a higher intended use of conversational agents in banking ($p= .17$). Privacy and security concerns between the age groups ($p= .30$, $p= .83$) or between German and U.S. respondents ($p= .29$) also pointed to no significant differences. In reference to nationalities, there were also no significant differences in regards to adoption likelihood ($p= .29$). The analysis suggests that cultural factors were less of a variable than anticipated.

The age groups responded with partial differences regarding percieved conversational agents usefulness. 18-29 year olds find CAs to be more useful ($M= 3.43$) compared to the 50+ age group ($M= 2.73$), showing a statistically significant difference ($p< .001$). However, there was no significant difference between the youngest participants and the 30-49 age group ($p= 0.21$). A significant difference regarding perceived usefulness was seen between the genders, as males reported higher usefulness evaluations compared to females ($p<.01$). This variable however was not directly tested as a predictor of adoption.

Descriptive results suggest some neutrality regarding individuals leaving their bank that only use non-human agents ($M= 3.14$, $SD= 1.32$) and feeling safe regarding privacy when using CAs ($M= 2.75$, $SD= 1.20$). Participants showed low agreement with being fine interacting with AI ($M = 2.47$, $SD = 1.18$), which explains the moderate intention to adopt these tools.

Lastly, there was a correlation between individuals being dissatisfied with conversational agents and their intention to leave a bank where only non-human service options were available ($r= -28$, $p< .001$). While conversational agents may enhance efficiency, the results suggest that improper implementation could potentially harm customer retention.

In conclusion, even though the results suggest some differences by demographics (age, nationality, and gender), psychological and perceptual variables (such as empathy, trust, and general AI aittitude) seem to play a greater role in determining the likelihood of conversational agent adoption. Most importantly, participants demonstrated openness towards AI integration in banking, if human touchpoints remain available.

5.2 Theoretical Implications

This section combines the empirical findings with the theoretical framework in Chapter 2. The goal was to examine customers of Financial Institutions and their perception on the potential use of conversational agents in customer service, and how this affects their trust in the company, and the willingness to adopt these technologies. The results implied that the overall acceptance in the banking context is mainly driven by psychological and relational factors. Therefore, established technology acceptance models (e.g. TAM) are useful for supporting this concept. However, the banking context requires a stronger emphasis on trust and relationship-oriented factors.

5.2.1 Implications for Technology Acceptance Models (TAM/UTAUT)

The Technology Acceptance Model (TAM) explains and forecasts if individuals will accept the use of a specific information system as it relates to perceived usefulness and ease of use, shaping their attitudes or intentions to use the systema. This was accordingly laid out in chapter 2.5.1. The present study documents a moderate average willingness to use conversational agents in a banking context ($M = 2.80$). This suggests that potential efficiency advantages, such as around-the-clock availability and faster response times, may not be sufficient on their own to generate strong adoption intentions. From a TAM perspective, an assumption can be made that conversational agents existing as an option alone is not enough, as customers form intentions of use for a specific technology only when the system is also seen in a positive light. Existing merely as an option is not enough.

An additional insight of the study was a strong association between general AI attitudes in banking and the willingness to use conversational agents ($r= .62$; $R^2= .39$). This indicates that acceptance in banking does not solely depend upon the system being perceived as useful, but also if the individual is comfortable enough using a conversational agent driven by AI. This is where extended acceptance models are needed for better understanding, such as TAM2/TAM3 and UTAUT/UTAUT2, which incorporate additional psychological and context-specific variables (Chapter 2.5.3.). The results imply that general AI attitude is partially shaped by external factors beyond the immediate banking context, including prior exposure to AI technologies.

5.2.2 Banking-Specific Acceptance Driver

In the literature, it was established that banks are highly regulated (Ali, Murray, Al-Ahmad, Jeon and Dwivedi, 2025, p.9), while at the same time AI systems rely on large volumes of sensitive personal data, elevating privacy and security concerns. As stated in chapter 2.6.4., individuals may have concerns regarding fraud and transaction failures, especially for high value transactions, therefore preferring conventional modes of transactions. Ignoring this may contribute to lower trust levels. The empirical findings partially support this theoretical argument. While overall willingness to use CAs was moderate, there was a positive correlation for participants with higher empathy-based trust in conversational agents showing a greater intention to use them for complex or sensitive banking issues ($r= .36$). This indicates that trust becomes particularly relevant when interactions have to deal with what are seen as important service requests. Bank customers may use CA services for simple issues, but require greater trust for more sensitive issues. 62.72% of participants indicated that they would use conversational agents only for simple, non-critical actions. From a theoretical perspective, this result suggests that trust may function as a boundary condition for adoption, whereby limited trust confines usage to low-risk interactions, while higher trust levels are associated with greater openness toward complex or sensitive service encounters.

Surprisingly, individuals with prior experience with CAs in other industries and an intention to adopt these tools in banking did not have a strong correlation ($p= .17$). The findings imply that familiarity alone is not a guarantee of acceptance in the high-risk banking sector. In conclusion, even if customers used these agents in retail or entertainment, there may be hesistation using these tools when sensitive and financial information are in play. Also, there was also no significant correlation between participants who had used conversational agents in banking and who also responded with an intention to use these tools for sensitive actions.

5.2.3 Perceived Empathy and Expected Service Outcomes

A central finding of the study relates to empathy and its influence on respondents who are more likely to trust a conversational agent if it exhibits empathy in response to a user's emotions, as well as on respondents who are more likely to feel satisfied with the customer service experience if the agent demonstrates empathy ($r = .73$; $R^2 = .53$). This supports the theoretical discussion around the role of emotion in the service and the effects of anthropomorphism (chapters 2.4.2. and 2.4.3.). The literature review highlighted that automated systems are often perceived to be efficient, but also struggle to replicate empathy in customer service in the way a human being would do so (Ferraro, Demsar, Sands, Restrepo and Campbell, 2024, p. 554). This can affect customer service ratings. The results in this study somewhat reinforce this theory, as customers who perceive CAs as empathetic, tend to trust the systems more. Not only may customer satisfaction be affected, trust also plays a crucial role in adoption intentions (Daly, Wiewiora and Hearn, 2025, p.1Importantly, the current findings reflect customer expectations and evaluative criteria rather than empirically observed effects in actual service interactions.Drawing on anthropomorphism theory, CAs showing human-like characteristics and qualities and emotionally responsive language may positively affect customer service feedback. Regarding perceived naturalness, 50.88% of respondents identified text-based chatbots as the most natural conversational agent.

5.2.4 Privacy, Transparency, and Risk Considerations

Existing literature, and as mentioned in the literature review, emphasizes that privacy concerns and transparency (such as chapter 2.6) may influence an individual's intention to adopt AI, especially in the highly regulated banking industry. In this study, individuals feeling comfortable regarding their personal data when using conversational agents was met with a moderate response (M= 2.75), while no significant difference appears as it relates to different age groups or nationality. The results imply that privacy may not be the dominant factor affecting adoption in the examined sample. However, at the same time existing literature recognizes that privacy concerns could play a role as it pertains specifically to the financial sector (Ali, Murray, Al-Ahmad, Jeon and Dwivedi, 2025, p.9), while some studies indicate that banking customers may continue using chatbot services if they are seen to be trustworthy and useful, and at the same time customer needs are satisfied (Nguyen, Chiu & Le, 2021, p. 16). As long as these expectations are met, privacy concerns alone may not serve as a decisive predictor of acceptance to adopt such a service.

5.2.5 Demographics and Culture as Secondary Drivers

The current study also focused on demographic and cultural variations. While age and gender can potentially affect perceived usefulness (H4 partially supported and H5 supported), nationality differences, at least in this case between German and U.S. respondents, were not significant as it pertains to privacy concerns or adoption intentions (H7 and H8 not supported). The indication is that the cultural difference between the U.S. and German respondents does not seem to be as influential as originally predicted. It could suggest that the acceptance of CAs in banking is more influenced by psychological and perceptual factors, such as trust, empathy, and general attitudes toward AI, instead of nationality.

5.2.6 Summary of Theoretical Implications

In summary, the combination of empirical findings and established technology theories demonstrates that adoption of conversational agents in a banking context is driven more by psychological and perceptual factors as compared to demographic or cultural differences. Perceived usefulness and ease of use are major factors regarding traditional models such as TAM, but the results of this study rather highlight the central role of trust, empathy, and general attitudes toward AI in the banking context. Trust appears to be a decisive factor since, in it absence, it limits usage to simple tasks, or even to no adoption at all. At the same time, trust enables adoption for complex issues when it is high.

5.3 Practical Implications

The results of this study provides several insights for financial institutions considering the integration of conversational agents into their customer service operations. The study suggests that successful adoption in the banking context especially depends on relationship methods, trust-building mechanisms, and service integration strategies.

As the willingness to use conversational agents came tends to be moderate (M= 2.80), it can be assumed that customers will most likely not adopt such tools automatically. While on the one hand, customers had moderate feelings about their personal data when using CAs (M= 2.75), individuals simultaneously also appear cautious, as almost 90% would not use conversational bots for complex or sensitive actions. To combat this, banks would be advised to prioritize trust-centered implementation strategies.

One way of tackling this issue, is not to replace all human advisors, especially in high-stakes interactions. This strategy is consistent with the findings of the present survey, in which customers expressed very high approval of hybrid service models (M = 4.60), with a strong preference for human interaction (M= 4.11). Managers should therefore implement hybrid service models that initially route customers through conversational agents, while deferring to human operators when necessary (Ranieri, Di Bernardo and

Mele, 2024, p.208). As a result of such systems, employees will be enabled to access prior interaction data, provide personalized support, and improve efficiencies.

Providing information and certain reassurances about data security, regulatory compliance, and overall transparency may further strengthen confidence in conversational agents. Considering that there was a moderate response regarding individuals in this study who trust banks less when only non-human agents are available (M= 3.14), there is room for trust-building efforts through transparent communications and service design choices. In addition, positioning CAs as a support system along human service, rather than cost-saving substitutes, may increase usage and adoption rates.

The strong correlation between respondents who are more likely to trust a conversational agent when it demonstrates empathy and those who report higher anticipated satisfaction under the same condition underscores the importance of emotionally responsive system design. While CAs cannot fully replicate emotional intelligence, the results suggest an integration of empathetic language, such as expressing understanding and acknowledgement of client concerns, may boost perceived service quality. Therefore, managers should consider designing conversational agents that extend functional accuracy. CAs should consequently have dialogue scripts that incorporate supportive and context-sensitive phrasing to improve trust perceptions and contribute to broader adoption intentions.

The findings therefore underscore that CAs in banking should be implemented into a secure relationship-oriented service framework focused on trust and transparency. The preference of conversational agents complementing human-agents indicate that automation should not fully replace human expertise, but rather support them.

5.4 Limitations

This study provides valuable information about conversational agents and its adoption and perception in a banking context. Several limitations still need some consideration.

First, rather than analysing real banking interactions, observation was performed with individuals who subjectively responded to a scenario-based survey. Therefore, the answers in this survey could possibly differ from real-life scenarios. In short, the results are based on perceived attitudes rather than with a real-world banking context.

Second, this study was not conducted with a broad population, as the survey recorded 228 sufficient respondents. While this number is applicable for a correlation and group comparison analysis, a larger and more diverse sample would strengthen the study results and validity. Due to the fact that the majority of respondents were recruited from the online social-media platform Reddit, a certain sampling bias may have been introduced, as online communities can attract certain demographic and attitudes. Therefore, the results may have differed compared to a broader range of banking customers.

Third, the recruitment of the survey focused on German and U.S. respondents and not wider population. Consequently, the results should not be generalized to other nationalities.

Fourth, looking back, the age groups (18-29; 30-49; 50+) may be considered to be too broad. Having more differentiated age groups would perhaps capture more nuanced differences and deeper insights. Even though being the same group, early 30 year participants may have more digital finesse compared to those in their late 40s. Regarding age segmentation, the groups are not equally spread, with 30-49 year olds only representing 14.47% of the survey, while the 18-29 age group had a representation of 57.46%.

Additionally, the survey did not specifically examine whether stronger emphasis on efficiency benefits would influence individuals intention to use CAs. In previous literature, increased efficiency was often being cited as being a benefit of automation and perhaps would play a greater role.

Even though this is not a crucial limitation, there were some minor structural differences between the German and English surveys. While in the German survey the item measuring general usefulness of conversational agents was in the overall experience section, this part was positioned in the banking-related section in the English questionnaire. The wording remained largely consistent, however the different sections may have affected interpretation.

Overall, these limitations should be considered when interpreting the analysis of this paper. However, the results still provide meaningful insights for better understanding the adoption of CAs in a banking context.

5.5 Directions for Future Research

Regarding some of the limitations of this study, certain directions for future research can be identified.

Unlike with this study, other examiners should analyze conversational agent adoption using real banking interactions. If that is not possible, behavioral or experimental designs would be an extension to this study, as this research relied on scenario-based survey responses. With an experimental study, it could be possible to simulate real banking interactions and measure observable behavioral outcomes.

Secondly, a study that observes participants over time could provide deeper insights into how trust evolves regarding CAs. As trust is a variable that can be established over time via repeated positive interactions, this could help investigate whether a positive trust development over time would increase willingness to use conversational agents for complex or sensitive financial tasks. As a result, a study so designed could better analyze relationships and trust-building mechanisms.

Thirdly, cross-cultural research could be examined beyond a handful of cultures or nationalities. Unlike with the present research, the inclusion of additional countries with varying variables, such as regulatory policies, technological infrastructure, or cultural attitudes toward AI and automation might be helpful. It could determine if country-specific results as in this study involving German and U.S. respondents are sufficient or if additionally, a broader and more global set of participants is helpful or even necessary to draw relevant conclusions about adoption. Regarding demographics, future research should focus on a more detailed age categorization, as the result could help better examine nuances between different ages.

Lastly, the exploration of the role of empathy and anthropomorphic design elements using controlled experimental conversational agents could further future research. Analyzing different emotionsand dialogues could help get insights into how certain design features influence trust and adoption.

In summary, conversational agents should be further examined to identify improvements that would enhance their use a relational service tool, instead of primarily being seen as a technical advancement for achieving efficiencies.

6 Conclusion

The main objective of this study was to examine how customers of financial institutions perceive the potential use of conversational agents in customer service. Both how this affects customer trust in companies that use such agents as well as the willingness of users to adopt these technologies. This research aimed to collect empirical insights into a customer‘s perspective on these tools within a trust-sensitive industry like banking at a time in which CAs have already been implemented in the service sector more than ever (Prinz, 2022, p.2).

After examination, results showed that customers had moderate willingness to interact with banking conversational agents. Participants did not generally express strong disapproval towards these technologies, however support for fully automated service models remained limited. Hybrid service models on the other hand, in which human agents are accompanied by bot services received high levels of approval, suggesting that clients are not seeking a complete substitution but rather conversational agents serving as a complementary tool that supports traditional service structures.

One of the main findings of this research was that adoption had a strong influence upon psychological and relational variables, as general attitudes toward AI and perceived empathy of conversational agents specifically being important predictors. For example, participants who felt indifferently towards interacting with AI showed a higher willingness to adopt conversational agents in banking. In addition, a strong correlation was found between respondents who perceived CAs being empathetic if at the same time customer satisfaction is maintained as well as a moderately positive correlation between empathy-based trust and willingness to interact with conversational agents for complex and sensitive issues. Both correlations highlighting the critical role of emotional responsiveness and trust formation in digital service environments.

In contrast, several demographic and cultural assumptions did not have the expected influence as predicted. Younger as well as male participants had more positive views about conversational agents pertaining to, for example, usefulness. However, there were seemingly no significant influences regarding the difference between Germans and U.S respondents perceptions on privacy concerns and adoption. This reflects the notion that psychological perceptions, such as trust and general AI attitudes, outweigh demographic or cultural variables.

Looking through the lens of theoretical perspective, the insights align with the central assumption of the Technology Acceptance Model (TAM). The results also demonstrated the relevance of perceived usefulness shaping behavioral intention. However, due to the fact that this research focused on banking, it appears that an extended framework that goes beyond traditional acceptance constructs is needed since both trust and emotional reassurance function as factors for adoption, especially regarding high-risk services involving sensitive financial matters. Efficiency and performance as factors alone cannot explain the likely acceptance of CAs, meaning that extended frameworks are needed.

Therefore, managers of banks are advised not to promote conversational agents as a cost-saving replacement for human advisors. Rather it is advisable for management to offer customers hybrid service models that combine human interaction and automation. To strengthen customer trust, data protection, regulatory compliance, and service escalation need to be made transparent. Additionally, if CAs express context-sensitivity and empathetic language, customers may reach higher trust-levels, while also perceiving better service-quality.

In conclusion, conversational agents may offer banks an opportunity to enhance their efficiency and service accessibility. However, their success depends less on these technological factors and more on the psychological perceptions of clients regarding acceptance and trust. While digital transformation is taking over the financial sector, banks need to understand which factors can most motivate their customers to accept and adopt AI. In doing so, they must also recognize that trust will continue to remain the foundation of any long-lasting relationship with the customer.

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8 Appendix

English survey (next page):

Customer Perception of Conversational Agents in Banking

This survey is for a Bachelor thesis, trying to understand how customers perceive non-human conversational agents, such as chatbots or voice assistants.

The survey takes approximately 5 minutes. Your responses are ***anonymous*** and will be used for academic purposes only.

* Indicates required question

1. I consent to participate in this anonymous survey *

Check all that apply.

☐ Yes, I would like to continue

About you

2. What is your age group? *

Mark only one oval.

◯ 18-29

◯ 30-49

◯ 50+

3. What is your gender? *

Mark only one oval.

- Male
- Female
- Divers/non-Binary

4. What is your nationality? *

Mark only one oval.

- US-American
- German
- Other: ____

Your general experience with Conversational Agents

5. Have you ever interacted with a conversational agent before (chatbot, voice assistant like Siri/Alexa, or a virtual assistant etc.)? *

Mark only one oval.

- Yes
- No
- not sure

6. If you have used a conversational agent before, how would you rate your past experience with it?

Don't answer if this doesn't apply to you.

Mark only one oval.

	1	2	3	4	5	
Very	◯	◯	◯	◯	◯	very positive

7. What type of conversational agents have you used?
You may choose more than one

Check all that apply.

☐ Text-based Chatbots (e.g., ChatGPT, customer-service chatbot on a website or app, website help bot)
☐ Voice assistant (e.g., Alexa, Siri)
☐ Virtual assistant (e.g., avatar-like assistant)
☐ I´m not sure
☐ None

8. Which of the conversational agents felt the most human-like to you?

Mark only one oval.

◯ Text-based Chatbots (e.g., ChatGPT, customer-service chatbot on a website or app, website help bot)

◯ Voice assistant (e.g., Alexa, Siri)

◯ Virtual assistant (e.g., avatar-like assistant)

◯ Unsure

9. Have you ever used a conversational agent in customer service before?

Mark only one oval.

- Yes
- No
- Not sure

10. Have you ever used a conversational agent in one of the following industries before?
You may choose more than one

Check all that apply.

- [ ] Banking & Finance
- [ ] Healthcare
- [ ] Telecommunications
- [ ] Travel & Tourism
- [ ] Retail / Online Shopping
- [ ] I´m not sure
- [ ] None
- [ ] Other: ______________________

11. Have you ever used a conversational agent in your bank's customer service before? *

Mark only one oval.

- Yes
- No
- Not sure

Conversational agents in Banking

12. I believe conversational agents are generally (not only banking) useful. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly agree

13. I am open to use a conversational agent for banking services in the future. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

14. I would feel more comfortable only talking to human agents for customer service. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

15. I would prefer to have the option to talk to a human agent in addition to a conversational agent. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

16. I feel safe in regards to my personal data when using a conversational agent. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

17. I would feel indifferent interacting with artificial intelligence in the bank's customer service (e.g., chatbots, voice assistants). *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Srongly agree

18. I trust banks that use conversational agents less than those that rely on humans. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

19. If my bank only offered non-human conversational agents, I would consider switching to another bank. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

20. *Trust:* I'm more likely to trust a conversational agent if it demonstrates empathy and responds to my emotions. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

21. *Satisfaction:* I feel more content with the customer service experience if the conversational agent demonstrates empathy (e.g., "I'm sorry you're having this issue"). *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

Final Question

22. Would you use the conversational agent in banking for complex and sensitive issues? *

Mark only one oval.

- Only for simple issues (e.g., general information, technical support, checking balances, FAQs)
- For both simple and complex/sensitive issues
- Not at all
- Not sure

Thank you for participating!

All responses are kept anonymous.

German survey (next page):

Kunden-Wahrnehmung von konversationellen Agenten bei Banken

SurveyCircle-Nutzerinnen und -Nutzer erhalten für ihre Teilnahme Punkte, die genutzt werden können, um kostenlose Umfrageteilnehmende auf **SurveyCircle.com** zu rekrutieren.

Diese Umfrage dient einer Bachelorarbeit, die untersuchen soll, wie Kunden nicht-menschliche Gesprächspartner wie Chatbots oder Sprachassistenten wahrnehmen.

Die Umfrage dauert etwa 5 Minuten. Ihre Antworten sind anonym und werden ausschließlich für akademische Zwecke verwendet.

~~* Indicates required question~~

1. Ich stimme der Teilnahme an dieser anonymen Umfrage zu. *

   Mark only one oval.

   ◯ Ja, ich würde gerne die Umfrage durchführen

Über Sie

2. Welcher Altersgruppe gehören Sie an? *

   Mark only one oval.

   ◯ 18-29

   ◯ 30-49

   ◯ 50+

3. Geben Sie Ihr Geschlecht an. *

Mark only one oval.

- Weiblich
- Männlich
- Divers/ nicht-binär

4. Was ist Ihre Nationalität? *

Mark only one oval.

- Deutsch
- US-Amerikanisch
- Sonstiges

5. Falls Sie „Sonstiges“ angegeben haben, schreiben Sie Ihre Antwort hier hinein.

Ihre Erfahrung mit konversationelle Agenten

Arten von konversationellen Agenten:
Chatbot (ein Computerprogramm, das menschliche Gespräche simuliert)
Sprachassistenten wie Alexa oder Siri
Virtueller
Assistent

6. Haben Sie jemals mit einem konversationellen Agenten (Chatbot, Sprachassistenten wie Alexa oder Siri oder Virtueller Assistent) interagiert? *

Mark only one oval.

- ⬭ Ja
- ⬭ Nein
- ⬭ Weiß ich nicht

7. Falls Sie schon mal mit einem konversationellen Agenten interagiert haben, wie würden Sie Ihre Erfahrung bewerten?

Bitte nicht antworten falls dies nicht auf Sie zutrifft.

Mark only one oval.

	1	2	3	4	5	
Sehı	⬭	⬭	⬭	⬭	⬭	Sehr positiv

8. Welche der folgenden konversationellen Agenten haben Sie schon einmal benutzt?

Sie können mehr als eine Antwort auswählen.

Check all that apply.

- ☐ Textbasierter Chatbot (ChatGPT, Chatbot eines Kundenservices auf einer Webseite oder in einer App, Webseite-Hilfsbot usw.)
- ☐ Sprachassistenten (z.B. Alexa oder Siri)
- ☐ Virtueller Assistent (z.B. Avatar-ähnlicher Assistent)
- ☐ Nicht sicher
- ☐ Gar keinen

9. Welche der folgenden konversationellen Agenten finden Sie am natürlichsten?

Mark only one oval.

- Textbasierter Chatbot (ChatGPT, Chatbot eines Kundenservices auf einer Webseite oder in einer App, Webseite-Hilfsbot usw.)
- Sprachassistenten (z.B. Alexa oder Siri)
- Virtueller Assistent (z.B. Avatar-ähnlicher Assistent)
- Nicht sicher

10. Generell finde ich konversationellen Agenten nützlich. *

Mark only one oval.

	1	2	3	4	5	
Stir						Stimme voll und ganz zu

11. Haben Sie jemals mit einem konversationellen Agenten im Kundenservice interagiert?

Mark only one oval.

- Ja
- Nein
- Weiß ich nicht

12. In welcher der folgenden Branchen haben Sie einen konversationellen Agenten benutzt?

Sie können mehr als eine Antwort auswählen.

Check all that apply.

- [ ] Bankwesen und Finanzen
- [ ] Versicherung/Gesundheitswesen
- [ ] Telekommunikation
- [ ] Tourismus
- [ ] Einzelhandel / Online-Shopping
- [ ] nicht sicher
- [ ] Gar keinen
- [ ] Sonstiges

13. Falls Sie „Sonstiges“ angegeben haben, schreiben Sie Ihre Antwort hier hinein.

14. Haben Sie jemals mit einem konversationellen Agenten im Kundenservice Ihrer Bank interagiert?

Mark only one oval.

- ( ) Ja
- ( ) Nein
- ( ) Weiß ich nicht

Konversationelle Agenten in der Bank

15. Ich habe nichts dagegen, in Zukunft konversationelle Agenten im Kundenservice meiner Bank zu benutzen. *

Mark only one oval.

	1	2	3	4	5	
Stim	◯	◯	◯	◯	◯	Stimme voll und ganz zu

16. Ich würde mich wohler fühlen, wenn ich im Kundenservice nur mit menschlichen Mitarbeitern sprechen würde. *

Mark only one oval.

	1	2	3	4	5	
Stim	◯	◯	◯	◯	◯	Stimme voll und ganz zu

17. Ich würde es bevorzugen, in Kombination mit einem konversationellen Agenten auch die Option zu haben, mit einem menschlichen Mitarbeiter zu sprechen. *

Mark only one oval.

	1	2	3	4	5	
Stim	◯	◯	◯	◯	◯	Stimme voll und ganz zu

18. Ich fühle mich sicher genug, um meine persönlichen Daten bei der Nutzung eines konversationellen Agenten anzugeben. *

Mark only one oval.

	1	2	3	4	5	
Stir	◯	◯	◯	◯	◯	Stimme voll und ganz zu

19. Mir wäre es egal, wenn ich mit künstlicher Intelligenz im Kundenservice einer Bank interagieren müsste (z. B. Chatbots, Sprachassistenten). *

Mark only one oval.

	1	2	3	4	5	
Stir	◯	◯	◯	◯	◯	Stimme voll und ganz zu

20. Banken, die konversationelle Agenten benutzen, vertraue ich weniger als diejenigen, die menschliche Mitarbeiter benutzen. *

Mark only one oval.

	1	2	3	4	5	
Stir	◯	◯	◯	◯	◯	Stimme voll und ganz zu

21. Ich würde es mir überlegen, die Bank zu wechseln, wenn sie nur nicht-humane konversationelle Agenten anbieten würde. *

Mark only one oval.

	1	2	3	4	5	
Stir	◯	◯	◯	◯	◯	Stimme voll und ganz zu

22. Ich würde einem konversationellen Agenten mehr vertrauen, wenn es Empathie zeigt und auf meinen Emotionen regiert. *

Mark only one oval.

	1	2	3	4	5	
Stir	◯	◯	◯	◯	◯	Stimme voll und ganz zu

23. Ich wäre zufriedener mit dem Kundenservice, wenn der konversationelle Agent Empathie zeigen würde (z.B. "Es tut mir leid, dass Sie dieses Problem haben"). *

Mark only one oval.

	1	2	3	4	5	
Stir	◯	◯	◯	◯	◯	Stimme voll und ganz zu

Finale Frage

24. Würden Sie den konversationellen Agenten bei Ihrer Bank für komplexe und vertrauliche Probleme benutzen?

Mark only one oval.

- ◯ Nur für einfache Anliegen (z. B. allgemeine Informationen, technischer Support, Kontostandsabfrage, FAQs)
- ◯ Für einfache Anliegen und komplexe/vertrauliche Probleme
- ◯ Überhaupt nicht
- ◯ Weiß nicht

Vielen Dank, dass Sie mitgemacht haben!

Alle Antworten wurden anonym erfasst.

Löse den folgenden **Umfragecode** unter https://www.surveycircle.com ein und erhalte **kostenlose Umfrageteilnehmende** über SurveyCircle.

Der **Umfragecode** lautet: **RM8G-GH94-RGUZ-33V1**.

Declaration of Academic Integrity

I hereby declare that this bachelor thesis was written independently and without unauthorized assistance. All sources used are properly cited.

Brendan McMahon