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Factors Driving Adoption of Humanoid Service Robots in Banks

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Factors Driving Adoption of Humanoid Service Robots in Banks

Abstract

We examine the technological and socioenvironmental factors influencing the adoption of humanoid service robots in Austrian, German, and Swiss banks. We integrate the technology acceptance model and the technology–organization–environment framework, and employ structural equation modeling to analyze data from the top management of 106 banks. We find that the relative advantage of the innovation, top management support, competitive pressure, and customer acceptance drive the perceived usefulness of humanoid service robots. Moreover, customer acceptance significantly enhances perceived ease of use by the bank. Together, perceived usefulness and perceived ease of use significantly increase banks' intention to adopt humanoid service robots. However, the actual adoption rate of humanoid service robots in banks remains low, indicating the presence of underlying barriers to adoption such as lack of organizational readiness, technical limitations, and regulatory concerns, which are especially relevant for smaller banks with limited resources. Furthermore, some banks perceive humanoid service robots as fascinating novelties rather than essential operational tools. As a result, banks are actively exploring alternatives such as digital avatars, chatbots, and voice bots for certain tasks while continuing to prioritize human-to-human interactions for non-online customer services.

JEL-Codes: L840, O320, O330.

Keywords: humanoid service robots, technology adoption, banking industry.

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1. Introduction

The banking sector has recently experienced a pronounced shift towards digital banking, which closely aligns with customer preferences (Hentzen et al., 2022). The demand for in-person banking nevertheless persists, especially for specific banking operations such as financial advice, large cash withdrawals, depositing and collection of handwritten bank checks, and other traditionally paper-based financial transactions. In-person banking is particularly important for demographic groups less inclined to use digital services (Northey et al., 2022; Hajiabbasi et al., 2023). However, high operational costs, digital integration complexities, safety concerns during health crises, labor shortages, and a decrease in physical branches highlight the need for technological advancements in physical bank branches (Khon et al., 2022; Hajiabbasi et al., 2023). Humanoid service robots have emerged as a promising solution, facilitating the development of hybrid cyber–physical bank branches that are efficient, cost-effective, and safe while retaining the personal touch of in-branch services (Hajiabbasi et al., 2023). Japanese banks pioneered the adoption of humanoid service robots (McCurry, 2015), with applications ranging from welcoming guests and providing entertainment to managing a fully automated bank branch (Khan, 2018; Tyagi, 2021). Figure 1 illustrates the widespread phenomenon of humanoid service robot deployment in banks.

[Figure 1 around here]

Service robots are among the most dramatic recent developments in the service industry (Mende et al., 2019). They are defined as system-based, autonomous, and adaptable interfaces that interact, communicate with, and offer services to a company's customers (Wirtz et al., 2018). Equipped with advanced features like artificial intelligence (AI), natural language processing, and machine learning, humanoid service robots have spurred research on customer acceptance as well as their implications for employees in general and in the banking sector specifically (Wirtz et al., 2018; Lu et al., 2020; Volpe et al., 2020; Amelia et al., 2022). Despite these findings, an important research question remains: What are the factors driving a bank's decision to adopt humanoid service robots?

Addressing this research question will provide insights for banks, banking associations, manufacturers, software solution providers, and policymakers to facilitate the adoption process. Such adoption could mitigate labor shortages, streamline banking processes, reduce employee workloads, and enhance multilingual communication capabilities (Wirtz et al., 2018; Volpe et al., 2020; Amelia et al., 2022). Despite these

advantages, the initial enthusiasm for humanoid service robots in banks across Austria, Germany, and Switzerland in 2018 and 2019 seems to have waned,¹ highlighting the need to reassess the current state of adoption. The Austrian, German, and Swiss region, which has significant technological expertise, robust financial infrastructure, and cohesive cultural and economic ties, provides an intriguing context for our study.

We find that the relative advantage of the innovation, top management support, competitive pressure, and customer acceptance significantly drive the perceived usefulness of humanoid service robots, and that the total effects of these factors positively affect the intention to adopt. Customer acceptance significantly enhances perceived ease of use, which, along with perceived usefulness, also significantly increases banks' intention to adopt. The actual adoption rate of humanoid service robots in banks nevertheless remains low, suggesting underlying barriers. Our analysis indicates that organizational readiness is a necessary requirement rather than an adoption driver. Qualitative responses highlight that technical limitations and regulatory concerns further impede adoption, especially for smaller banks with limited resources. Some banks also perceive humanoid service robots as interesting "gimmicks" rather than necessary operational tools. As a result, banks are actively exploring alternatives such as digital avatars and bots, which are considered more appropriate for certain banking tasks, while continuing to prioritize human-to-human interactions for non-online customer services.

To explore the factors driving the adoption of humanoid service robots at the organizational level in banking, we integrate the technology–organization–environment (TOE) framework (Tornatzky and Klein, 1990) to account for the external variables within the technology acceptance model (TAM) (Davis et al., 1989). Recognizing that technology adoption factors are often latent constructs, we operationalized these constructs based on an extensive literature review. To examine the impact of various drivers on the intention to adopt humanoid service robots, we conducted an online survey among 106 Austrian, German, and Swiss banks and estimate a model using partial least squares structural equation modeling (PLS-SEM). This method is particularly suitable for new research areas and complex models due to its flexibility with small samples, diverse data distributions, and its ability to quantify responses without strict sample size limits (Hair et al., 2019). Furthermore, the survey

¹ Media coverage in 2018 and 2019 highlighted the adoption of humanoid service robots in banks (Hertlein 2018). In subsequent years reports on the topic significantly declined.

contains qualitative questions to enrich our quantitative findings and to identify causal channels.

By integrating these qualitative insights with our quantitative results, we offer a nuanced view of the perceptions and experiences of adopting humanoid service robots, also identifying emerging trends in banking technology adoption. Our findings reveal varied perspectives, highlighting the potential of digital avatars and the enduring importance of human-to-human interaction. From a managerial standpoint, we provide strategic recommendations for banks and banking associations to facilitate the integration of humanoid service robots. We also highlight implications for manufacturers and software solution providers, suggesting the development of user-friendly interfaces, robust technical support, and compatibility with existing banking infrastructure. Furthermore, policymakers should address regulatory concerns to facilitate the adoption of new technologies in the banking sector, which could help mitigate labor shortages and enhance multilingual communication capabilities. We further contribute to existing literature by examining the factors influencing the adoption of humanoid service robots, thereby addressing an existing research gap. Contrary to the prevailing view that organizational readiness drives technology adoption (Chatterjee et al., 2021), our findings suggest that organizational readiness is a necessary requirement rather than an adoption driver. Additionally, our results indicate the importance of including customer acceptance in technology adoption research, especially when the adoption directly affects bank customers (cf. Nam et al., 2021).

The study is organized as follows: Section 2 reviews theoretical frameworks on technology adoption, proposes a research framework, and formulates our research hypotheses. Section 3 outlines the research method, including the instrument, data collection, and analysis method. Section 4 reports the descriptive statistics, evaluates the measurement model, assesses the structural model, and presents robustness tests. Section 5 discusses the main findings, theoretical contributions, managerial implications, limitations, and avenues for future research. Section 6 concludes the study.

2 Theoretical Background

2.1 Technology Adoption Models

Selecting an appropriate technology adoption model for our study requires distinguishing between different adopter levels: individual, group or team, and organizational (Liu et al., 2008). Fishbein and Ajzen's (1975) theory of reasoned action, Ajzen's (1991) theory of planned behavior, and Venkatesh et al.'s (2003) unified theory of acceptance and use of technology primarily predict individual adoption behaviors (Williams et al., 2009; Oliveira & Martins, 2011). This limitation also applies to van Doorn et al.'s (2017) automated social presence framework, Wirtz et al.'s (2018) service robot acceptance model, and Gursoy et al.'s (2019) model of acceptance of artificial intelligence device use. In contrast, the TAM and the TOE framework apply and are widely used for exploring technology adoption at the organizational level (Gangwar et al., 2014). Chatterjee et al. (2021) argue, for example, that the TAM and the TOE framework effectively explain the adoption of AI-related technologies within an organization.

TAM extends the theory of reasoned action, which posits that individuals' attitudes and social norms determine their behavior. TAM refines this theory by focusing on two key factors: perceived usefulness and perceived ease of use. Perceived usefulness is an individual's belief that using a technology will enhance job performance, while perceived ease of use is the belief that the technology will be free of effort. Perceived ease of use has a direct effect on the intention to use the technology and an indirect effect by influencing the perceived usefulness. Thus, TAM suggests that perceived usefulness and perceived ease of use are predictors of an individual's intention to use technology, which, in turn, predicts actual usage (Davis et al., 1989). Figure 2 shows TAM schematically.

[Figure 2 around here]

We choose TAM for this study because of its applicability to organizational contexts, simplicity, relevance, and effectiveness in understanding IT adoption processes (Lee et al., 2003; Carr et al., 2010). Numerous studies confirm that TAM is a reliable and influential framework (King & He, 2006; Gangwar et al., 2015). TAM is also preferred over its more complex successors or related models because the successor models entail statistically highly correlated variables, which can lead to an unnaturally high explained variance (Chatterjee et al., 2021). However, a limitation of TAM is its lack of predefined external variables (Gangwar et al., 2014).

The TOE framework provides a comprehensive model for analyzing technology adoption, focusing on technological, organizational, and environmental factors (Tornatzky & Fleischer, 1990). Intan Salwani et al. (2009) argue that the technological context aligns with the explanations provided by Rogers's (1961) diffusion of innovation theory (DIT). In this context, empirical evidence highlights the relative advantage of an innovation, compatibility, and complexity as pivotal factors influencing technology adoption (Tornatzky & Klein, 1982; Ifinedo, 2011). The organizational context of the TOE framework examines internal factors affecting the adoption of technology, such as operational scope, management structure, organizational size, and readiness for technological change (Oliveira et al., 2014). The environmental context includes interactions with external entities such as the government, competitors, and business partners, which, in addition to customer acceptance, can drive technology adoption (Zhu et al., 2006; Nam et al., 2021). Figure 3 illustrates the TOE framework.

[Figure 3 around here]

The TOE framework is often favored over DIT because of its more comprehensive scope (Gangwar et al., 2015; Clohessy et al., 2019). However, the TOE framework has seen limited theoretical advancements since its original proposal (Gangwar et al., 2014). The framework also lacks specific constructs, which Zhu and Kraemer (2005) argue impedes theoretical progress. Dedrick and West (2003) describe the TOE framework as a taxonomy for classifying variables rather than a theoretical model. Low et al. (2011) point out the absence of key constructs and the high context-dependency of its variables. Despite these criticisms, Zhu et al. (2006) and Awa et al. (2017) acknowledge the significant impact of the TOE framework on technology adoption research, noting its broad applicability across various industries and organizational sizes.

2.2 Research Framework and Hypotheses

To address the TOE framework's generality and lack of clearly defined constructs, Oliveira and Martins (2011) propose enhancing the framework by incorporating models with specific constructs. Agarwal and Prasad (1997) recommend extending TAM to enrich its explanatory power. Thus, Wang et al. (2010) suggest combining TAM with the TOE framework to address their respective limitations. Using this combined approach, we aim to thoroughly examine the factors influencing the decision to adopt humanoid service robots in the banking sector. Following the models proposed by Gangwar et al. (2015) and Chatterjee et al. (2021), we incorporate the TOE framework to account for the external variables within

TAM. However, integrating the models presents challenges due to the variability and contextual dependency of external variables in TAM and the numerous factors encompassed by the TOE framework (Gangwar et al., 2014). This complexity means that there is no standardized set of variables that can reliably predict technology adoption in different contexts and technologies (Wang et al., 2010). Table 1 displays several studies that employ various adoption factors. Since the significance of specific factors can vary depending on the technology and country of implementation (Tornatzky & Klein, 1982; Gangwar et al., 2015), we derive our adoption factors from theoretical reasoning and empirical evidence.

[Table 1 around here]

To investigate the technological context, we focus on the three pivotal factors of DIT: relative advantage, complexity, and compatibility. Relative advantage, as defined by Rogers (2003), is the degree to which an innovation is perceived as superior to its predecessor. For humanoid service robots, the relative advantages encompass several dimensions, such as operational cost reduction, process optimization, increased customer outreach, reduction of employees' routine workload, multilingual communication capabilities, innovative customer service, and seamless AI integration (van Doorn et al., 2017; Wirtz et al., 2018; Volpe et al., 2020; Amelia et al., 2022). Moore and Benbasat (1991) equate perceived usefulness with the concept of relative advantage, which is supported by subsequent research (Hashimy et al., 2023). However, Gangwar et al. (2015) distinguish between the two concepts, noting that relative advantage involves comparisons with prior innovations and encompasses a broader range of factors, whereas perceived usefulness focuses explicitly on the impact on job performance, making them conceptually distinct (Wang et al., 2008).

Although some studies focus on specific constructs such as cost savings (Katebi et al., 2022) or system quality (Sulaiman et al., 2023), we use the construct of relative advantage to capture the multifaceted benefits of humanoid service robots. Technologies that offer substantial operational and strategic improvements compared to current solutions are likely to be perceived as more useful and easier to use (Gangwar et al., 2015). Building on these insights, we hypothesize the following:

Hypothesis 1a. The relative advantage of an innovation has a significant positive effect on its perceived usefulness.

Hypothesis 1b. The relative advantage of an innovation has a significant positive effect on its perceived ease of use.

Complexity pertains to the extent to which an innovation is perceived as challenging to understand and implement (Rogers, 2003), which is a barrier to adopting AI and humanoid service robots in general (Nam et al., 2021). Complexity involves multiple factors, including integration with existing systems, operational challenges, employee training, and software development (Premkumar & Roberts, 1999; Lian et al., 2014). While Moore and Benbasat (1991) suggest that perceived ease of use and complexity are similar, we consider them as distinct yet related constructs (Wang et al., 2008; Gangwar et al., 2015). Sonnenwald et al. (2001) argue that complexity can hinder employees' ability to use new technologies effectively, thereby diminishing employees' recognition of their potential usefulness. Similarly, Wang et al. (2010) find that, as complexity increases, the perceived usefulness and the perceived ease of use of new technologies tend to decrease. Therefore, we propose the following hypotheses:

Hypothesis 2a. The complexity of an innovation has a significant negative effect on its perceived usefulness.

Hypothesis 2b. The complexity of an innovation has a significant negative effect on its perceived ease of use.

Rogers (2003) defines compatibility as the degree to which an innovation aligns with the existing values, past experiences, and needs of potential adopters. Compatibility is crucial in integrating new technologies with existing organizational frameworks (Calisir et al., 2009). Chen and Tan (2004) and Wang et al. (2010) highlight compatibility as a pivotal factor influencing technology adoption decisions. In the banking sector, particularly when adopting humanoid service robots, these robots must complement existing workflows and technological infrastructures and comply with data security and privacy standards. Conversely, a lack of compatibility may decrease perceptions of the robots' usefulness and ease of use. Thus, we hypothesize:

Hypothesis 3a. The compatibility of an innovation has a significant positive effect on its perceived usefulness.

Hypothesis 3b. The compatibility of an innovation has a significant positive effect on its perceived ease of use.

We consider two specific factors when theorizing about the organizational context: top management support and organizational readiness. Top management support refers to the commitment and efforts of senior executives to facilitate the adoption of new technologies (Intan Salwani et al., 2009). This support involves establishing a strategic long-term vision and a willingness to take risks (Wang et al., 2010; Lian et al., 2014). Research has

demonstrated the importance of top management support in technology adoption across different domains (Yang et al., 2015), with Gangwar et al. (2015), highlighting its positive effect on perceived usefulness and perceived ease of use. The foundation for the subsequent hypotheses is the ability of top management to cultivate a conducive organizational environment and allocate the necessary resources for technology adoption (Awa et al., 2017). By affirming the strategic value of the technology, top management support may enhance its perceived usefulness. Additionally, this support can navigate potential obstacles and render new systems more accessible, enhancing perceived ease of use. Hence, we hypothesize:

Hypothesis 4a. Top management support has a significant positive effect on perceived usefulness.

Hypothesis 4b. Top management support has a significant positive effect on perceived ease of use.

Iacovou et al. (1995) define organizational readiness as the extent to which an organization possesses the necessary resources to adopt a new technology. The ability to embrace innovation hinges on the availability of technological, financial, and human resources (Parasuraman, 2000). Enhanced knowledge and experience also facilitate more efficient technology utilization, underscoring the critical role of expertise in successful technology adoption (Nam et al., 2021). Employee resistance is another crucial determinant influencing the adoption of new technologies (van de Weerd et al., 2016; Nam et al., 2021). Volpe et al. (2020) find that concerns about job displacement by humanoid service robots tend to be temporary as employees become aware of the robots' limitations. However, addressing these concerns is essential (Huang & Rust, 2018). Conversely, insufficient organizational readiness may lead to employee difficulties in using the technology, thus diminishing the perceived usefulness and perceived ease of use (Chatterjee et al., 2021). Therefore, we propose the following hypotheses:

Hypothesis 5a. Organizational readiness has a significant positive effect on perceived usefulness.

Hypothesis 5b. Organizational readiness has a significant positive effect on perceived ease of use.

With respect to environment, we examine the influence of competitive pressure, customer acceptance, and regulatory support. Competitive pressure, defined as the intensity of competition within an industry, can significantly influence the rate at which organizations

adopt technologies (Zhu et al., 2006). This impact is more pronounced when emerging technologies have the potential to alter the competitive landscape (Awa et al., 2017). One firm's successful deployment of new technology, which initially enables it to gain a competitive advantage, often prompts its competitors to adopt similar technologies to preserve their market position (Oliveira et al., 2014). Thus, observing competitors' implementation of humanoid service robots can potentially prompt organizations to reassess and enhance their perceptions of the technology's usefulness and ease of use. Therefore, we hypothesize:

Hypothesis 6a. Competitive pressure has a significant positive effect on perceived usefulness.

Hypothesis 6b. Competitive pressure has a significant positive effect on perceived ease of use.

The environmental factor of customer acceptance is sporadically addressed in the literature, possibly due to the indirect impact many technologies have on customer experience (Nam et al., 2021). For humanoid service robots, however, customer acceptance is crucial for successful integration (Wirtz et al., 2018). Banks deploying these technologies must adapt their services to meet the various needs of diverse customer segments (Amelia et al., 2022). Variations in technology acceptance among demographic segments—shaped by factors such as age, education, income, and cultural background (Hajiabbasi et al., 2023)—highlight the significant influence of customer diversity on the perceived usefulness and ease of use of new technologies within organizations. If a bank expects that its customers will be accepting of interactions with humanoid service robots, this bank is likely to perceive these robots as more useful and easier to integrate into its services. Therefore, we propose:

Hypothesis 7a. Customer acceptance has a significant positive effect on perceived usefulness.

Hypothesis 7b. Customer acceptance has a significant positive effect on perceived ease of use.

Regulatory support, defined as the degree to which legal issues influence the adoption process (Oliveira et al., 2014), is a crucial consideration for banks introducing new technologies. Regulatory considerations often encompass privacy, security, and adherence to government regulations (Hsu & Yeh, 2017). In particular, ensuring compliance with legal requirements is essential within the banking sector. Thus, regulatory support is likely to

influence the perceived usefulness and perceived ease of use of humanoid service robots. Therefore, we hypothesize:

Hypothesis 8a. Regulatory support has a significant positive effect on perceived usefulness.

Hypothesis 8b. Regulatory support has a significant positive effect on perceived ease of use.

The advantages offered by humanoid service robots significantly shape banks' and employees' perceptions of usefulness. This perception arises through a cognitive process where the technology's capabilities are compared against job requirements (Venkatesh & Davis, 2000). Banks that recognize the usefulness of humanoid service robots are more likely to adopt this technology. Hence, we propose the following hypothesis:

Hypothesis 9. Perceived usefulness has a significant positive effect on the intention to adopt.

If humanoid service robots are perceived as easily understandable and employees can quickly familiarize themselves with their functionality, the technology will be adopted with minimal physical and mental effort (Davis et al., 1989). This perception directly influences the intention to adopt the technology and indirectly enhances the perceived usefulness of the system. Conversely, if robots are perceived as difficult to use, their benefits may be less recognizable, potentially overshadowing the advantages and leading to reluctance in adoption (Nam et al., 2021). Therefore, we hypothesize:

Hypothesis 10. Perceived ease of use has a significant positive effect on perceived usefulness.

Hypothesis 11. Perceived ease of use has a significant positive effect on intention to adopt.

We focus on two essential phases in adopting humanoid service robots: the intention to adopt and the actual adoption. The intention phase reflects an organization's perception of technology, which can vary from positive to negative. This phase precedes the actual adoption phase, during which specific steps are taken to procure and deploy the technology (Davis & Venkatesh, 1996). Venkatesh et al. (2012) highlight that the intention to adopt technology is a robust predictor of adoption. Hence, we suggest the following hypothesis:

Hypothesis 12. Intention to adopt has a significant positive effect on adoption.

[Figure 4 around here]

Figure 4 presents the proposed research framework. Recognizing the influence of organizational size on technology adoption (Oliveira et al., 2014), we include several control variables to ensure comprehensive analysis of the actual adoption variable. Specifically, we

control for the bank's category, country of operation, number of employees, scope of business operation, number of bank branches, and total assets from the previous financial year.

3. Method

3.1 Research Instrument

To examine the hypotheses within the research framework, we employ PLS-SEM, using a survey as the research instrument for data collection. Only validated scales from previous literature are used to measure the latent constructs. We adopt a multi-item approach to ensure a thorough representation of each construct's breadth and depth, which reduces the measurement error (Hair et al., 2022). Where necessary, we slightly modify certain items to align them better with the specific context of our study. Additionally, we have asked participants to share their perspectives on adopting humanoid service robots in the banking industry, providing qualitative insights that enrich our quantitative findings.

To ensure the questionnaire's clarity and comprehensibility for respondents, we conducted a pre-test following a two step-approach. The first step involved a review by four academics who also provided feedback on the content validity of the items. Following the incorporation of their feedback, the second step involved a pre-test with six banking professionals. After this pre-test phase, we finalized the questionnaire with 41 items to measure the latent constructs and two qualitative questions.

Table 2 displays each latent construct, its items, and each item's corresponding references. Following Nam et al. (2021), we exclude items related to return on investment due to the assessment complexities emerging from diverse interpretations and the intricate nature of AI technology. Because the study was conducted among Austrian, German, and Swiss banks, we translated the survey items into German without altering their structure or content. Following Davis and Venkatesh (1996), we group the items by their corresponding latent construct to maintain participant satisfaction and minimize the risk of output interference.²

[Table 2 around here]

Technology adoption research predominantly employs five-point and seven-point Likert scales to measure the values of survey items (Hashimy et al., 2023). Babakus and Mangold (1992) and Bouranta et al. (2009) recommend the five-point Likert scale, highlighting its effectiveness in enhancing response rates, improving data quality, and

² See Table A1 for the German translations of the measurement items.

reducing respondent frustration. Additionally, Dawes (2008) shows the practical benefits of the five-point scale's conciseness, facilitating the presentation of all response options to participants. Thus, we employ a five-point Likert scale ranging from "strongly agree" to "strongly disagree" in our survey.

3.2 Data Collection

For the study population, we use the list of monetary financial institutions from the European Central Bank (2024) and the list of authorized banks and security firms from the Swiss Financial Market Supervisory Authority (2024). Thus, we define our population as all credit institutions in Germany, Austria, and Switzerland, without considering credit institutions in partial concession or in liquidation. Importantly, we do not focus solely on institutions with at least one bank branch, because there might be use cases for humanoid service robots in a bank without a branch. As of February 16, 2024, the population from which we draw our sample encompasses 2,013 banks: 427 credit institutions in Austria, 1,341 in Germany, and 245 in Switzerland. On February 19, 2024, we emailed each bank asking its board members to participate in the survey. We collected data until March 18, 2024. A total of 106 banks responded, yielding a response rate of 5.3%. Responses came primarily from the board level (40.6%) or heads of the department (32.1%) responsible for robot adoption.³

To determine the minimum sample size, Barclay et al. (1995) suggest that the sample be at least ten times the largest number of structural paths directed at a particular latent construct in the structural model or at least ten times the highest number of formative indicators used to measure one latent construct. Given our research framework, the minimum sample size is 80. Nonetheless, to ensure statistical robustness, traditional measures of statistical power should be considered to determine the requisite sample size *a posteriori* (Hair et al., 2021). Considering the maximum of eight independent variables in our models, we require at least 84 observations to achieve R^2 values of 0.25 with a 5% error probability and an 80% power level (Cohen, 1992). An alternative approach is the inverse square root method, which hinges on the anticipated magnitude of the smallest significant path coefficient. Assuming the coefficient ranges from 0.21 to 0.30, with a common power level of 80% and a significance level of 5%, the minimum required sample size is 69 (Hair et al., 2022). Our sample size surpasses all minimum thresholds.

³ Responses were further provided by team leaders (15.1%), administrative assistants (6.6%), and others (5.6%); for detailed demographics of the respondent bank, see Table 3.

Because this study relies on respondent data collected through a survey that includes all latent constructs, there is the potential for common method bias (Chang et al., 2010).⁴ The academic discourse on common method bias remains inconclusive (Podsakoff et al., 2024), and this extends to the technology adoption literature.⁵ However, eliminating common method bias is challenging due to the limitations of current statistical methods (Podsakoff et al., 2024). Following Podsakoff et al. (2024), we employ *ex-ante* procedural remedies to mitigate common method bias as far as this is possible within the scope of our study. These strategies encompass question sequencing, diverse measurement scales, ensuring respondent anonymity, and emphasizing the absence of “right” or “wrong” answers. Given that common method bias is aggravated when respondents do not fully engage with or understand the survey, the pretest was designed to ensure the clarity of the questions. Moreover, by offering participants the opportunity to access the survey results, we have sought to elicit more thoughtful and accurate responses, minimizing common method bias and non-response bias (Sax et al., 2003; Podsakoff et al., 2024).

Addressing response bias is essential for the credibility and reliability of our findings. However, we do not employ Levene’s test to assess non-response bias, as this test is better suited to evaluate differences between the first and final group of respondents rather than addressing non-response bias directly (Lin & Schaeffer, 1995). Alongside pre-testing and ensuring anonymity and confidentiality, we incorporate positive and negative items to prevent consistent response patterns and promote active engagement (Podsakoff et al., 2003). Participants were informed of the study’s academic nature at the outset and were not provided with monetary incentives.

3.3 Statistical Approach

Given the exploratory context of this study, we employ PLS-SEM using SmartPLS 4.0 (Ringle et al., 2024). PLS-SEM is particularly suited for contexts where theories are in developmental stages or the primary objective is to explain and predict target constructs (Hair et al., 2019). We opted for PLS-SEM over covariance-based SEM due to PLS-SEM’s compatibility with various data characteristics, complex models, and small sample sizes (Hair

⁴ For a review of common method bias, see Podsakoff et al. (2024).

⁵ Gangwar et al. (2015), Yang et al. (2015), Katebi et al. (2022), and Sulaiman et al. (2023) do not address common method bias. Conversely, Oliveira et al. (2014), Chatterjee et al. (2021), and Chittipaka et al. (2023) utilize Harman’s single-factor test, while Fosso Wamba et al. (2020) and Jo and Bang (2023) apply alternative methodologies.

et al., 2022). One notable advantage of PLS-SEM is its foundation in regression analysis while being nonparametric, implying that PLS-SEM does not assume a specific distribution for the data or the residuals. PLS-SEM allows for metric-scale measurements and equally applies to equidistant ordinal scales and binary-coded data (Hair et al., 2019). Additionally, using weighted composite variables in PLS-SEM presents advantages over traditional regression analyses, which often assume equal contributions from all indicators to a composite variable (Henseler et al., 2015). We employ the standard PLS-SEM algorithm, preferred for exploratory studies, models with complex structures, or small sample sizes (Hair et al., 2022).

PLS-SEM follows an iterative two-step approach. The first step focuses on evaluating the measurement model by examining indicator reliability, internal consistency, convergent validity, and discriminant validity. The subsequent step assesses the structural model and involves identifying potential collinearity issues and evaluating the significance and relevance of the paths. This step also examines the model's explanatory and predictive power (Hair et al., 2022).

4. Results

4.1 Descriptive statistics

Table 3 reports the demographics of the respondent organizations. Of the 106 banks, 78 (73.6%) are from Germany, 26 (24.5%) are from Austria, and two (1.9%) are from Switzerland. In terms of sector classification, 32 (30.2%) of the banks are savings banks, 61 (57.5%) are cooperative banks, nine (8.5%) are credit banks, and four (3.8%) are other credit institutions. Concerning the operational scope, eight (7.5%) banks have a local scope, 86 (81.1%) operate regionally, five (4.7%) have a national scope, and seven (6.6%) operate internationally. On average, respondents completed the survey in less than six minutes.

[Table 3 around here]

Only three banks (2.8%) reported using at least one humanoid service robot, with two banks deploying a single robot, while the third bank deployed two robots. The limited number of adopters of humanoid service robots and their being in the early stages of adoption present significant challenges for conducting logistic regression analysis on the binary dependent variable of actual adoption. The scarcity of adopters could diminish the statistical power, leading to the model's inability to discern significant effects and affecting the precision of

the model's estimates. The risk of overfitting may also reduce the model's applicability to broader datasets. The predominance of non-adopters might skew the model's predictive accuracy towards non-adopters, inflating overall accuracy and reducing the predictive reliability for the smaller group of adopters (Hosmer et al., 2013). Given these challenges, we do not conduct logistic regression analysis on the binary dependent adoption variable (ADOP1), and we will not further analyze the number of humanoid service robots deployed (ADOP2). Instead, we focus on the intention to adopt as the dependent variable within the PLS-SEM analysis.

Table 4 provides an overview of the summary statistics for the survey items. Given PLS-SEM's applicability to non-normal data distributions, where excess kurtosis and skewness values within the range of -2 to +2 are acceptable (Hair et al., 2022), we consider the data distribution appropriate for PLS-SEM analysis.

[Table 4 around here]

4.2 Evaluation of the Measurement Model

Evaluating the measurement model necessitates distinguishing between reflective and formative measurement perspectives (Coltman et al., 2008). In our study, a reflective measurement model is supported theoretically and empirically. Theoretically, the latent constructs are assumed to causally affect their indicators, suggesting that changes in the latent constructs lead to changes in the observed items. Empirically, the items of our study have been previously validated in reflective research models. This validation ensures the items' nomological validity and accurate reflection of the latent constructs (Coltman et al., 2008).

Before proceeding with the analysis, we verify the algorithm's convergence after seven iterations, affirming the algorithm's stability. Evaluation of the reflective measurement model begins with examining indicator reliability. An outer loading value above 0.708 is recommended, signifying that the construct explains more than half of the indicator's variance. Indicators that display outer loadings within the range of 0.4 to 0.708 may be eliminated if doing so enhances the internal consistency reliability without diminishing the construct's content validity. Items with outer loadings below 0.4 must be excluded from the analysis (Hair et al., 2011). Table 5 shows that among the 41 items evaluated, 38 items exhibit outer loadings above the threshold of 0.708. Three items fall below the threshold: CPLX1, CMPA4, and OR2. Thus, we determine whether to include or exclude any of the three items

through subsequent evaluations of internal consistency reliability and convergent validity (Hair et al., 2022).

To evaluate internal consistency reliability in the second step, we use Cronbach's alpha, composite reliability, and rho- α . Acceptable values are above 0.7, although values exceeding 0.95 indicate highly redundant items and are also undesirable (Hair et al., 2022). Table 5 shows that each construct meets the thresholds of the various criteria. Only the composite reliability for the intention to adopt is slightly too high at 0.96. Since Cronbach's alpha and rho- α values are below 0.95, we confirm the internal consistency reliability for the intention to adopt.

The third step involves evaluating each construct's convergent validity by calculating the average variance extracted (AVE). An AVE value of 0.5 or above is acceptable (Hair et al., 2011). Table 5 indicates that the AVE for all constructs exceeds the threshold of 0.5, confirming their convergent validity. Because all constructs exceed all internal consistency reliability and convergent validity thresholds, we do not exclude any item from the analysis.

[Table 5 around here]

The fourth step in the analysis entails examining discriminant validity. Henseler et al. (2015) show that the Fornell-Larcker criterion and the cross-loadings analysis may be unreliable. However, any violation of the Fornell-Larcker criterion is strong evidence of a severe discriminant validity problem (Hair et al., 2021). Table 6 displays that the Fornell-Larcker criterion is not violated because the AVE of each construct exceeds the squared correlations between constructs within the model.

[Table 6 around here]

As an improved measure, Henseler et al. (2015) propose using the heterotrait–monotrait (HTMT) ratio of correlations for a more robust assessment of discriminant validity. The HTMT ratio should not exceed 0.9, and for more conceptually distinct constructs, a stricter threshold of 0.85 is advised. Henseler et al. (2015) further recommend bootstrapping to verify that the HTMT ratio's 95% confidence interval does not include 1 or a contextually appropriate lower threshold, such as 0.9 or 0.85 (Franke & Sarstedt, 2019). We use the percentile method with 10,000 bootstrap samples to derive confidence intervals (Aguirre-Urreta & Rönkkö, 2018). The results in Table 7 and Table A2 show that all HTMT ratios are below the thresholds and the confidence intervals do not include 1, confirming the discriminant validity of our latent constructs.

[Table 7 around here]

4.3 Assessment of the Structural Model

To address concerns of multicollinearity, we calculate the variance inflation factor (VIF) values in Table 8. Because all VIF values are below the threshold of 3, multicollinearity is not a concern in our model (Mason & Perreault, 1991; Becker et al., 2015)

[Table 8 around here]

In a second step, we test the hypotheses using a nonparametric bootstrap procedure to evaluate the significance of the estimated path coefficients. We run this procedure with 10,000 samples. Table 9 presents the path coefficients for the hypothesized relationships in the structural model. Eight of the 19 analyzed paths exhibit statistically significant relationships, while the other twelve paths lack statistical significance. Specifically, the relative advantage of the innovation strongly predicts perceived usefulness of humanoid service robots, while top management support also significantly influences perceived usefulness. Interestingly, organizational readiness negatively impacts perceived usefulness, suggesting internal challenges that reduce the robots' perceived benefits. Competitive pressure influences perceived usefulness, and the construct of customer acceptance significantly affects perceived usefulness and perceived ease of use, underlining the importance of customer acceptance in technology adoption. Perceived ease of use, while not a significant predictor of perceived usefulness, significantly affects the intention to adopt. Lastly, perceived usefulness significantly predicts the intention to adopt.

[Table 9 around here]

Additionally, we assess the total effects, which encapsulate the direct impact, if applicable, alongside all indirect influences that link one latent construct to another within the model (Nitzl et al., 2016). This comprehensive evaluation sheds light on the cumulative impact of the eight exogenous TOE constructs on the intention to adopt a humanoid service robot. Table 10 shows that the relative advantage of the innovation and customer acceptance emerge as the most influential factors on the intention to adopt. Furthermore, top management support and competitive pressure significantly positively affect the intention to adopt. In contrast, complexity, compatibility, and regulatory support do not significantly influence the intention to adopt. Notably, organizational readiness also reveals a significant negative total effect on the intention to adopt, further suggesting the presence of internal challenges that may impede the adoption process.

[Table 10 around here]

The third step assesses the coefficient of determination R^2 and the adjusted coefficient of determination $R^2_{adjusted}$ for all endogenous latent constructs. Benchmarks for classifying the explanatory power of these models often use 0.75, 0.50, and 0.25 as indicators of substantial, moderate, and weak effects, respectively (Hair et al., 2011).⁶

[Table 11 around here]

Table 11 reveals that the model exhibits moderate explanatory power for the intention to adopt and perceived ease of use constructs, while the model possesses substantial explanatory power in predicting perceived usefulness. Figure 5 presents the proposed research model, displaying path coefficients, their significance, and the R^2 values for the endogenous variables.

[Figure 5 around here]

The fourth step involves assessing the effect size metric f^2 , which determines the impact of excluding a specific predecessor construct on the R^2 value of an endogenous construct. An f^2 value of 0.02 indicates a weak effect, 0.15 indicates a moderate effect, and 0.35 indicates a large effect (Cohen, 1992).⁷ As illustrated in Table 12, perceived usefulness has a large effect, whereas perceived ease of use has a weak effect on the intention to adopt. For perceived usefulness, relative advantage has the highest effect size ($f^2 = 0.443$), indicating a large effect. In terms of perceived ease of use, the latent construct of customer acceptance emerges as the most influential predecessor construct ($f^2 = 0.243$), exhibiting a moderate effect size.

[Table 12 around here]

We employ the Q^2 index through blindfolding to assess the model's out-of-sample predictive power (Geisser, 1974; Stone, 1974). Q^2 values exceeding 0.02, 0.15, and 0.35 indicate the model's low, moderate, and high predictive capabilities, respectively (Ringle et al., 2012). To further assess the model's predictive accuracy, Hair et al. (2022) recommend employing root mean square error (RMSE) and mean absolute error (MAE). Interpreting these predictive error metrics involves benchmarking them against a naïve linear regression model (LM). The predictive power is high when all indicators demonstrate lower errors than the naïve LM, moderate when the majority do, and low when only a few indicators do. The absence of lower errors across all indicators suggests a lack of predictive power (Shmueli et

⁶ Alternatively, Chin (1996) suggests slightly lower thresholds of 0.67, 0.33, and 0.19 for categorizing effects as substantial, moderate, and weak in terms of explanatory power.

⁷ According to Ringle et al. (2012), these values are 0.02, 0.15, and 0.30, respectively.

al., 2019). To assess the predictive power, we run the $PLS_{predict}$ function with ten folds and ten repetitions with the fixed seed option in SmartPLS 4.0 (Ringle et al., 2024).

[Table 13 around here]

Table 13 shows that the Q^2 values for PEOU2 and PEOU3 indicate moderate predictive capabilities, while the values for all other items suggest high predictive capabilities. A comparison of the RMSE and MAE values reveals that PLS-SEM consistently yields lower prediction errors across all items. This result suggests robust predictive power for the model.⁸

[Table 14 around here]

Hair et al. (2022) further recommend employing the cross-validated predictive ability test (CVPAT), which evaluates the PLS-SEM model's predictive performance against the indicator average (IA) loss values. As illustrated in Table 14, the analysis yields a negative average loss value difference for the overall model, indicating that PLS-SEM achieves lower average loss values than the IA and LM benchmarks. With all p -values below 0.05, PLS-SEM's predictive performance is significantly superior to the two benchmarks.

4.4 Robustness Tests

For ensuring model robustness, Sarstedt et al. (2020) highlight the need to evaluate endogeneity, nonlinear effects, and unobserved heterogeneity. However, Sarstedt et al. (2020), Basco et al. (2022), and Vaithilingam et al. (2024) find that only a minority of papers conduct robustness tests.⁹

To address potential endogeneity concerns, Park and Gupta (2012) introduce the Gaussian copula approach, which models the correlation between a predecessor construct and the error term of an endogenous construct. This approach is advantageous when control or instrumental variables are not available (Hult et al., 2018). One prerequisite to applying the Gaussian copula approach is a non-normal distribution of the potentially endogenous regressors (Becker et al., 2022). Hence, we use the Lilliefors-corrected Kolmogorov-Smirnov test, incorporating 1,000,000 Monte Carlo simulations to estimate the p -values, to examine the distribution of the latent scores of the potentially endogenous variables (Sarstedt et al.,

⁸ Shmueli et al. (2019) emphasize that the absolute difference in prediction errors is of secondary importance for two reasons. First, the size of the prediction errors largely depends on the measurement scale of the items. The range of possible differences is limited since we measure the items on a five-point Likert scale. Second, the prediction errors generated by the PLS-SEM are highly stable. Hence, even marginal differences in the prediction error values are typically significant.

⁹ A systematic literature review among 1,228 papers by Vaithilingam et al. (2024) on PLS-SEM in business research reveals that only 2.3% addressed endogeneity, 2.4% examined unobserved heterogeneity, and 1.3% explored nonlinearity.

2020). The results indicate that, for intention to adopt and perceived ease of use, the null hypothesis of normal distribution cannot be rejected, with p -values of 0.055 and 0.063, respectively. For perceived usefulness the p -value is 0.006, suggesting a non-normal distribution. Thus, only perceived usefulness meets the criteria for employing the Gaussian Copula approach. However, Becker et al. (2022) show that the Gaussian copula approach should not be used for a sample size below 200, and hence a reliable assessment of endogeneity is unfortunately not feasible.

[Table 15 around here]

To evaluate unobserved heterogeneity in our model, we use the finite mixture partial least squares (FIMIX-PLS) method. Our sample size limits the analysis to two segments (Sarstedt et al., 2020). The results in Table 15 show inconsistent recommendations across various criteria: lower values for AIC, AIC₃, and HQ indicate a two-segment solution, while lower values for AIC₄, BIC, CAIC, MDL₅, and LnL favor a one-segment solution. Collectively, the criteria do not unambiguously point to a specific segmentation, indicating that unobserved heterogeneity may not significantly influence the model. Additionally, the second segment in the two-segment solution, consisting of 30 units (28.3% of the sample), does not meet the minimum sample size requirements (Sarstedt et al., 2020).

To test for nonlinearities, we follow Svensson et al. (2018) and conduct two tests. First, we run Ramsey's (1969) regression equation specification error test (RESET), which considers quadratic and cubic effects, using the estimated latent construct scores as inputs (Sarstedt et al., 2020). The RESET results for perceived usefulness (RESET = 0.594, df = 94, p -value = 0.554), perceived ease of use (RESET = 2.041, df = 95, p -value = 0.136), and intention to adopt (RESET = 0.693, df = 101, p -value = 0.502) indicate no significant nonlinear relationships. Second, we incorporate quadratic terms in PLS-SEM, following Hair et al. (2023), who suggest that quadratic modeling often suffices in social sciences. If the interaction term's effect is significant and positive (negative), the strength of the predecessor construct's effect increases (decreases) at higher values of the predecessor construct. Insignificant interaction terms, however, suggest the linear effect's robustness (Sarstedt et al., 2020). As shown in Table A3, the bootstrapping results with 10,000 samples indicate that, with three exceptions, all other quadratic effects are insignificant (p -value > 0.05), suggesting predominantly linear relationships in the model.¹⁰

¹⁰ For a more detailed discussion of the quadratic effects, see Appendix 1.

4.5 Qualitative Responses

Eleven respondents provided qualitative answers to enrich the quantitative findings.¹¹ Some banks have been exploring the utilization of humanoid service robots across various functions such as marketing, pilot projects, customer service, and planned customer engagement initiatives. These explorations reveal a balance of advantages and disadvantages. Notable advantages include enhanced process efficiency and reduced routine tasks for employees. These findings suggest that service robots could effectively manage routine inquiries, providing employees relief from repetitive tasks. Nonetheless, these advantages are offset by drawbacks, as one participant mentioned that the robots' technical limitations resulted in limited utility in the banking branch.

“Technical limitations of the robots have led to their deployment in branches providing only limited benefits [...]” (Respondent 3).

Moreover, high operational costs and fragile hardware susceptible to frequent breakdowns hinder the practical deployment of humanoid service robots. Regulatory constraints and challenges in technical integration also pose substantial obstacles. In practice, humanoid service robots primarily serve as a novelty, failing to substantially contribute to the core service offerings.

“We consider service robots such as ‘Pepper’ and the like to be nothing more than a ‘nice gimmick’ in on-site service [...]” (Respondent 7).

One respondent indicated that regional credit institutions face challenges due to insufficient monetary and technological resources. Another participant mentioned that banking associations' supportive role in providing financial and technological assistance is essential. However, employing such technologies can be inconsistent with the fundamental orientation of regional cooperative banks, which prioritize human-to-human interaction.

“As a regional cooperative bank, however, the introduction does not correspond to our general orientation, which is strongly based on personal contact” (Respondent 9).

As an alternative to humanoid service robots, some banks state a growing preference for digital avatars and bots, accessible on touchscreens and capable of handling simple service processes. These digital alternatives seem to gain greater acceptance because they

¹¹ For ease of reference, the qualitative questions and the responses are presented in Table A4, considering the operations, and Table A5, considering the comments on humanoid service robots. We removed specific parts from the answers to ensure anonymity.

emphasize overcoming language barriers and resolving basic queries through user-friendly interactions.

“Robots are not the solution (they are too expensive to repair and break easily). The solution will be bots that are made available on touch screens” (Respondent 1).

“We prefer avatars over humanoid robots. On a 27-inch monitor, the avatar breaks down language barriers and completes simple service processes, for example, by displaying a QR code and linking to the online branch” (Respondent 6).

“We are committed to significantly more innovative ways of optimizing service and customer guidance. For instance, an avatar [...] is used to direct our customers in the headquarters, answer simple questions, or inform consultants about customer arrivals” (Respondent 7).

Another innovative approach is using interactive “service pylons,” which enable customers to receive assistance from actual employees via remote video links. As part of the digital transformation in branches, banks utilize chatbots and voice bots to enhance the efficiency of telephone and online communication channels. One respondent acknowledges that, although there is a current preference for human-to-human interaction, this preference may change over time.

“We have made the experience and are convinced that people prefer to be served by people rather than by avatars or humanoid service robots. This may change at some point, but at the moment, I do not believe that this technology will significantly change the banking business” (Respondent 10).

The qualitative responses reveal that banks anticipate customers’ preference for maintaining a human-centric approach, even as digital solutions evolve. Due to the various limitations encountered with humanoid service robots, banks are currently leaning towards other digital solutions, such as avatars and bots. These alternatives are perceived to be more widely accepted by customers as they are better tailored to their preferences and the banks’ ability to integrate modern technologies.

5. Discussion

5.1 Main Findings

By analyzing the outer weights of each latent construct, we can identify the most impactful items contributing to each construct. Table 16 presents the outer weights, with higher values signifying a greater impact on the respective latent construct (Hair et al., 2021).

[Table 16 around here]

The outer weights analysis of the latent construct of relative advantage underscores humanoid service robots' benefits to banking services. Specifically, items RA2, RA3, RA4, and RA5 are pivotal, collectively delineating the extensive scope of robotic advancements. Item RA2 emphasizes the potential for process improvements, which points to the potential of automation in refining operational workflows (Huang & Rust, 2018). Adopting humanoid service robots could streamline banking processes, enhance transactional efficiency, and minimize errors in routine tasks, thereby potentially increasing operational productivity. RA3 highlights the potential of humanoid service robots in reaching new customers. This observation aligns with Amelia et al. (2022), who discuss the appeal of technological innovations in capturing the interest of a digitally oriented customer demographic. Hence, the first deployments of humanoid service robots in banks can serve as a novel attraction to customers. RA4's emphasis on workload reduction aligns with Volpe et al. (2020) on allocating routine tasks to robots, relieving employees for more complex and consultative tasks. This shift could improve customer service quality and enhance employees' job satisfaction by diversifying roles and responsibilities (Lu et al., 2020; Volpe et al., 2020). Lastly, RA5 highlights the crucial advantage of multilingual communication, a key offering in today's diverse service environments (Čaić et al., 2018). The ability of humanoid service robots to interact in multiple languages can create more inclusive and personalized banking services, enhancing the customer experience. Therefore, perceiving a relative advantage is a pivotal factor driving the adoption of humanoid service robots, consistent with findings by Premkumar and Roberts (1999), Oliveira et al. (2014), and Chittipaka et al. (2023) for other technologies.

In assessing top management support, the essential role of senior leadership in fostering an environment conducive to technology adoption is clear. TMS1 highlights the strategic importance of humanoid service robots, aligning with organizational goals and echoing Intan Salwani et al. (2009) on the necessity of leadership endorsement for innovation. TMS2 reflects management's readiness to embrace the risks associated with new technologies, which is critical for nurturing an innovative culture (Wang et al., 2010; Lian et al., 2014). TMS3 underlines the commitment to allocate financial resources, which is essential for overcoming financial barriers to adoption (Awa et al., 2017). These factors demonstrate how top management support significantly impacts technology adoption, corroborating findings across various studies (Gangwar et al., 2015; Yang et al., 2015; Chatterjee et al., 2021).

Within the competitive pressure construct, items CP1 and CP3 are particularly influential. CP1 underscores the competitive advantages that humanoid service robots might bring, emphasizing organizations' need to adapt to technological shifts that can alter the competitive landscape (Zhu et al., 2006). This adaptation is often motivated by the desire to maintain a competitive edge and avoid falling behind in a swiftly changing industry (Awa et al., 2017). CP3 reflects the direct pressures banks face, driving them to adopt humanoid service robots in response to their competitors' actions. Oliveira et al. (2014) suggest that one firm's successful technology integration can trigger a domino effect among competitors, who adopt similar technologies to stay competitive. This scenario highlights the reactive nature of technology adoption, which is influenced by the strategic decisions of competitors (Hsu & Yeh, 2017). Together, these items illustrate how perceived strategic benefits and competitive pressures interplay to drive the adoption of humanoid service robots, demonstrating the impact of competitive dynamics in promoting technological advancements (Katebi et al., 2022).

The outer weights of the three items of customer acceptance are all impactful for the latent construct. CUS1 assesses perceived customer readiness to engage with humanoid service robots, focusing on willingness and adaptability to new service formats. This readiness is crucial for adjusting to novel delivery modes (Volpe et al., 2020). CUS2 explores the expected appeal of interactions with humanoid service robots, which is a pivotal factor in customer acceptance that depends on the innovation and perceived advantages of such interactions (Wirtz et al., 2018). Enhancing this appeal with engaging and personalized interactions can accommodate the diverse preferences of customers (Amelia et al., 2022). CUS3 addresses customer acceptance, highlighting expectations for ongoing satisfaction and comfort with robot interactions beyond initial readiness or appeal (Wirtz et al., 2018). Amelia et al. (2022) and Hajiabbasi et al. (2023) emphasize the importance of tailoring services to diverse customer demographics. Overall, the successful deployment of humanoid service robots in banking critically depends on understanding and addressing customer perspectives, from readiness and appeal to acceptance.

In the context of perceived usefulness, the items PU1 and PU2 display the highest outer weights. PU1 points to the efficiency gains from deploying these robots, suggesting their potential to streamline banking operations. PU2 highlights the robots' contribution to increasing productivity, reinforcing their workplace value. Regarding perceived ease of use, item PEOU1 has the largest outer weight, indicating that the simpler the banks perceive the operation of humanoid service robots, the higher their intention to adopt such robots. Thus,

we find that perceived usefulness and perceived ease of use are important drivers of the intention to adopt humanoid service robots.

With regard to organizational readiness, our analysis reveals that, as organizational readiness increases, the perceived usefulness of humanoid service robots decreases, with a significant negative total effect on the intention to adopt, as well. Specifically, the outer weights analysis identifies OR1, OR3, and OR5 as the most impactful items. OR1 measures the bank's technological resource readiness for robot adoption, OR3 assesses human resource availability, and OR5 gauges the bank's capacity to manage employee apprehensions about adopting robots. The negative path coefficient reveals two pivotal insights. First, banks displaying a higher intention to adopt despite lower organizational readiness (primarily regional savings or cooperative banks) typically face constraints due to limited financial, technological, and human resources. Second, banks with higher organizational readiness but lower adoption intention show that possessing the necessary resources and expertise does not automatically lead to a greater intention to adopt. This discrepancy suggests that organizational readiness is more of a prerequisite than a driver for the intention to adopt humanoid service robots in the banking industry.

[Table 17 around here]

As depicted in Table 17, the distribution of responses regarding the intention to adopt shows a considerable number of banks agreeing with items ItA1–ItA3 (humanoid service robots are advantageous, bank is in favor of using them, and bank intends to use them). However, the disparity between the expressed intention to adopt and the actual adoption decision by only three banks highlights the importance of identifying and addressing adoption barriers. Qualitative responses indicate technical limitations, high costs, and hardware fragility as pivotal obstacles to effective deployment. These challenges are particularly pronounced for regional banks, which might not possess the necessary financial or technological resources. The results also suggest that the initial enthusiasm for humanoid service robots has faded. Despite current challenges, however, the potential for humanoid service robots remains significant, especially in the event of continued integration of large language models. Ongoing employee shortages might further prompt the adoption of such technologies. Finally, the growing trend toward hybrid solutions, incorporating humanoid service robots, digital avatars, and other technologies, highlights the dynamic evolution of technological integration in the banking industry.

Considering the qualitative responses alongside the statistical analysis, we identify regulatory concerns, particularly data protection and privacy, as barriers to deploying

humanoid service robots. Our findings emphasize the complex interactions between technological innovation, adherence to regulations, and governmental oversight, suggesting the need for a multidisciplinary approach to address these challenges and to preserve data security and trust in banking.

Some relationships in the structural model are insignificant, highlighting the intricate nature of technology adoption studies. These findings align with Tornatzky and Klein (1982), Wang et al. (2010), and Chatterjee et al. (2021), indicating that context and sample characteristics influence the significance of specific relationships.

5.2 Theoretical Contributions

Our study is one of the first to analyze the adoption of humanoid service robots in the banking sector, providing insights into the factors that can either drive or hinder adoption. Our findings indicate that the relative advantage of the innovation, top management support, competitive pressure, and customer acceptance drives the perceived usefulness of humanoid service robots. Additionally, customer acceptance increases the perceived ease of use, which, together with perceived usefulness, significantly elevates the banks' intention to adopt them. Contrary to the perspective that organizational readiness facilitates technology adoption (Chatterjee et al., 2021), our findings indicate that organizational readiness is a necessary requirement rather than an adoption driver. Our study also underscores the importance of including customer acceptance as a latent factor when technology adoption directly impacts customers (Nam et al., 2021).

By examining curvilinearities, and hence deviating from the traditional linear analysis in technology adoption studies, we identify significant quadratic effects in three relationships: (1) compatibility → perceived ease of use; (2) organizational readiness → perceived ease of use; (3) customer acceptance → perceived usefulness. This finding reveals that the influence of the nonlinear factors on the dependent variables (PU and PEOU) vary at different levels of the explanatory variables, suggesting more complex relationships in technology adoption (Titah & Barki, 2009).

Integrating qualitative insights with quantitative data, we provide a detailed analysis of the barriers and drivers affecting the adoption of humanoid service robots in banks. Our study also reveals diverse perspectives on forthcoming technological integrations in the banking sector, highlighting the promise of digital avatars as well as the enduring value of human-to-human interaction.

5.3 Managerial Implications

Our findings offer important insights for banks, banking associations, humanoid service robot manufacturers, and software providers. While the relative advantages of humanoid service robots enhance their perceived usefulness and intention to adopt, banks have thus far been hesitant to embrace this technology.

Top management support is crucial in facilitating the adoption of humanoid service robots. Therefore, bank executives should take a proactive and strategic approach to create an environment conducive to technology adoption. Such an environment includes strategic planning with precise task allocations and delineated roles and expectations for employees. Addressing automation concerns and incorporating employees into the adoption process are essential to mitigate resistance (Volpe et al., 2020). To foster humanoid service robot adoption, managers should emphasize the usefulness of these robots while ensuring ease of use. Achieving organizational readiness and ensuring the availability of necessary resources are pivotal. For smaller banks with limited organizational readiness, seeking support from banking associations could help facilitate adoption. Even when acting responsively to competitive pressure, failing to address organizational readiness may prevent the benefits of humanoid service robots from translating into economic value.

Customer acceptance is also a crucial factor in the adoption process of humanoid service robots. Despite some banks' apparent preference for human-to-human interaction, there is an acknowledgment of the potential shift in customer attitudes over time. With increasing preferences for digital channels (Hentzen et al., 2022), banks should continuously monitor customer receptiveness to technological innovations. Providing human assistance to optimize human-robot interactions may facilitate a smooth integration. As a way of integrating them into human-to-human service encounters, humanoid service robots could serve as interpreters or secondary advisors during meetings to overcome language barriers. Such a dual role would provide customers with personalized services and assist employees in enhancing service delivery. Humanoid service robots could also enable banks to engage in targeted marketing campaigns, showcasing innovative services to attract new customers. Management should continuously evaluate the changing boundary relations in the triangle relationship between humanoid service robots, employees, and customers (Volpe et al., 2020), ensuring that these robots augment rather than disrupt banking services.

Regulatory compliance is another critical aspect. Especially for banks in the European Union, introducing humanoid service robots may present regulatory challenges. In addition to financial market regulation, there are specific data and technology regulations that must

be heeded. The ability of these robots to process and store personal data necessitates compliance with the General Data Protection Regulation. Additionally, the AI Act, which targets the regulation of AI systems such as those embedded in humanoid service robots, will add complexity to the regulatory environment. Banks will need to ensure that their deployment of humanoid service robots conforms to all relevant regulations.

The software providers of humanoid service robots should guarantee that their solutions are functional, accessible, and seamlessly integrated into banking operations. Advanced technological capabilities are insufficient if the robots are perceived as too complex, which could pose a barrier to adoption (Nam et al., 2021). Thus, designing user-friendly interfaces and providing thorough technical support are crucial for overcoming programming and system integration challenges, enhancing the robots' usability and assimilation into existing operations. Demonstrating the robots' benefits through banking-specific use cases, such as unlocking online banking access, offering portfolio advice, or providing in-branch entertainment, can help shift the perceptions from robots being technological "gimmicks" to becoming essential organizational tools. Manufacturers should highlight the distinct advantages of humanoid service robots over other technologies such as digital avatars or bots by articulating their unique value proposition. After all, humanoid service robots have a more human-like appearance, which may be more appealing to people than avatars or bots. Additionally, they can move from point A to point B more easily than fixed monitors, potentially allowing for greater privacy.

5.4 Limitations and Future Research

While providing important insights into technology adoption within the banking sector, our study has some limitations inherent to the research field and our specific method. We follow the prevailing factor approach in technology adoption research, which posits that increased technology-related needs and capabilities correlate with higher adoption levels in terms of frequency, earliness, and extent (Fichman, 2004). However, this approach may introduce theoretical biases, such as assuming all adoptions are beneficial and decisions are made rationally (Fichman, 2004; Robey et al., 2008). Alternative or complementary frameworks, such as the technology–task fit (TTF) model (Goodhue & Thompson, 1995) or different model integrations, could provide complementary insights. Unlike prior research that has primarily examined the antecedents of intention and use, the TTF model focuses on exploring the post-adoption aspect of technology utilization (Goodhue & Thompson, 1995). We thus expect that the TTF model will offer valuable insights when adoption rates are higher and humanoid service robots are deployed in various tasks.

Although widely employed, survey-based methods are subject to specific limitations, including biases from self-reported data and the reliance on responses from just one individual per organization. While we employed numerous strategies to minimize common method bias, we cannot guarantee its elimination (Podsakoff et al., 2024). Additionally, we cannot exclude response biases such as straight-lining (Kim et al., 2019). In general, however, there is no reason to assume that participants have a particular incentive to misrepresent their answers in our context, nor that responses vary systematically within organizations.

The sparse number of adopters limits our study by preventing a detailed analysis of actual adoption as the dependent variable. This limitation highlights the need for future research to study a larger group of adopters to examine these dynamics comprehensively. As the service robot market is expected to grow (Research & Markets, 2023), revisiting adoption patterns in the coming years should provide more profound insights. While we examine adoption factors that explain a substantial portion of the variance in the dependent variables, these factors are not exhaustive. Therefore, our study paves the way for future research and the refinement of constructs to better understand the factors driving the adoption of humanoid service robots in the banking sector.

Our study's geographical focus on banks in Austria, Germany, and Switzerland may only partially account for cultural influences on adoption, as perceptions of robots can vary significantly across regions (Della Corte et al., 2023). For example, East Asian countries like Japan and South Korea generally perceive robots more positively, viewing them as symbols of progress. Conversely, Western cultures often express skepticism or fear, primarily due to concerns over job displacement and reduced human interaction (Song & Kim, 2022). Exploring how cultural differences impact the adoption of humanoid service robots presents a promising avenue for future research.

Our sample may be biased towards banks already interested in the technology, which could limit the representativeness of our study. Although the sample of 106 responses meets statistical requirements, the sample size remains small, constraining the generalizability of our findings. The results should thus be considered preliminary and exploratory, providing initial insights into an emerging technology within a specific industry and cultural context. Additionally, the small sample size hinders our ability to reliably test for endogeneity using the Gaussian copula approach. Identifying significant nonlinear effects within three relationships also challenges the robustness of the PLS-SEM results. Future research should aim for more extensive and varied sample sizes to build upon and expand our initial insights.

Exploring the gap between the intention to adopt and the actual adoption of humanoid service robots offers valuable insights for developing targeted strategies to facilitate their

implementation. Investigating aspects such as multilingual capabilities or organizational readiness, along with observing changes in adoption patterns through longitudinal studies, will be vital as the technology evolves. Additionally, identifying and interpreting nonlinear relationships, which require theoretical reasoning, may reveal further interesting findings. The potential role of digital avatars in banking also warrants deeper investigation (Ooi et al., 2023). A comparative analysis of avatars and humanoid service robots could elucidate their respective functionalities and effectiveness within the banking environment. Field experiments could also provide academically and practically relevant findings.

6. Conclusion

Adopting humanoid service robots such as Pepper, NAO, and Sanbot Elf in the banking sector represents a shift towards enhancing customer experiences and operational efficiency. We investigate the technological and socioenvironmental factors driving banks to adopt these robots. We integrate the TOE framework to account for the external variables within TAM and employ PLS-SEM to examine our research framework. An online survey targeting banks in Austria, Germany, and Switzerland yielded responses from the top management of 106 banks. We also included qualitative questions to gain further insights into the banks' perspectives on humanoid service robots, enriching our analysis.

Our findings indicate that the relative advantage of the innovation, top management support, competitive pressure, and customer acceptance significantly drive the perceived usefulness of humanoid service robots, and that the total effects of these factors positively affect banks' intention to adopt. Customer acceptance significantly enhances perceived ease of use, which, along with perceived usefulness, also significantly increases intention to adopt. Despite growing interest in humanoid service robots, adoption rates remain low, suggesting underlying adoption obstacles. Our analysis indicates that organizational readiness is a necessary requirement rather than an adoption driver. Additionally, our qualitative findings highlight that technical limitations and regulatory concerns further hinder humanoid service robot deployment, especially for smaller banks with limited resources and a characteristic emphasis on personal interactions. Furthermore, some banks perceive humanoid service robots as "gimmicks" rather than essential operational tools. This perception leads banks to explore alternatives such as digital avatars and bots, which are considered more suitable for specific tasks while maintaining a focus on human-to-human interaction.

To facilitate the transition from novelty to necessity in banking, we recommend designing user-friendly interfaces, providing robust technical support, and ensuring

compatibility with existing banking infrastructure. In addition, low-code solutions can help bank employees develop their own implementations, which should increase the acceptance of robots among employees. Lighthouse projects and specific use cases that evidence the distinct benefits over other digital solutions could further enhance the perceived value of humanoid service robots, leading to broader adoption in the sector.

Our study contributes seminal insights into humanoid service robot adoption in banks and lays the foundation for future research. Subsequent studies might investigate cultural influences on adoption, the gap between intention to adopt and actual adoption, and the comparative advantages and disadvantages of humanoid service robots versus other digital solutions. Understanding these dynamics will be pivotal as AI and robotics continue to advance. Humanoid service robots will likely become more prevalent, enhancing organizational performance and customer experiences while strengthening resilience against future uncertainties in banking and other service industries.

References

- Agarwal, Ritu; Prasad, Jayesh, 1997. The role of innovation characteristics and perceived voluntariness in the acceptance of information technologies. *Decision Sciences* 28 (3), 557–582.
- Aguirre-Urreta, Miguel I.; Rönkkö, Mikko, 2018. Statistical inference with PLS using bootstrap confidence intervals. *MIS Quarterly* 42 (3), 1001–1020.
- Ajzen, Icek, 1991. The theory of planned behavior. *Organizational Behavior and Human Decision Processes* 50 (2), 179–211.
- Alam, Syed Shah; Ali, Md. Yunus; Jani, Mohd. Fauzi Mohd., 2011. An empirical study of factors affecting electronic commerce adoption among SMES in Malaysia. *Journal of Business Economics and Management* 12 (2), 375–399.
- Amelia, Amelia; Mathies, Christine; Patterson, Paul G., 2022. Customer acceptance of frontline service robots in retail banking: A qualitative approach. *Journal of Service Management* 33 (2), 321–341.
- Awa, Hart O.; Ojiabo, Ojiabo Ukoha; Orokor, Longlife E., 2017. Integrated technology–organization–environment (T-O-E) taxonomies for technology adoption. *Journal of Enterprise Information Management* 30 (6), 893–921.
- Babakus, E.; Mangold, W.G., 1992. Adapting the SERVQUAL scale to hospital services: An empirical investigation. *Health services research* 26 (6), 767–786.
- Barclay, D.; Higgins, C.; Thompson, R., 1995. The partial least squares (PLS) approach to causal modeling: Personal computer adoption and use as an illustration. *Technology Studies* 2 (1), 285–309.
- Basco, Rodrigo; Hair, Joseph F.; Ringle, Christian M.; Sarstedt, Marko, 2022. Advancing family business research through modeling nonlinear relationships: Comparing PLS-SEM and multiple regression. *Journal of Family Business Strategy* 13 (3), 1–16.
- Becker, Jan-Michael; Ringle, Christian M.; Sarstedt, Marko; Völckner, Franziska, 2015. How collinearity affects mixture regression results. *Marketing Letters* 26 (4), 643–659.
- Becker, Jan-Michael; Proksch, Dorian; Ringle, Christian M., 2022. Revisiting Gaussian copulas to handle endogenous regressors. *Journal of the Academy of Marketing Science* 50 (1), 46–66.
- Becker, Jan-Michael; Cheah, Jun-Hwa; Gholamzade, Rasoul; Ringle, Christian M.; Sarstedt, Marko, 2023. PLS-SEM's most wanted guidance. *International Journal of Contemporary Hospitality Management* 35 (1), 321–346.
- Bouranta, Nancy; Chitiris, Leonidas; Paravantis, John, 2009. The relationship between internal and external service quality. *International Journal of Contemporary Hospitality Management* 21 (3), 275–293.
- Brown, Irwin; Russell, John, 2007. Radio frequency identification technology: An exploratory study on adoption in the South African retail sector. *International Journal of Information Management* 27 (4), 250–265.
- Čaić, Martina; Odekerken-Schröder, Gaby; Mahr, Dominik, 2018. Service robots: Value co-creation and co-destruction in elderly care networks. *Journal of Service Management* 29 (2), 178–205.
- Calisir, Fethi; Altin Gumussoy, Cigdem; Bayram, Armagan, 2009. Predicting the behavioral intention to use enterprise resource planning systems. *Management Research News* 32 (7), 597–613.
- Carr, Amelia S.; Zhang, Man; Klopping, Inge; Min, Hokey, 2010. RFID Technology: Implications for healthcare organizations. *American Journal of Business* 25 (2), 25–40.

- Chan, Felix T.S.; Chong, Alain Yee-Loong, 2013. Determinants of mobile supply chain management system diffusion: A structural equation analysis of manufacturing firms. *International Journal of Production Research* 51 (4), 1196–1213.
- Chang, I. Chiu; Hwang, Hsin-Ginn; Hung, Ming-Chien; Lin, Ming-Hui; Yen, David C., 2007. Factors affecting the adoption of electronic signature: Executives' perspective of hospital information department. *Decision Support Systems* 44 (1), 350–359.
- Chang, Sea-Jin; van Witteloostuijn, Arjen; Eden, Lorraine, 2010. From the editors: Common method variance in international business research. *Journal of International Business Studies* 41 (2), 178–184.
- Chatterjee, Sheshadri; Rana, Nripendra P.; Dwivedi, Yogesh K.; Baabdullah, Abdullah M., 2021. Understanding AI adoption in manufacturing and production firms using an integrated TAM-TOE model. *Technological Forecasting and Social Change* 170 (120880), 1–14.
- Chen, Lei-Da; Tan, Justin, 2004. Technology adaptation in e-commerce. *European Management Journal* 22 (1), 74–86.
- Chin, Wynne W., 1996. The partial least squares approach for structural equation modeling. In: Marcoulides, George A. (Ed.), *Modern Methods for Business Research*. Lawrence Erlbaum Associates Publishers, 295–336.
- Chittipaka, Venkataiah; Kumar, Satish; Sivarajah, Uthayasankar; Bowden, Jana Lay-Hwa; Baral, Manish Mohan, 2023. Blockchain technology for supply chains operating in emerging markets: An empirical examination of technology-organization-environment (TOE) framework. *Annals of Operations Research* 327 (1), 465–492.
- Choi, Youngjoon; Choi, Miju; Oh, Munhyang (Moon); Kim, Seongseop (Sam), 2020. Service robots in hotels: Understanding the service quality perceptions of human-robot interaction. *Journal of Hospitality Marketing & Management* 29 (6), 613–635.
- Clohesy, Trevor; Acton, Thomas, 2019. Investigating the influence of organizational factors on blockchain adoption. *Industrial Management & Data Systems* 119 (7), 1457–1491.
- Cohen, Jacob, 1992. A power primer. *Psychological Bulletin* 112 (1), 155–159.
- Coltman, Tim; Devinney, Timothy M.; Midgley, David F.; Venaik, Sunil, 2008. Formative versus reflective measurement models: Two applications of formative measurement. *Journal of Business Research* 61 (12), 1250–1262.
- Della Corte, Valentina; Sepe, Fabiana; Gursoy, Dogan; Prisco, Anna, 2023. Role of trust in customer attitude and behaviour formation towards social service robots. *International Journal of Hospitality Management* 114 (103587), 1–10.
- Davis, Fred D.; Bagozzi, Richard P.; Warshaw, Paul R., 1989. User acceptance of computer technology: A comparison of two theoretical models. *Management Science* 35 (8), 982–1003.
- Davis, Fred D., 1989. Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly* 13 (3), 319–340.
- Davis, Fred D.; Venkatesh, Viswanath, 1996. A critical assessment of potential measurement biases in the technology acceptance model: Three experiments. *International Journal of Human-Computer Studies* 45 (1), 19–45.
- Dawes, John, 2008. Do data characteristics change according to the number of scale points used? An experiment using 5-point, 7-point and 10-point scales. *International Journal of Market Research* 50 (1), 61–104.
- Dedrick, Jason; West, Joel, 2003. Why firms adopt open source platforms: A grounded theory of innovation and standards adoption. *MISQ Special Issue Workshop: Standard Making: A Critical Research Frontier for Information Systems* 1 (1), 236–257.

- van Doorn, Jenny; Mende, Martin; Noble, Stephanie M.; Hulland, John; Ostrom, Amy L.; Grewal, Dhruv; Petersen, J. Andrew, 2017. Domo arigato Mr. Roboto. *Journal of Service Research* 20 (1), 43–58.
- European Central Bank, 2024. Monetary Financial Institutions (MFIs), Version: 16/02/2024, 1 page, Internet: https://www.ecb.europa.eu/stats/financial_corporations/list_of_financial_institutions/html/daily_list-MID.en.html, retrieved on: 16/02/2024.
- Fichman, Robert, 2004. Going beyond the dominant paradigm for information technology innovation research: Emerging concepts and methods. *Journal of the Association for Information Systems* 5 (8), 314–355.
- Fishbein, Martin A.; Ajzen, Icek, 1975. Belief, Attitude, Intention and Behaviour: An Introduction to Theory and Research. Reading, MA: Addison-Wesley.
- Fong, Terrence; Nourbakhsh, Illah; Dautenhahn, Kerstin, 2003. A survey of socially interactive robots. *Robotics and Autonomous Systems* 42 (3–4), 143–166.
- Fornell, Claes; Larcker, David F., 1981. Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research* 18 (1), 39–50.
- Fosso Wamba, Samuel; Queiroz, Maciel M.; Trinchera, Laura, 2020. Dynamics between blockchain adoption determinants and supply chain performance: An empirical investigation. *International Journal of Production Economics* 229 (107791), 1–15.
- Franke, George; Sarstedt, Marko, 2019. Heuristics versus statistics in discriminant validity testing: A comparison of four procedures. *Internet Research* 29 (3), 430–447.
- Gangwar, Hemlata; Date, Hema; Rao, A.D., 2014. Review on IT adoption: Insights from recent technologies. *Journal of Enterprise Information Management* 27 (4), 488–502.
- Gangwar, Hemlata; Date, Hema; Ramaswamy, R., 2015. Understanding determinants of cloud computing adoption using an integrated TAM-TOE model. *Journal of Enterprise Information Management* 28 (1), 107–130.
- Geisser, Seymour, 1974. A predictive approach to the random effect model. *Biometrika* 61 (1), 101–107.
- Ghobakhloo, Morteza; Arias-Aranda, Daniel; Benitez-Amado, Jose, 2011. Adoption of e-commerce applications in SMEs. *Industrial Management & Data Systems* 111 (8), 1238–1269.
- Goodhue, Dale L.; Thompson, Ronald L., 1995. Task–technology fit and individual performance. *MIS Quarterly* 19 (2), 213–236.
- de Graaf, Maartje M.A., 2016. An ethical evaluation of human–robot relationships. *International Journal of Social Robotics* 8 (4), 589–598.
- Grandón, Elizabeth E.; Nasco, Suzanne A.; Mykytyn, Peter P., 2011. Comparing theories to explain e-commerce adoption. *Journal of Business Research* 64 (3), 292–298.
- Grover, Varun, 1993. An empirically derived model for the adoption of customer-based interorganizational systems. *Decision Sciences* 24 (3), 603–640.
- Gursoy, Dogan; Chi, Oscar Hengxuan; Lu, Lu; Nunkoo, Robin, 2019. Consumers acceptance of artificially intelligent (AI) device use in service delivery. *International Journal of Information Management* 49 (1), 157–169.
- Hair, Joe F.; Ringle, Christian M.; Sarstedt, Marko, 2011. PLS-SEM: Indeed a silver bullet. *Journal of Marketing Theory and Practice* 19 (2), 139–152.
- Hair, Joseph F.; Risher, Jeffrey J.; Sarstedt, Marko; Ringle, Christian M., 2019. When to use and how to report the results of PLS-SEM. *European Business Review* 31 (1), 2–24.

- Hair, Joe F.; Howard, Matt C.; Nitzl, Christian, 2020. Assessing measurement model quality in PLS-SEM using confirmatory composite analysis. *Journal of Business Research* 109 (1), 101–110.
- Hair, Joseph F.; Hult, G. Tomas M.; Ringle, Christian M.; Sarstedt, Marko; Danks, Nicholas P.; Ray, Soumya, 2021. *Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R*. Cham: Springer.
- Hair, Joseph F.; Sarstedt, Marko; Ringle, Christian M.; Gudergan, Siegfried P., 2023. *Advanced Issues in Partial Least Squares Structural Equation Modeling*, 2nd revised ed. New York: Sage.
- Hajiabbasi, Milad; Akhtarkavan, Ehsan; Majidi, Babak, 2023. Cyber–physical customer management for Internet of robotic things-enabled banking. *IEEE Access* 11 (1), 34062–34079.
- Hashimy, Loha; Jain, Geetika; Grifell-Tatjé, Emili, 2023. Determinants of blockchain adoption as decentralized business model by Spanish firms: An innovation theory perspective. *Industrial Management & Data Systems* 123 (1), 204–228.
- Henseler, Jörg; Ringle, Christian M.; Sarstedt, Marko, 2015. A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science* 43 (1), 115–135.
- Hentzen, Janin Karoli; Hoffmann, Arvid; Dolan, Rebecca; Pala, Erol, 2022. Artificial intelligence in customer-facing financial services: A systematic literature review and agenda for future research. *International Journal of Bank Marketing* 40 (6), 1299–1336.
- Hertlein, Johanna, 2018. Mein Name ist Numi – ich bin ein humanoider Roboter, Version: 06/09/2018, Internet: <https://www.der-bank-blog.de/bankroboter-sparkasse/technologie/36774/>, retrieved on: 28/05/2024.
- Hosmer, David W.; Lemeshow, Stanley; Sturdivant, Rodney X., 2013. *Applied Logistic Regression*. Hoboken: Wiley.
- Hsu, Ching-Wen; Yeh, Ching-Chiang, 2017. Understanding the factors affecting the adoption of the Internet of things. *Technology Analysis & Strategic Management* 29 (9), 1089–1102.
- Huang, Ming-Hui; Rust, Roland T., 2018. Artificial intelligence in service. *Journal of Service Research* 21 (2), 155–172.
- Hult, G. Tomas M.; Hair, Joseph F.; Proksch, Dorian; Sarstedt, Marko; Pinkwart, Andreas; Ringle, Christian M., 2018. Addressing endogeneity in international marketing applications of partial least squares structural equation modeling. *Journal of International Marketing* 26 (3), 1–21.
- Hung, Shin-Yuan; Hung, Wei-Hsi; Tsai, Chia-An; Jiang, Shu-Chen, 2010. Critical factors of hospital adoption on CRM system: Organizational and information system perspectives. *Decision Support Systems* 48 (4), 592–603.
- Iacovou, Charalambos L.; Benbasat, Izak; Dexter, Albert S., 1995. Electronic data interchange and small organizations: Adoption and impact of technology. *MIS Quarterly* 19 (4), 465.
- Ifinedo, Princely, 2011. An empirical analysis of factors influencing Internet/e-business technologies adoption by SMES in Canada. *International Journal of Information Technology & Decision Making* 10 (4), 731–766.
- Intan Salwani, Mohamed; Marthandan, Govindan; Daud Norzaidi, Mohd; Choy Chong, Siong, 2009. E-commerce usage and business performance in the Malaysian tourism sector: Empirical analysis. *Information Management & Computer Security* 17 (2), 166–185.

- Jo, Hyeon; Bang, Youngsok, 2023. Analyzing ChatGPT adoption drivers with the TOEK framework. *Scientific Reports* 13 (1), 1–17.
- Katebi, Ali; Homami, Peyman; Najmeddin, Mohammad, 2022. Acceptance model of precast concrete components in building construction based on technology acceptance model (TAM) and technology, organization, and environment (TOE) framework. *Journal of Building Engineering* 45 (103518), 1–17.
- Kenny, David A., 2018. Moderator variables: Introduction, Version: 15/09/2018, 1 page, Internet: <https://davidakenny.net/cm/moderation.htm>, retrieved on: 14/04/2024.
- Khan, Shazma, 2018. China opens world's first human-less bank, Version: 30/04/2018, 1 page, Internet: <https://www.brecorder.com/news/415052>, retrieved on: 14/04/2024.
- Khon, Sergey; Nizam, Ahmed; Tan, David; Taraporevala, Zubin, 2022. Best of both worlds: Balancing digital and physical channels in retail banking, Version: 13/07/2022, 9 pages, Internet: <https://www.mckinsey.com/industries/financial-services/our-insights/best-of-both-worlds-balancing-digital-and-physical-channels-in-retail-banking>, retrieved on: 14/04/2024.
- Kim, Yujin; Dykema, Jennifer; Stevenson, John; Black, Penny; Moberg, D. Paul, 2019. Straightlining: Overview of measurement, comparison of indicators, and effects in mail–web mixed-mode surveys. *Social Science Computer Review* 37 (2), 214–233.
- King, William R.; He, Jun, 2006. A meta-analysis of the technology acceptance model. *Information & Management* 43 (6), 740–755.
- Kuan, Kevin K.Y.; Chau, Patrick Y.K., 2001. A perception-based model for EDI adoption in small businesses using a technology–organization–environment framework. *Information & Management* 38 (8), 507–521.
- Lee, Younghwa; Kozar, Kenneth A.; Larsen, Kai R.T., 2003. The technology acceptance model: Past, present, and future. *Communications of the Association for Information Systems* 12 (1), 752–780.
- Lian, Jiunn-Woei; Yen, David C.; Wang, Yen-Ting, 2014. An exploratory study to understand the critical factors affecting the decision to adopt cloud computing in Taiwan hospital. *International Journal of Information Management* 34 (1), 28–36.
- Lin, I. Fen; Schaeffer, Nora C., 1995. Using survey participants to estimate the impact of nonparticipation. *The Public Opinion Quarterly* 59 (2), 236–258.
- Liu, Zhenhua; Min, Qingfei; Ji, Shaobo, 2008. A comprehensive review of research in IT adoption. *2008 4th International Conference on Wireless Communications, Networking and Mobile Computing, IEEE*, 1–5.
- Low, Chinyao; Chen, Ychsueh; Wu, Mingchang, 2011. Understanding the determinants of cloud computing adoption. *Industrial Management & Data Systems* 111 (7), 1006–1023.
- Lu, Vinh Nhat; Wirtz, Jochen; Kunz, Werner H.; Paluch, Stefanie; Gruber, Thorsten; Martins, Antje; Patterson, Paul G., 2020. Service robots, customers and service employees: What can we learn from the academic literature and where are the gaps? *Journal of Service Theory and Practice* 30 (3), 361–391.
- Mason, Charlotte H.; Perreault, William D., 1991. Collinearity, power, and interpretation of multiple regression analysis. *Journal of Marketing Research* 28 (3), 268–280.
- McCurry, Justin, 2015. Japanese bank introduces robot workers to deal with customers in branches, Version: 04/02/2015, 1 page, Internet: <https://www.theguardian.com/world/2015/feb/04/japanese-bank-introduces-robot-workers-to-deal-with-customers-in->

- branches#:~:text=Nao%2C%20a%2058%2Dcentimetre%20(,UFJ%20Financial%20Group%20from%20April, retrieved on: 14/04/2024.
- Moore, Gary C.; Benbasat, Izak, 1991. Development of an instrument to measure the perceptions of adopting an information technology innovation. *Information Systems Research* 2 (3), 192–222.
- Nam, Kichan; Dutt, Christopher S.; Chathoth, Prakash; Daghfous, Abdelkader; Khan, M. Sajid, 2021. The adoption of artificial intelligence and robotics in the hotel industry: Prospects and challenges. *Electronic Markets* 31 (3), 553–574.
- Nitzl, Christian; Roldan, Jose L.; Cepeda, Gabriel, 2016. Mediation analysis in partial least squares path modeling. *Industrial Management & Data Systems* 116 (9), 1849–1864.
- Northey, Gavin; Hunter, Vanessa; Mulcahy, Rory; Choong, Kelly; Mehmet, Michael, 2022. Man vs machine: How artificial intelligence in banking influences consumer belief in financial advice. *International Journal of Bank Marketing* 40 (6), 1182–1199.
- Oliveira, Tiago; Martins, Maria Fraga, 2011. Literate review of information technology adoption models at the firm level. *The Electronic Journal Information Systems Evaluation* 14 (1), 110–121.
- Oliveira, Tiago; Thomas, Manoj; Espadanal, Mariana, 2014. Assessing the determinants of cloud computing adoption: An analysis of the manufacturing and services sectors. *Information & Management* 51 (5), 497–510.
- Ooi, Keng-Boon; Tan, Garry Wei-Han; Aw, Eugene Cheng-Xi; Cham, Tat-Huei; Dwivedi, Yogesh K.; Dwivedi, Rohita; Hughes, Laurie; Kar, Arpan Kumar; Loh, Xiu-Ming; Mogaji, Emmanuel; Phau, Ian; Sharma, Anshuman, 2023. Banking in the metaverse: A new frontier for financial institutions. *International Journal of Bank Marketing* 41 (7), 1829–1846.
- Parasuraman, A., 2000. Technology Readiness Index (Tri): A multiple-item scale to measure readiness to embrace new technologies. *Journal of Service Research* 2 (4), 307–320.
- Park, Sungho; Gupta, Sachin, 2012. Handling endogenous regressors by joint estimation using copulas. *Marketing Science* 31 (4), 567–586.
- Podsakoff, Philip M.; MacKenzie, Scott B.; Lee, Jeong-Yeon; Podsakoff, Nathan P., 2003. Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology* 88 (5), 879–903.
- Podsakoff, Philip M.; Podsakoff, Nathan P.; Williams, Larry J.; Huang, Chengquan; Yang, Junhui, 2024. Common method bias: It's bad, it's complex, it's widespread, and it's not easy to fix. *Annual Review of Organizational Psychology and Organizational Behavior* 11 (1), 17–61.
- Premkumar, G.; Roberts, Margaret, 1999. Adoption of new information technologies in rural small businesses. *Omega* 27 (4), 467–484.
- Ramsey, J.B., 1969. Tests for specification errors in classical linear least-squares regression analysis. *Journal of the Royal Statistical Society. Series B (Methodological)* 31 (2), 350–371.
- Research & Markets, 2023. Global social robots market 2023–2027, Version: 01/07/2023, Internet: <https://www.researchandmarkets.com/reports/5509246/global-social-robots-market-2023-2027#product--toc>, retrieved on: 28/05/2024.
- Riegger, Anne-Sophie; Klein, Jan F.; Merfeld, Katrin; Henkel, Sven, 2021. Technology-enabled personalization in retail stores: Understanding drivers and barriers. *Journal of Business Research* 123 (1), 140–155.
- Ringle, Christian M.; Sarstedt, Marko; Straub, Detmar W., 2012. Editor's comments: A critical look at the use of PLS-SEM in "MIS Quarterly." *MIS Quarterly* 36 (1), 3–15.

- Ringle, Christian M.; Wende, Sven; Becker, Jan-Michael, 2024. SmartPLS 4, Version: 14/04/2024, Bönningstedt: SmartPLS, Internet: <https://www.smartpls.com>, retrieved on: 14/04/2024.
- Robey, Daniel; Im, Ghiyoung; Wareham, Jonathan, 2008. Theoretical foundations of empirical research on interorganizational systems: Assessing past contributions and guiding future directions. *Journal of the Association for Information Systems* 9 (9), 497–518.
- Rogers, Everett M., 1962. Diffusion of Innovations. New York: Free Press.
- Rogers, Everett M., 2003. Diffusion of Innovations, 5th revised ed. New York: Free Press.
- Sarstedt, Marko; Ringle, Christian M.; Cheah, Jun-Hwa; Ting, Hiram; Moisesescu, Ovidiu I.; Radomir, Lacramioara, 2020. Structural model robustness checks in PLS-SEM. *Tourism Economics* 26 (4), 531–554.
- Sax, Linda J.; Gilmartin, Shannon K.; Bryant, Alyssa N., 2003. Assessing response rates and nonresponse bias in web and paper surveys. *Research in Higher Education* 44 (4), 409–432.
- Schillewaert, Niels; Ahearne, Michael J.; Frambach, Ruud T.; Moenaert, Rudy K., 2005. The adoption of information technology in the sales force. *Industrial Marketing Management* 34 (4), 323–336.
- Shmueli, Galit; Sarstedt, Marko; Hair, Joseph F.; Cheah, Jun-Hwa; Ting, Hiram; Vaithilingam, Santha; Ringle, Christian M., 2019. Predictive model assessment in PLS-SEM: Guidelines for using PLSpredict. *European Journal of Marketing* 53 (11), 2322–2347.
- Soliman, Khalid S.; Janz, Brian D., 2004. An exploratory study to identify the critical factors affecting the decision to establish Internet-based interorganizational information systems. *Information & Management* 41 (6), 697–706.
- Song, Christina Soyoung; Kim, Youn-Kyung, 2022. The role of the human-robot interaction in consumers' acceptance of humanoid retail service robots. *Journal of Business Research* 146 (1), 489–503.
- Sonnenwald, Diana H.; Maglaughlin, Kelly L.; Whitton, Mary C., 2001. Using innovation diffusion theory to guide collaboration technology evaluation: Work in progress. *10th IEEE International Workshops on Enabling Technologies: Infrastructure for Collaborative Enterprises (WETICE 2001)*, 114–119.
- Stone, M., 1974. Cross-validatory choice and assessment of statistical predictions. *Journal of the Royal Statistical Society. Series B (Methodological)* 36 (2), 111–147.
- Sulaiman, Twana Tahseen; Mahomed, Anuar Shah Bali; Rahman, Azmawani Abd; Hassan, Mazlan, 2023. Understanding antecedents of learning management system usage among university lecturers using an integrated TAM-TOE model. *Sustainability* 15 (3), 1–24.
- Svensson, Göran; Ferro, Carlos; Høgevoid, Nils; Padin, Carmen; Carlos Sosa Varela, Juan; Sarstedt, Marko, 2018. Framing the triple bottom line approach: Direct and mediation effects between economic, social and environmental elements. *Journal of Cleaner Production* 197 (1), 972–991.
- Swiss Financial Market Supervisory Authority, 2024. Authorised banks and securities firms, Version: 16/02/2024, 1 page, Internet: <https://www.finma.ch/en/~media/finma/dokumente/bewilligungstraeger/pdf/beh.pdf?la=de>, retrieved on: 16/02/2024.
- Tan, Jing; Tyler, Katherine; Manica, Andrea, 2007. Business-to-business adoption of eCommerce in China. *Information & Management* 44 (3), 332–351.

- Thiesse, Frédéric; Staake, Thorsten; Schmitt, Patrick; Fleisch, Elgar, 2011. The rise of the “next-generation bar code”: An international RFID adoption study. *Supply Chain Management: An International Journal* 16 (5), 328–345.
- Titah, Ryad; Barki, Henri, 2009. Nonlinearities between attitude and subjective norms in information technology acceptance: A negative synergy? *MIS Quarterly* 33 (4), 827–846.
- Tornatzky, L. G.; Klein, K. J., 1982. Innovation characteristics and innovation adoption-implementation: A meta-analysis of findings. *IEEE Transactions on Engineering Management* 29 (1), 28–45.
- Tornatzky, L. G.; Fleischer, M., 1990. The Processes of Technological Innovation. University of Michigan: Lexington Books.
- Tyagi, Riya, 2021. How humanoid robots elevate your banking hospitality service: The case of Rabobank, Version: 31/03/2021, 1 page, Internet: <https://www.aldebaran.com/en/blog/news-trends/how-humanoid-robots-elevate-your-banking-hospitality-service-case-rabobank>, retrieved on: 14/04/2024.
- Vaithilingam, Santha; Ong, Chu Sun; Moisesescu, Ovidiu I.; Nair, Mahendhiran S., 2024. Robustness checks in PLS-SEM: A review of recent practices and recommendations for future applications in business research. *Journal of Business Research* 173 (114465), 1–10.
- Venkatesh, Viswanath; Davis, Fred D., 2000. A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science* 46 (2), 186–204.
- Venkatesh, Viswanath; Morris, Michael G.; Davis, Gordon B.; Davis, Fred D., 2003. User acceptance of information technology: Toward a unified view. *MIS Quarterly* 27 (3), 425–478.
- Venkatesh, Viswanath; Thong, James Y. L.; Xu, Xin, 2012. Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly* 36 (1), 157–178.
- Volpe, Gabriella; Schulte-Althoff, Matthias; Dillmann, David; Maurer, Emmanuelle; Niedenzu, Yannic; Schließer, Philipp; Fürstenau, Daniel, 2020. Humanoid social robots and the reconfiguration of customer service. In: Bandi, Rajendra K.; Ranjini, C. R.; Klein, Stefan; Madon, Shirin; Monteiro, Eric (Eds.), *The Future of Digital Work: The Challenge of Inequality*. Cham: Springer.
- Wang, Youwei; Meister, Darren; Wang, Yinglei, 2008. Relative advantage and perceived usefulness: The adoption of competing ICTs. *DIGIT 2008 Proceedings*, 1–21.
- Wang, Yu-Min; Wang, Yi-Shun; Yang, Yong-Fu, 2010. Understanding the determinants of RFID adoption in the manufacturing industry. *Technological Forecasting and Social Change* 77 (5), 803–815.
- van de Weerd, Inge; Mangula, Ivonne Sartika; Brinkkemper, Sjaak, 2016. Adoption of software as a service in Indonesia: Examining the influence of organizational factors. *Information & Management* 53 (7), 915–928.
- Williams, Michael D.; Dwivedi, Yogesh K.; Lal, Banita; Schwarz, Andrew, 2009. Contemporary trends and issues in IT adoption and diffusion research. *Journal of Information Technology* 24 (1), 1–10.
- Wirtz, Jochen; Patterson, Paul G.; Kunz, Werner H.; Gruber, Thorsten; Lu, Vinh Nhat; Paluch, Stefanie; Martins, Antje, 2018. Brave new world: Service robots in the frontline. *Journal of Service Management* 29 (5), 907–931.

- Wu, Wei-Wen, 2011. Developing an explorative model for SaaS adoption. *Expert Systems with Applications* 38 (12), 15057–15064.
- Yang, Zhaojun; Sun, Jun; Zhang, Yali; Wang, Ying, 2015. Understanding SaaS adoption from the perspective of organizational users: A tripod readiness model. *Computers in Human Behavior* 45 (1), 254–264.
- Yap, C.S.; Thong, J.Y.L.; Raman, K.S., 1994. Effect of government incentives on computerisation in small business. *European Journal of Information Systems* 3 (3), 191–206.
- Zhu, Kevin; Kraemer, Kenneth L., 2005. Post-adoption variations in usage and value of e-business by organizations: Cross-country evidence from the retail industry. *Information Systems Research* 16 (1), 61–84.
- Zhu, Kevin; Kraemer, Kenneth L.; Xu, Sean, 2006. The process of innovation assimilation by firms in different countries: A technology diffusion perspective on e-business. *Management Science* 52 (10), 1557–1576.

FIGURE 1
Deployments of Humanoid Service Robot in Banks Around the World.

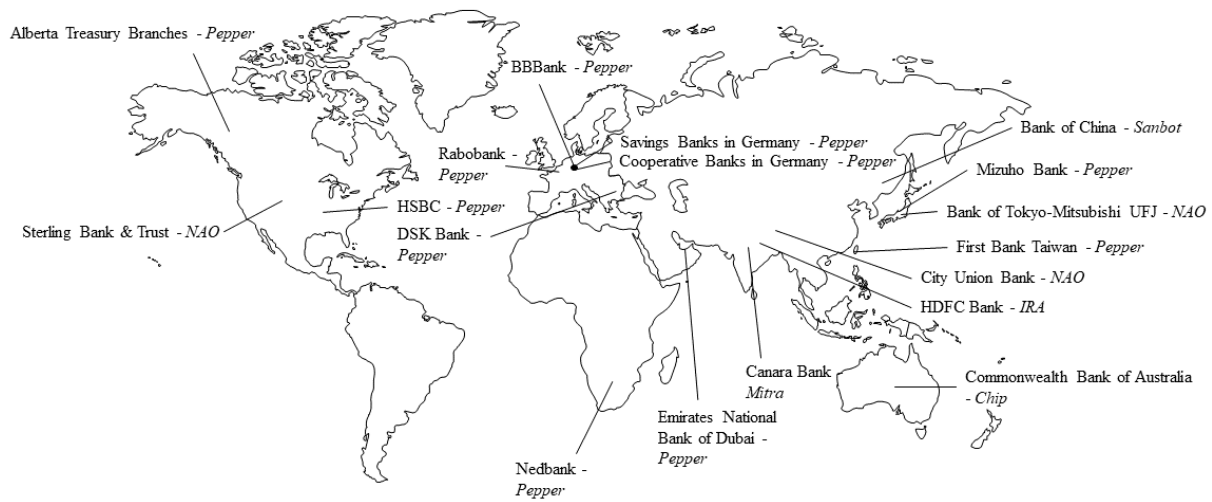


FIGURE 2
Technology Acceptance Model.

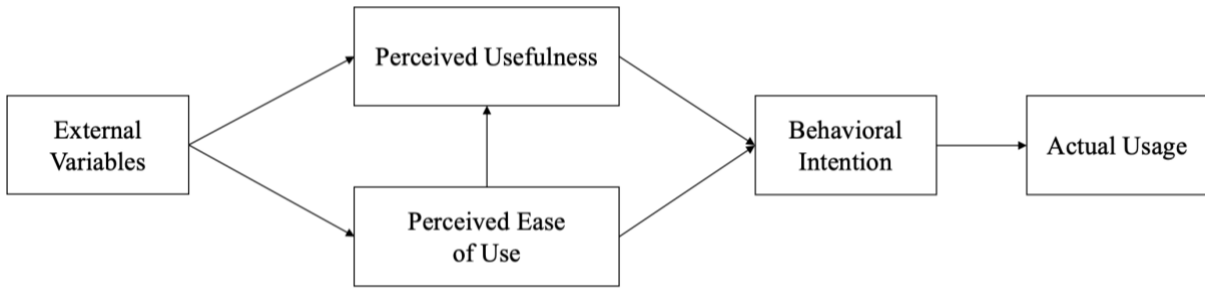


FIGURE 3
Technology–Organization–Environment Framework.

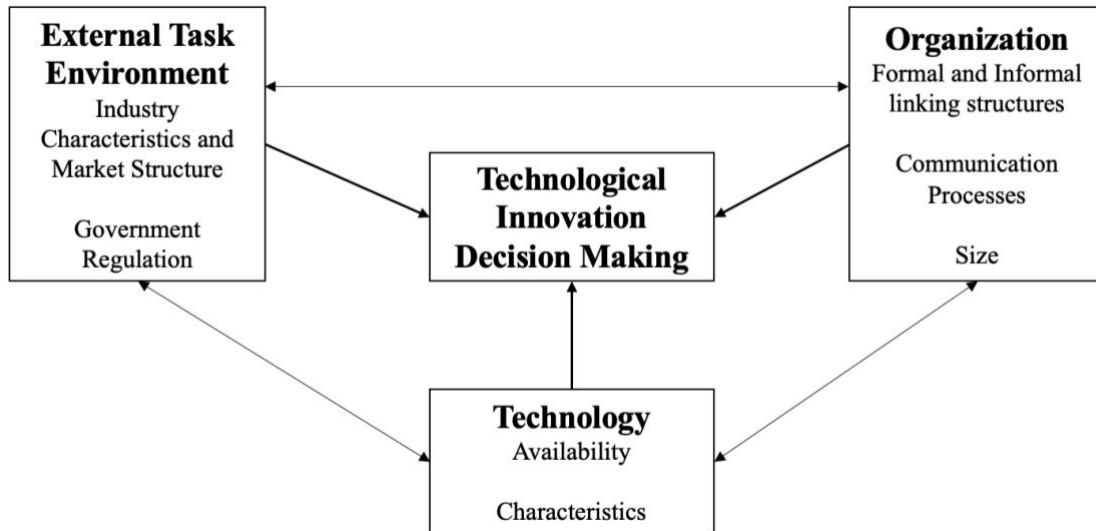


FIGURE 4
Proposed Research Framework.

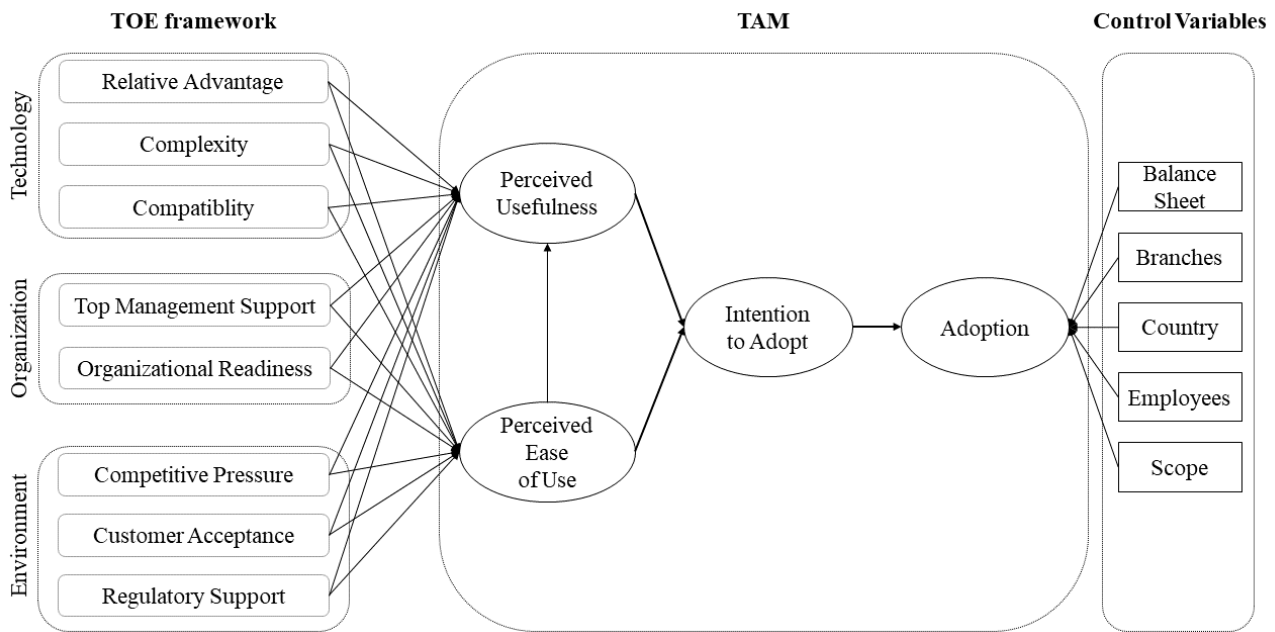


FIGURE 5
Structural Model Results.

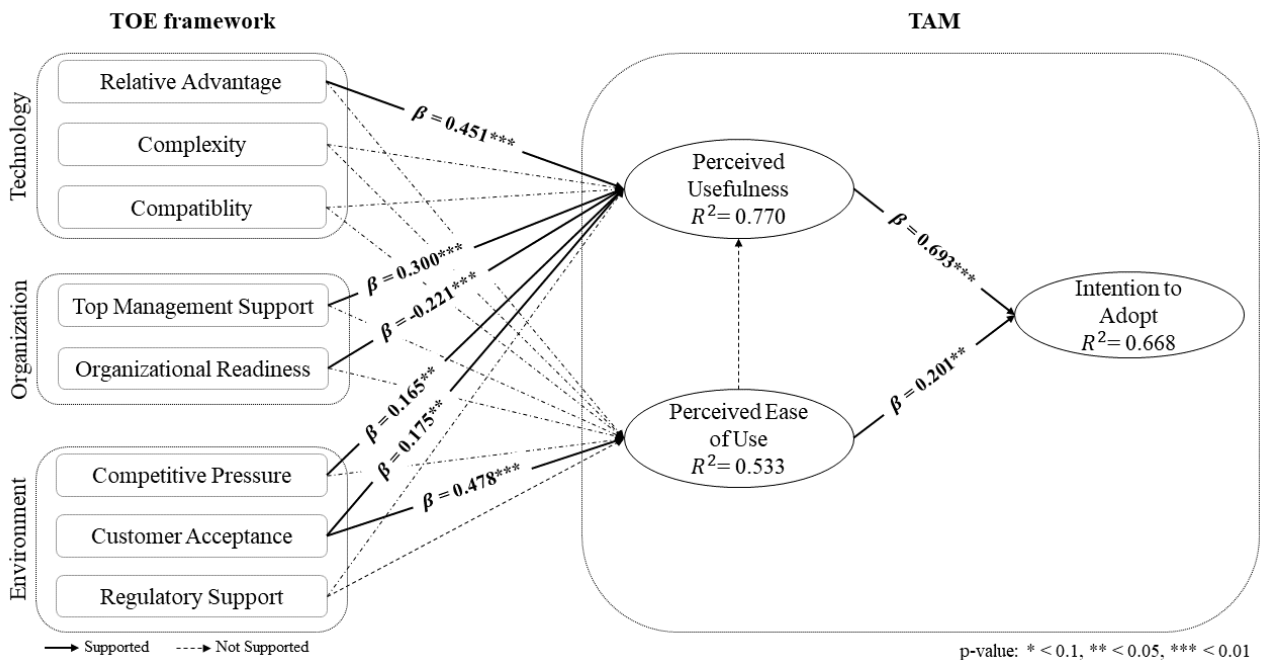


TABLE 1
Different Technology Adoption Factors.

This table presents an overview of various studies analyzing the adoption factors of different technologies. The first column lists the authors and the publication year. The second column specifies the technology studied in each paper. The subsequent three columns present each study's technological, organizational, and environmental adoption factors.

Authors	Technology studied	Technological	Adoption Factors Organizational	Environmental
Zhu et al. (2006)	E-business	technological readiness, technological integration	firm size, global scope, managerial obstacles	competition intensity, regulatory
Wang et al. (2010)	Radio frequency identification	relative advantage, compatibility, complexity	management support, firm size, technology competence	competitive pressure, trading partner pressure, information intensity
Ifinedo (2011)	Internet/ e-business technologies	perceived benefits	management commitment and support, organizational IT competence	external pressure, IS vendor support and pressure, financial resources availability
Gangwar et al. (2015)	Cloud computing	relative advantage, compatibility, complexity	organizational competency, training and education, top management support	competitive pressure, trading partner support
Hsu & Yeh (2017)	Internet of things	technology infrastructure, integration, IT expertise. Additional factor: security	expected benefits, top management support, organizational readiness	government policy, supporting industry, competitive pressure
Chatterjee et al. (2021)	AI adoption in manufacturing and production firms	perceived usefulness, perceived ease of use	organizational competency, organizational complexity, organizational readiness, organizational combability	competitive advantage, partner support
Nam et al. (2021)	Artificial intelligence and robotics in the hotel industry	relative advantage, complexity, IT expertise	financial justification, resistance of employees	customer, competition, legal issues
Katebi et al. (2022)	Precast concrete components in building construction	perceived risk, combability	cost, organizational readiness	competitive pressure, government support
Chittipaka et al. (2023)	Blockchain Technology for Supply Chains	relative advantage, trust, compatibility, security	firms' IT resources, higher authority support, firm size, monetary resources	rivalry pressure, business partner's pressure, regulatory support
Hashimy et al. (2023)	Blockchain adoption as decentralized business model	relative advantage, complexity	top management support, competency	competitive pressure
Jo & Bang (2023)	ChatGPT	accessibility, network quality, system response	organizational culture	social influence

TABLE 2
Measurement Items

This table shows the measurement items utilized to operationalize the latent constructs for analyzing the adoption of humanoid service robots within the banking sector. We list each measurement item alongside its respective sources, which we adapted to fit the context of our study. Specifically, we operationalize the relative advantage of the innovation through six items (RA1–RA6), complexity, and compatibility through four items each (CPLX1–CPLX4; CMPA1–CMPA4). Considering the organizational adoption factors, we measure top management support using three items (TMS1–TMS3) and organizational readiness using five items (OR1–OR5). We operationalize competitive pressure, customer acceptance, and regulatory support to measure the environmental factors through three items each (CP1–CP3; CUS1–CUS3; RS1–RS3). We measure perceived usefulness with four items (PU1–PU4) and perceived ease of use with three items (PEOU1–PEOU3). We operationalize the latent construct of intention to adopt via three items (ItA1–ItA3). Actual adoption (ADOP1) is a binary variable, where one indicates that the bank currently employs at least one humanoid service robot and zero, if not. We also request the number of robots deployed for banks using at least one humanoid service robot (ADOP2).

Measurement Items	Adapted Source
RA1 Using humanoid service robots in our bank would help to reduce our operational costs.	Moore & Benbasat (1991), Premkumar & Roberts (1999), Wang et al. (2010), Hung et al. (2010), Chan & Chong (2013), Chatterjee et al. (2021)
RA2 Using humanoid service robots in our bank would help to improve specific banking processes.	Moore & Bensabat (1991), Premkumar & Roberts (1999), Ifinedo (2011), Oliveira et al. (2014)
RA3 Using humanoid service robots in our bank would help to reach new customers.	Awa et al. (2017), motivated by Amelia et al. (2022)
RA4 Using humanoid service robots would help to reduce the routine workload of our employees.	Gangwar et al. (2015), motivated by Volpe et al. (2020) and Wirtz et al. (2018)
RA5 Using humanoid service robots in our bank would help to enhance customer service through multilingual communication capabilities.	Gangwar et al. (2015), motivated by Čaić et al. (2018)
RA6 The seamless integration of AI in humanoid service robots offers new opportunities for innovative customer service.	Moore & Bensabat (1991), Ghobakhloo et al. (2011), Ifinedo (2011), Oliveira et al. (2014)
CPLX1 Integrating humanoid service robots with our current technologies is a difficult task for our bank.	Premkumar & Roberts (1999), Chang et al. (2007), Gangwar et al. (2015), Chatterjee et al. (2021)
CPLX 2 Using humanoid service robots is too complex for our business operations.	Moore & Bensabat (1991), Chang et al. (2007), Wang et al. (2010), Ifinedo (2011), Thiesse et al. (2011), Oliveira et al. (2014)
CPLX 3 Learning the required skills to use humanoid service robots is too complex for our employees.	Moore & Bensabat (1991), Premkumar & Roberts (1999), Thiesse et al. (2011), Oliveira et al. (2014)
CPLX 4 Developing applications for humanoid service robots is too complex for our bank.	Premkumar & Roberts (1999), Chang et al. (2007), Lian et al. (2014)
CMPA1 Humanoid service robots are compatible with the existing business operations in our bank.	Moore & Benbasat (1991), Gangwar et al. (2015), Chatterjee et al. (2021)
CMPA2 Humanoid service robots are compatible with the existing technologies in our bank.	Zhu et al. (2006), Ifinedo (2011), Thiesse et al. (2011), Oliveira et al. (2014), Awa et al. (2017)
CMPA3 Humanoid service robots are compatible with our bank's corporate culture and value system.	Grover (1993), Premkumar & Roberts (1999), Zhu et al. (2006), Ifinedo (2011), Thiesse et al. (2011), Oliveira et al. (2014)
CMPA4 Humanoid service robots are compatible with data security and privacy requirements in our bank.	Kuan & Chau (2001), Soliman & Janz (2004), Zhu et al. (2006), Thiesse et al. (2011), Wu (2011), Lian et al. (2014), Oliveira et al. (2014), Chittipaka et al. (2023)
TMS1 Our top management is likely to consider the adoption of humanoid service robots as strategically important.	Wang et al. (2010), Gangwar et al. (2015)
TMS2 Our top management is willing to take risks involved in the adoption of humanoid service robots.	Wang et al. (2010), Thiesse et al. (2011), Chan & Chong (2013), Oliveira et al. (2014), Gangwar et al. (2015)
TMS3 Our top management is likely to allocate financial resources for the adoption of humanoid service robots.	Premkumar & Roberts (1999), Wang et al. (2010), Lian et al. (2014)
OR1 Our bank has the necessary technological resources to adopt humanoid service robots.	Iacovou et al. (1995), Tan et al. (2007), Gangwar et al. (2015), Chatterjee et al. (2021)

Measurement Items		Adapted Source
OR2	Our bank has the necessary financial resources to adopt humanoid service robots.	Yap et al. (1994), Iacovou et al. (1995), Chang et al. (2007), Chan & Chong (2013), Lian et al. (2014), Chittipaka et al. (2023)
OR3	Our bank has the necessary human resources to adopt humanoid service robots.	Yap et al. (1994), Chang et al. (2007), Chatterjee et al. (2021), Chittipaka et al. (2023)
OR4	Our bank contains a sufficient level of AI-related knowledge.	Kuan & Chau (2001), Chang et al. (2007), Hung et al. (2010), Wang et al. (2010), Lian et al. (2014), Chatterjee et al. (2021)
OR5	Our bank can manage employee concerns regarding the adoption of humanoid service robots.	Brown & Russel (2007), Thiesse et al. (2011), Chatterjee et al. (2021), motivated by Volpe et al. (2020) and Nam et al. (2021)
CP1	Our bank understands the competitive advantages offered by humanoid service robots in the banking industry.	Premkumar & Roberts (1999), Tan et al. (2007), Wang et al. (2010), Lian et al. (2014), Gangwar et al. (2015), Chatterjee et al. (2021)
CP2	Our bank is aware that humanoid service robots are implemented in our competitor organizations.	Tan et al. (2007), Ifinedo (2011), Gangwar et al. (2015), Chatterjee et al. (2021)
CP3	Our bank experiences competitive pressure to adopt humanoid service robots.	Iacovou et al. (1995), Wang et al. (2010), Ifinedo (2011), Chan & Chong (2013), Oliveira et al. (2014), Awa et al. (2017)
CUS1	Our bank expects that our customers are ready to interact with humanoid service robots.	Ifinedo (2011), motivated by Nam et al. (2021)
CUS2	Our bank expects our customers to find it appealing to interact with humanoid service robots.	Schillewaert et al. (2005)
CUS3	Our bank expects our customers to accept the interaction with humanoid service robots.	Ifinedo (2011), motivated by Wirtz et al. (2018) and Amelia et al. (2022)
RS1	There is legal protection in the use of humanoid service robots.	Zhu & Kramer (2005), Alam et al. (2011), Oliveira et al. (2014), Chittipaka et al. (2023)
RS2	The laws and regulations that govern the use of humanoid service robots are clear and well-defined.	Zhu & Kramer (2005), Alam et al. (2011), Oliveira et al. (2014), Chittipaka et al. (2023)
RS3	There is a supportive regulatory environment for the adoption of humanoid service robots in the banking industry.	Zhu & Kramer (2005), Oliveira et al. (2014), Chittipaka et al. (2023)
PU1	Our bank agrees that using humanoid service robots make our bank more efficient.	Davis (1989), Schillewaert et al. (2005), Gangwar et al. (2015), Chatterjee et al. (2021)
PU2	Our bank agrees that the use of humanoid service robots increase productivity in our bank.	Davis (1989), Schillewaert et al. (2005), Gangwar et al. (2015), Chatterjee et al. (2021)
PU3	Our bank agrees that the use of humanoid service robots would help to improve customer experience.	Grover (1993), Ifinedo (2011), Oliveira et al. (2014), Awa et al. (2017)
PU4	Our bank agrees that the use of humanoid service robots can improve the image of our bank.	Kuan & Chau (2001), Lian et al. (2014), motivated by Amelia et al. (2022)
PEOU1	The process of using humanoid service robots is easily understandable by our bank.	Davis (1989), Schillewaert et al. (2005), Wu (2011), Gangwar et al. (2015), Chatterjee et al. (2021)
PEOU2	It is easy for our bank to make use of humanoid service robots.	Davis (1989), Schillewaert et al. (2005), Wu (2011), Gangwar et al. (2015), Chatterjee et al. (2021)
PEOU3	Our bank agrees that all the related employees can quickly learn about the usage of humanoid service robots.	Davis (1989), Wu (2011), Gangwar et al. (2015), Chatterjee et al. (2021)
ItA1	Overall, our bank thinks that using humanoid service robots is advantageous.	Davis & Venkatesh (1996), Wu (2011), Gangwar et al. (2015), Chatterjee et al. (2021)
ItA2	Overall, our bank is in favor of using humanoid service robots.	Davis & Venkatesh (1996), Wu (2011), Gangwar et al. (2015), Chatterjee et al. (2021)

Measurement Items		Adapted Source
ItA3	Overall, our bank intends to use humanoid service robots	Davis & Venkatesh (1996), Grandon et al. (2011), Wu (2011)
ADOP1	Does your bank currently use humanoid service robots?	Wang et al. (2010)
ADOP2	How many humanoid service robots does your bank currently use?	

TABLE 3**Demographics of the Responding Banks**

This table offers an overview of the demographics of banks that responded to our survey on adopting humanoid service robots. It details various characteristics, including the current adoption status of robots, the number of robots adopted, geographic distribution by country, sector affiliation, operational scope, total assets, employee counts, and number of branches. Additionally, the table categorizes respondents by job role and function. We provide frequency and percentage distributions for each category within these characteristics, given the sample size of 106.

Characteristic	Category	Frequency	Percentage
Adoption of Humanoid Service Robots	Current adoption	3	2.8%
	No current adoption	103	97.2%
Number of Humanoid Service Robots adopted	0	103	97.2%
	1	2	1.9%
	2	1	0.9%
Country	Germany	78	73.6%
	Austria	26	24.5%
	Switzerland	2	1.9%
Sector	Credit Bank	9	8.5%
	Savings Bank	32	30.2%
	Cooperative Bank	61	57.5%
	Other Credit Institutions	4	3.8%
Scope	Local	8	7.5%
	Regional	86	81.1%
	National	5	4.7%
	International	7	6.6%
Total Assets in Mio. EUR or CHF	<500	26	24.5%
	500 – <1,000	11	10.4%
	1,000 – <10,000	61	57.6%
	>= 10,000	8	7.6%
Employees	<100	32	30.2%
	100 – <250	23	21.7%
	250 – <500	26	24.5%
	500 – <1000	16	15.1%
	>= 1000	9	8.5%
Branches	<10	49	46.2%
	10 – <25	25	23.6%
	25 – <50	27	25.5%
	>= 50	5	4.7%
Job Role	Management	49	46.2%
	Finance/Controlling/Accounting	2	1.9%
	Sales/Marketing/Communication	17	16.0%
	Technology/IT/Innovation	29	27.4%
	Other	9	8.5%
Job Function	Board Member	43	40.6%
	Head of Department	34	32.1%
	Team Leader	16	15.1%
	Administrative Assistant	7	6.6%
	Other	6	5.6%

TABLE 4
Summary Statistics of the Survey Item Responses

This table provides summary statistics of the 41 measurement items for the latent constructs and shows the mean, median, standard deviation, minimum, maximum, excess kurtosis, skewness, and number of observations.

Item	Mean	Median	Standard Deviation	Minimum	Maximum	Excess Kurtosis	Skewness	N
RA1	2.642	3.0	1.134	1.0	5.0	-0.712	0.194	106
RA2	2.962	3.0	1.251	1.0	5.0	-1.137	-0.192	106
RA3	2.151	2.0	1.062	1.0	5.0	-0.224	0.651	106
RA4	3.094	3.0	1.233	1.0	5.0	-0.996	-0.305	106
RA5	3.236	3.0	1.162	1.0	5.0	-0.797	-0.291	106
RA6	3.377	4.0	1.153	1.0	5.0	-0.517	-0.520	106
CPLX1	4.075	5.0	1.139	1.0	5.0	-0.352	-0.928	106
CPLX2	3.292	3.0	1.141	1.0	5.0	-0.712	-0.172	106
CPLX3	2.981	3.0	1.124	1.0	5.0	-0.616	0.118	106
CPLX4	3.802	4.0	1.349	1.0	5.0	-0.819	-0.732	106
CMPA1	2.547	3.0	1.109	1.0	5.0	-0.469	0.343	106
CMPA2	2.349	2.0	1.019	1.0	5.0	-0.547	0.337	106
CMPA3	2.651	3.0	1.190	1.0	5.0	-0.959	0.129	106
CMPA4	2.858	3.0	1.068	1.0	5.0	-0.499	0.052	106
TMS1	2.575	3.0	1.197	1.0	5.0	-0.922	0.204	106
TMS2	2.500	2.0	1.135	1.0	5.0	-0.834	0.295	106
TMS3	2.670	3.0	1.147	1.0	5.0	-0.796	0.146	106
OR1	2.283	2.0	1.155	1.0	5.0	-0.654	0.543	106
OR2	3.321	3.0	1.186	1.0	5.0	-0.558	-0.407	106
OR3	2.472	2.0	1.238	1.0	5.0	-0.777	0.459	106
OR4	2.236	2.0	1.104	1.0	5.0	-0.353	0.586	106
OR5	3.085	3.0	1.150	1.0	5.0	-0.589	-0.131	106
CP1	2.708	3.0	1.000	1.0	5.0	-0.539	0.044	106
CP2	2.943	3.0	1.196	1.0	5.0	-0.915	0.010	106
CP3	1.915	2.0	1.083	1.0	5.0	0.370	1.076	106
CUS1	2.500	3.0	0.993	1.0	5.0	-0.546	0.147	106
CUS2	2.472	3.0	0.983	1.0	5.0	-0.752	0.020	106
CUS3	2.651	3.0	1.055	1.0	5.0	-0.722	0.009	106
RS1	2.368	3.0	0.965	1.0	5.0	-0.415	0.094	106
RS2	2.019	2.0	0.869	1.0	5.0	-0.476	0.314	106
RS3	2.019	2.0	0.961	1.0	5.0	-0.058	0.608	106
PU1	3.113	3.0	1.184	1.0	5.0	-0.900	-0.257	106
PU2	2.943	3.0	1.089	1.0	5.0	-0.730	-0.153	106
PU3	2.811	3.0	1.150	1.0	5.0	-0.969	-0.226	106
PU4	2.717	3.0	1.088	1.0	5.0	-0.676	-0.127	106
PEOU1	2.358	2.0	1.011	1.0	5.0	-0.511	0.338	106
PEOU2	2.094	2.0	0.947	1.0	5.0	-0.277	0.552	106
PEOU3	2.575	3.0	1.046	1.0	5.0	-0.659	0.173	106
ItA1	2.896	3.0	1.181	1.0	5.0	-0.794	-0.005	106
ItA2	2.575	3.0	1.173	1.0	5.0	-0.718	0.314	106
ItA3	2.226	2.0	1.168	1.0	5.0	-0.478	0.628	106

TABLE 5
Construct Reliability and Convergent Validity.

This table presents the construct reliability and convergent validity of the measurement items. We report every item's factor loading and indicator reliability to evaluate how much of each indicator's variance is explained by its construct. Factor loadings above 0.708 are recommended because they indicate that the construct explains more than 50 percent of the indicator's variance. The evaluation of the internal consistency reliability includes Cronbach's alpha, composite reliability, and rho- α . Reliability values between 0.60 and 0.70 are considered "acceptable in exploratory research," whereas values between 0.70 and 0.95 range from "satisfactory to good." Values above 0.95 are problematic because they indicate that the indicators are redundant, reducing construct validity. The metric used for evaluating a construct's convergent validity is the average variance extracted (AVE). The minimum acceptable AVE is 0.50 (cf. Hair et al., 2022).

Construct	Item	Factor Loading	Indicator Reliability	Cronbach's Alpha	Composite Reliability	Rho- α	AVE
Relative Advantage				0.901	0.925	0.908	0.673
	RA1	0.764	0.584				
	RA2	0.906	0.821				
	RA3	0.753	0.567				
	RA4	0.906	0.821				
	RA5	0.807	0.651				
	RA6	0.769	0.591				
Complexity				0.749	0.839	0.793	0.569
	CPLX1	0.620	0.385				
	CPLX2	0.848	0.720				
	CPLX3	0.782	0.611				
	CPLX4	0.749	0.560				
Compatibility				0.810	0.874	0.835	0.637
	CMPA1	0.892	0.796				
	CMPA2	0.786	0.617				
	CMPA3	0.812	0.659				
	CMPA4	0.690	0.477				
Top Management Support				0.872	0.922	0.876	0.797
	TMS1	0.848	0.719				
	TMS2	0.924	0.853				
	TMS3	0.905	0.819				
Organizational Readiness				0.867	0.902	0.913	0.651
	OR1	0.880	0.775				
	OR2	0.701	0.491				
	OR3	0.910	0.829				
	OR4	0.725	0.526				
	OR5	0.796	0.634				
Competitive Pressure				0.765	0.862	0.792	0.677
	CP1	0.854	0.730				
	CP2	0.765	0.585				
	CP3	0.846	0.716				
Customer Acceptance				0.883	0.928	0.883	0.811
	CUS1	0.896	0.803				
	CUS2	0.870	0.756				
	CUS3	0.935	0.875				
Regulatory Support				0.819	0.892	0.829	0.733
	RS1	0.847	0.717				
	RS2	0.869	0.755				
	RS3	0.852	0.726				
Perceived Usefulness				0.858	0.904	0.868	0.702

Construct	Item	Factor Loading	Indicator Reliability	Cronbach's Alpha	Composite Reliability	Rho- α	AVE
	PU1	0.889	0.791				
	PU2	0.886	0.784				
	PU3	0.785	0.617				
	PU4	0.785	0.617				
Perceived Ease of Use				0.829	0.898	0.840	0.746
	PEOU1	0.911	0.829				
	PEOU2	0.876	0.767				
	PEOU3	0.801	0.643				
Intention to Adopt				0.938	0.960	0.942	0.890
	ItA1	0.941	0.888				
	ItA2	0.965	0.933				
	ItA3	0.924	0.849				

TABLE 6
Fornell-Larcker Criterion

The table reports the Fornell-Larcker criterion as one metric to evaluate discriminant validity. This metric measures the extent to which a construct is empirically distinct from other constructs in the structural model. Each construct's AVE (squared variance within) should be compared to the squared inter-construct correlation (as a measure of shared variance between constructs) of that same construct and all other reflectively measured constructs in the structural model. The shared variance between all model constructs should not be larger than their AVEs (cf. Fornell & Larcker, 1981).

	RA	CPLX	CMPA	TMS	OR	CUS	RS	CP	PEOU	PU	ItA
RA	0.820										
CPLX	-0.290	0.754									
CMPA	0.630	-0.495	0.798								
TMS	0.484	-0.447	0.594	0.893							
OR	0.321	-0.424	0.486	0.542	0.807						
CUS	0.610	-0.387	0.581	0.623	0.431	0.901					
RS	0.220	-0.161	0.353	0.321	0.309	0.281	0.856				
CP	0.500	-0.388	0.605	0.722	0.415	0.607	0.307	0.823			
PEOU	0.413	-0.396	0.453	0.551	0.450	0.679	0.321	0.559	0.864		
PU	0.755	-0.350	0.604	0.675	0.265	0.703	0.230	0.673	0.546	0.838	
ItA	0.701	-0.378	0.670	0.753	0.462	0.662	0.308	0.755	0.579	0.800	0.943

TABLE 7
Heterotrait-Monotrait Ratios.

The table presents the heterotrait-monotrait (HTMT) ratio of correlations also to evaluate discriminant validity. The HTMT is defined as the mean value of the indicator correlations across constructs (i.e., the heterotrait–heteromethod correlations) relative to the (geometric) mean of the average correlations for the indicators measuring the same construct (i.e., the monotrait–heteromethod correlations). Henseler et al. (2015) propose a threshold value 0.90 for structural models with conceptually very similar constructs. However, a lower threshold value is suggested when constructs are conceptually more distinct, such as 0.85.

	RA	CPLX	CMPA	TMS	OR	CUS	RS	CP	PEOU	PU	ItA
RA											
CPLX	0.326										
CMPA	0.728	0.572									
TMS	0.541	0.521	0.687								
OR	0.345	0.492	0.534	0.586							
CUS	0.679	0.433	0.675	0.707	0.461						
RS	0.249	0.240	0.439	0.378	0.340	0.325					
CP	0.569	0.486	0.752	0.862	0.459	0.714	0.383				
PEOU	0.469	0.489	0.537	0.639	0.487	0.794	0.340	0.678			
PU	0.847	0.391	0.696	0.779	0.289	0.821	0.271	0.804	0.656		
ItA	0.749	0.414	0.752	0.832	0.466	0.725	0.347	0.881	0.650	0.878	

TABLE 8
Variance Inflation Factor Values.

This table shows the variance inflation factor (VIF) values to assess indicator collinearity. When VIF values are higher, the level of collinearity is greater. VIF values of 5 or above indicate collinearity problems. However, collinearity issues can also occur at lower VIF values of 3 (cf. Hair et al., 2022).

Predictor Constructs	Perceived Ease of Use	Perceived Usefulness	Intention to Adopt
Relative Advantage	1.984	1.982	
Complexity	1.461	1.485	
Compatibility	2.508	2.528	
Top Management Support	2.716	2.718	
Organizational Readiness	1.598	1.629	
Competitive Pressure	2.442	2.512	
Customer Acceptance	2.202	2.738	
Regulatory Support	1.201	1.222	
Perceived Ease of Use		2.139	1.425
Perceived Usefulness			1.425

TABLE 9**Bootstrapping Results and Hypothesis Validation with Bias Correction.**

This table reports the significance and relevance of each hypothesized path coefficient, including the hypothesized path, sign, path coefficient β , t -statistics, 90% confidence intervals (CI), and hypothesis validation. The significance assessment builds on bootstrapping standard errors to calculate t -statistics of path coefficients and confidence intervals. Regarding relevance, path coefficients are usually between -1 and +1, with coefficients closer to +1 (-1) representing strong positive (negative) relationships. For example, a path coefficient of 0.505 indicates that when the predictor construct increases by one standard deviation unit, the endogenous construct will increase by 0.505 standard deviation units (cf. Hair et al., 2022).

Hypothesized Path	Sign	Path Coefficient β	t -statistic	90% CI	Hypothesis Validation
<i>H1a</i> : Relative Advantage → Perceived Usefulness	+	0.449	5.570	[0.313;0.580]	Supported (p -value < 0.001)
<i>H1b</i> : Relative Advantage → Perceived Ease of Use	+	-0.031	0.320	[-0.180;0.140]	Not Supported (p -value = 0.749)
<i>H2a</i> : Complexity → Perceived Usefulness	-	-0.018	0.185	[-0.129;0.105]	Not Supported (p -value = 0.853)
<i>H2b</i> : Complexity → Perceived Ease of Use	-	-0.106	1.075	[-0.254;0.072]	Not Supported (p -value = 0.282)
<i>H3a</i> : Compatibility → Perceived Usefulness	+	0.018	0.195	[-0.129;0.168]	Not Supported (p -value = 0.845)
<i>H3b</i> : Compatibility → Perceived Ease of Use	+	-0.095	0.773	[-0.307;0.098]	Not Supported (p -value = 0.439)
<i>H4a</i> : Top Management Support → Perceived Usefulness	+	0.297	3.123	[0.155;0.466]	Supported (p -value = 0.002)
<i>H4b</i> : Top Management Support → Perceived Ease of Use	+	0.035	0.240	[-0.202;0.274]	Not Supported (p -value = 0.811)
<i>H5a</i> : Organizational Readiness → Perceived Usefulness	+	-0.228	3.526	[-0.343; -0.129]	Not Supported (p -value = 0.001)
<i>H5b</i> : Organizational Readiness → Perceived Ease of Use	+	0.121	1.254	[-0.038;0.279]	Not Supported (p -value = 0.210)
<i>H6a</i> : Competitive Pressure → Perceived Usefulness	+	0.169	2.007	[0.027;0.304]	Supported (p -value = 0.045)
<i>H6b</i> : Competitive Pressure → Perceived Ease of Use	+	0.181	1.394	[-0.047;0.384]	Not Supported (p -value = 0.163)
<i>H7a</i> : Customer Acceptance → Perceived Usefulness	+	0.178	2.054	[0.038;0.325]	Supported (p -value = 0.040)
<i>H7b</i> : Customer Acceptance → Perceived Ease of Use	+	0.500	4.110	[0.310;0.702]	Supported (p -value < 0.001)
<i>H8a</i> : Regulatory Support → Perceived Usefulness	+	-0.030	0.591	[-0.112;0.055]	Not Supported (p -value = 0.554)
<i>H8b</i> : Regulatory Support → Perceived Ease of Use	+	0.100	1.203	[-0.048;0.224]	Not Supported (p -value = 0.229)
<i>H9</i> : Perceived Usefulness → Intention to Adopt	+	0.690	11.664	[0.579;0.775]	Supported (p -value < 0.001)
<i>H10</i> : Perceived Ease of Use → Perceived Usefulness	+	0.081	0.919	[-0.064;0.227]	Not Supported (p -value = 0.358)
<i>H11</i> : Perceived Ease of Use → Intention to Adopt	+	0.202	2.501	[0.070;0.337]	Supported (p -value = 0.012)

TABLE 10**Bootstrapping Results of the Total Effects with Bias Correction.**

This table reports the significance and relevance of each hypothesized path coefficient, including the hypothesized path, sign, path coefficient β , t -statistics, 90% confidence intervals (CI), and hypothesis validation for the total effects. The size of a path coefficient should be assessed within the research context. Therefore, when analyzing the results from a structural model, the interpretation of the total effects, defined as the sum of the direct effect (if any) and all indirect effects linking one construct to another in the model, is important. Assessing the total effects, including all their indirect effects, offers a more comprehensive analysis of the structural model relationships (cf. Nitzl et al., 2016).

Hypothesized Path	Sign	Path Coefficient β	t -statistics	90% CI	Hypothesis Validation
Relative Advantage → Perceived Usefulness	+	0.447	5.558	[0.312; 0.578]	Supported (p -value < 0.001)
Relative Advantage → Perceived Ease of Use	+	-0.031	0.320	[-0.180; 0.140]	Not Supported (p -value = 0.749)
Relative Advantage → Intention to Adopt	+	0.302	4.662	[0.198; 0.408]	Supported (p -value < 0.001)
Complexity → Perceived Usefulness	-	-0.022	0.307	[-0.138; 0.095]	Not Supported (p -value = 0.759)
Complexity → Perceived Ease of Use	-	-0.106	1.075	[-0.254; 0.072]	Not Supported (p -value = 0.282)
Complexity → Intention to Adopt	-	-0.036	0.673	[-0.124; 0.054]	Not Supported (p -value = 0.501)
Compatibility → Perceived Usefulness	+	0.010	0.114	[-0.138; 0.150]	Not Supported (p -value = 0.909)
Compatibility → Perceived Ease of Use	+	-0.095	0.773	[-0.307; 0.098]	Not Supported (p -value = 0.439)
Compatibility → Intention to Adopt	+	-0.012	0.192	[-0.121; 0.088]	Not Supported (p -value = 0.848)
Top Management Support → Perceived Usefulness	+	0.299	3.085	[0.150; 0.469]	Supported (p -value = 0.002)
Top Management Support → Perceived Ease of Use	+	0.035	0.240	[-0.202; 0.274]	Not Supported (p -value = 0.811)
Top Management Support → Intention to Adopt	+	0.213	2.540	[0.076; 0.352]	Supported (p -value = 0.011)
Organizational Readiness → Perceived Usefulness	+	-0.218	3.308	[-0.335; -0.116]	Not Supported (p -value = 0.001)
Organizational Readiness → Perceived Ease of Use	+	0.121	1.254	[-0.038; 0.279]	Not Supported (p -value = 0.210)
Organizational Readiness → Intention to Adopt	+	-0.126	2.455	[-0.213; -0.046]	Not Supported (p -value = 0.014)
Competitive Pressure → Perceived Usefulness	+	0.183	2.178	[0.043; 0.321]	Supported (p -value = 0.029)
Competitive Pressure → Perceived Ease of Use	+	0.181	1.394	[-0.047; 0.384]	Not Supported (p -value = 0.163)
Competitive Pressure → Intention to Adopt	+	0.163	2.329	[0.046; 0.276]	Supported (p -value = 0.020)
Customer Acceptance → Perceived Usefulness	+	0.219	2.911	[0.106; 0.355]	Supported (p -value = 0.004)
Customer Acceptance → Perceived Ease of Use	+	0.500	4.110	[0.310; 0.702]	Supported (p -value < 0.001)
Customer Acceptance → Intention to Adopt	+	0.252	4.421	[0.172; 0.361]	Supported (p -value < 0.001)
Regulatory Support → Perceived Usefulness	+	-0.022	0.448	[-0.100; 0.062]	Not Supported (p -value = 0.654)
Regulatory Support → Perceived Ease of Use	+	0.100	1.203	[-0.048; 0.224]	Not Supported (p -value = 0.229)
Regulatory Support → Intention to Adopt	+	0.005	0.125	[-0.061; 0.073]	Not Supported (p -value = 0.901)
Perceived Ease of Use → Perceived Usefulness	+	0.081	0.919	[-0.064; 0.227]	Not Supported (p -value = 0.358)
Perceived Ease of Use → Intention to Adopt	+	0.258	2.755	[0.111; 0.421]	Supported (p -value = 0.006)
Perceived Usefulness → Intention to Adopt	+	0.690	11.664	[0.579; 0.775]	Supported (p -value < 0.001)

TABLE 11**Coefficient of Determination Values for the Structural Model.**

The table presents the coefficient of determination R^2 and the adjusted coefficient of determination $R^2_{adjusted}$ for all endogenous constructs. These values represent the variance explained in each of the endogenous constructs and is a measure of the model's explanatory power (Shmueli & Koppius, 2011), also referred to as in-sample predictive power (Rigdon, 2012). Benchmarks for classifying the explanatory power of these models often use 0.75, 0.50, and 0.25 as indicators of substantial, moderate, and weak effects, respectively (Hair et al., 2011).

Endogenous Variable	R^2	$R^2_{adjusted}$
Intention to Adopt	0.668	0.662
Perceived Usefulness	0.770	0.749
Perceived Ease of Use	0.533	0.494

TABLE 12**Effect Sizes.**

This table assesses the effect size metric f^2 , which determines the impact of excluding a specific predecessor construct on the R^2 value of an endogenous construct. Herein, an f^2 value of 0.02 indicates a weak effect, 0.15 indicates a moderate effect, and 0.35 indicates a large effect (Cohen, 1992).

Predecessor Constructs	Perceived Ease of Use	Perceived Usefulness	Intention to Adopt
Relative Advantage	0.001	0.443	
Complexity	0.016	0.001	
Compatibility	0.008	0.001	
Top Management Support	0.001	0.141	
Organizational Readiness	0.020	0.139	
Competitive Pressure	0.029	0.049	
Customer Acceptance	0.243	0.051	
Regulatory Support	0.018	0.003	
Perceived Ease of Use		0.013	0.086
Perceived Usefulness			1.006

TABLE 13**Predictive Relevance of the Structural Model.**

This table reports the predictive relevance of the structural model. We use the Q^2 index through blindfolding to assess the model's out-of-sample predictive power. Q^2 values exceeding 0.02, 0.15, and 0.35 indicate the model's low, moderate, and high predictive capabilities, respectively (Ringle et al., 2012). Interpreting the predictive error metrics RMSE and MAE involves benchmarking them against a naïve linear regression model (LM). The predictive power is high when all indicators demonstrate lower errors than the naïve LM, moderate predictive power when the majority do, and low when only a few indicators do. The absence of lower errors across all indicators suggests a lack of predictive power (Shmueli et al., 2019). To assess the predictive power, we run the $PLS_{predict}$ function with ten folds and ten repetitions with the fixed seed option in SmartPLS 4.0 (Ringle et al., 2024).

Item	Q^2	PLS-SEM RMSE	PLS-SEM MAE	LM RMSE	LM MAE
ItA1	0.649	0.706	0.550	0.819	0.628
ItA2	0.649	0.702	0.516	0.801	0.643
ItA3	0.496	0.838	0.652	0.966	0.732
PU1	0.577	0.779	0.625	0.917	0.712
PU2	0.563	0.728	0.541	0.832	0.662
PU3	0.449	0.861	0.649	0.965	0.784
PU4	0.403	0.848	0.633	1.053	0.819
PEOU1	0.369	0.812	0.606	0.911	0.704
PEOU2	0.276	0.813	0.647	0.913	0.703
PEOU3	0.252	0.912	0.731	1.140	0.896

TABLE 14**Cross-Validated Predictive Ability Test.**

This table shows the results of the cross-validated predictive ability test (CVPAT), which evaluates the PLS-SEM model's predictive performance against the indicator average (IA) loss values. PLS-SEM's average loss should be lower than the average loss of the benchmarks, which is expressed by a negative difference in the average loss values. CVPAT tests whether PLS-SEM's average loss is significantly lower than the average loss of the IA. Therefore, the difference of the average loss values should be significantly below zero to substantiate better predictive capabilities of the model compared to the IA (cf. Hair et al., 2022).

Latent Construct	PLS Loss	IA Loss	Average Loss Difference	<i>t</i> -statistic	<i>p</i> -value
Intention to Adopt	0.565	1.407	-0.842	7.105	<0.001
Perceived Usefulness	0.649	1.298	-0.649	6.021	<0.001
Perceived Ease of Use	0.718	1.024	-0.306	3.189	0.002
Overall	0.644	1.248	-0.604	7.001	<0.001

TABLE 15**Model Selection Criteria for Unobserved Heterogeneity.**

This table compares different model selection criteria for assessing unobserved heterogeneity using the finite mixture partial least squares (FIMIX-PLS) method. Due to our sample size, the analysis is limited to two segments (cf. Sarstedt et al., 2020). The presence of significant unobserved heterogeneity in the structural model is indicated when all model selection criteria uniformly show lower values for the two-segment solution.

Model Selection Criteria		1 Segment	2 Segments
AIC	Akaike's Information Criterion	592.822	557.085
AIC ₃	Modified Akaike's Information Criterion with Factor 3	614.822	602.085
AIC ₄	Modified Akaike's Information Criterion with Factor 4	636.822	647.085
BIC	Bayesian Information Criterion	651.417	676.940
CAIC	Consistent Akaike's Information Criterion	673.417	721.940
HQ	Hannan-Quinn Criterion	616.571	605.663
MDL ₅	Minimum Description Length with Factor 5	1,061.800	1,516.359
LnL	Log-Likelihood	-274.411	-233.543
EN	Normed Entropy Statistic	0.000	0.706
NFI	Non-Fuzzy Index	0.000	0.746
NEC	Normalized Entropy Criterion	0.000	31.214

TABLE 16**Outer Weights of the Latent Constructs.**

The table presents the outer weights for each item, with higher values signifying a greater impact on the respective latent construct.

Latent Construct	Item 1	Item 2	Item 3	Item 4	Item 5	Item 6
Relative Advantage	0.174	0.219	0.228	0.213	0.215	0.169
Complexity	0.332	0.472	0.254	0.261		
Compatibility	0.362	0.327	0.342	0.207		
Top Management Support	0.349	0.382	0.389			
Organizational Readiness	0.317	0.169	0.306	0.113	0.303	
Competitive Pressure	0.480	0.310	0.417			
Customer Acceptance	0.376	0.370	0.365			
Regulatory Support	0.434	0.406	0.329			
Perceived Usefulness	0.325	0.325	0.282	0.257		
Perceived Ease of Use	0.430	0.361	0.365			
Intention to Adopt	0.379	0.367	0.314			

TABLE 17
Intention to Adopt Survey Item Responses.

This table shows the distribution of responses regarding the three items for intention to adopt:

- ItA1: “Overall, our bank thinks that using humanoid service robots is advantageous,”
- ItA2: “Overall, our bank is in favor of using humanoid service robots,” and
- ItA3: “Overall, our bank intends to use humanoid service robots.”

Item	1 – Strongly Disagree	2	3	4	5 – Strongly Agree
ItA1	0	22	35	23	10
ItA2	23	29	31	16	7
ItA3	38	26	27	10	5

Appendix

APPENDIX 1

[Table A4 around here]

A significant quadratic effect between compatibility and perceived ease of use (p -value < 0.001) with a negative coefficient ($\beta = -0.344$) indicates an inverted U-shaped relationship. This finding suggests an optimal level of compatibility beyond which the perceived ease of use is smaller (Hair et al., 2023). Moreover, the positive coefficient ($\beta = 0.154$) in the quadratic effect between organizational readiness and perceived ease of use (p -value $= 0.026$) signifies an accelerating positive impact of organizational readiness on perceived ease of use. This finding indicates that, as organizational readiness increases, the impact on perceived ease of use grows exponentially, underscoring the role of organizational readiness in enhancing technology adoption ease. Conversely, while the customer acceptance construct shows a significant linear relationship with perceived usefulness, this relationship's significance fades when quadratic effects are considered (p -value $= 0.035$) with a negative coefficient ($\beta = -0.141$). This shift suggests that increasing customer focus enhances perceived usefulness up to a point, after which the perceived benefits diminish slightly. Interestingly, two significant quadratic effects (compatibility \rightarrow perceived ease of use; organizational readiness \rightarrow perceived ease of use) emerge in hypotheses not supported in the linear analysis, with their linear path coefficients remaining insignificant. Since significance does not imply relevance, the next step is to assess the strength of the nonlinear effect using the effect size f^2 (Hair et al., 2023). We observe a large effect size for the quadratic effect of compatibility on perceived ease of use ($f^2 = 0.204$). The effect sizes for organizational readiness on perceived ease of use ($f^2 = 0.054$) and customer acceptance on perceived usefulness ($f^2 = 0.069$) are also large, according to Becker et al. (2023) and Kenny (2018). Subsequently, Basco et al. (2022) recommend comparing the more complex nonlinear model with the more parsimonious linear model using the Bayesian information criterion. Including quadratic effects leads to BIC values of -96.931 for intention to adopt, -27.651 for perceived ease of use, and -86.946 for perceived usefulness. The BIC values for the linear model are -104.028 for intention to adopt, -39.640 for perceived ease of use, and -110.374 for perceived usefulness. Consequently, the analysis suggests the linear model as the preferred model (Sharma et al., 2019). Hair et al. (2023) emphasize the importance of careful theoretical reasoning when establishing nonlinear effects.

TABLE A1
Measurement Items in German.

As we conducted the study in Austria, Germany, and Switzerland, we translated the survey items into German without altering their structure or content (cf. Table 2).

Item	German translation
RA1	Unsere Bank geht davon aus, dass der Einsatz humanoider Serviceroboter unsere Betriebskosten senken wird.
RA2	Unsere Bank geht davon aus, dass der Einsatz humanoider Serviceroboter bestimmte Betriebsprozesse verbessern wird.
RA3	Unsere Bank geht davon aus, dass der Einsatz humanoider Serviceroboter uns hilft, neue Kunden zu erreichen.
RA4	Unsere Bank geht davon aus, dass der Einsatz humanoider Serviceroboter die routinemäßige Arbeitsbelastung unserer Mitarbeitenden verringern wird.
RA5	Unsere Bank geht davon aus, dass der Einsatz humanoider Serviceroboter den Kundenservice durch mehrsprachige Kommunikationsmöglichkeiten verbessern wird.
RA6	Die nahtlose Integration von KI in humanoide Serviceroboter bietet neue Möglichkeiten für einen innovativen Kundenservice.
CPLX1	Die Integration von humanoiden Servicerobotern in unsere derzeitigen Technologien ist eine schwierige Aufgabe für unsere Bank.
CPLX2	Der Einsatz von humanoiden Servicerobotern ist für unsere Geschäftsabläufe zu komplex.
CPLX3	Das Erlernen der für den Einsatz humanoider Serviceroboter erforderlichen Fähigkeiten ist für unsere Mitarbeitenden zu komplex.
CPLX4	Die Entwicklung von Anwendungen für humanoide Serviceroboter ist für unsere Bank zu komplex.
CMPA1	Humanoide Serviceroboter sind mit den bestehenden Geschäftsabläufen in unserer Bank kompatibel.
CMPA2	Humanoide Serviceroboter sind mit den bestehenden Technologien in unserer Bank kompatibel.
CMPA3	Humanoide Serviceroboter sind mit der Unternehmenskultur und dem Wertesystem unserer Bank vereinbar.
CMPA4	Humanoide Serviceroboter sind mit den Anforderungen an Datensicherheit und Datenschutz in unserer Bank vereinbar.
TMS1	Unsere Unternehmensleitung betrachtet die Einführung von humanoiden Servicerobotern wahrscheinlich als strategisch wichtig.
TMS2	Unsere Unternehmensleitung ist bereit, die mit der Einführung von humanoiden Servicerobotern verbundenen Risiken einzugehen.
TMS3	Unsere Unternehmensleitung ist wahrscheinlich bereit, finanzielle Mittel für die Einführung von humanoiden Servicerobotern bereitzustellen.
OR1	Unsere Bank verfügt über die notwendigen technologischen Ressourcen, um humanoide Serviceroboter einzusetzen.
OR2	Unsere Bank verfügt über die notwendigen finanziellen Mittel, um humanoide Serviceroboter einzuführen.
OR3	Unsere Bank verfügt über die notwendigen personellen Ressourcen, um humanoider Serviceroboter einzuführen.
OR4	Unsere Bank verfügt über ausreichende KI-Kenntnisse.
OR5	Unsere Bank kann mit den Bedenken der Mitarbeitenden hinsichtlich der Einführung humanoider Serviceroboter umgehen.
CP1	Unsere Bank ist sich der Wettbewerbsvorteile bewusst, die humanoide Serviceroboter im Bankensektor bieten.
CP2	Unsere Bank ist sich bewusst, dass humanoide Serviceroboter von unseren Konkurrenten eingesetzt werden.
CP3	Unsere Bank nimmt Wettbewerbsdruck wahr, humanoide Serviceroboter einzusetzen.
CUS1	Unsere Bank geht davon aus, dass unsere Kunden bereit sind, mit humanoiden Servicerobotern zu interagieren.
CUS2	Unsere Bank erwartet, dass unsere Kunden die Interaktion mit humanoiden Servicerobotern ansprechend finden.
CUS3	Unsere Bank erwartet, dass unsere Kunden die Interaktion mit humanoiden Servicerobotern akzeptieren.
RS1	Es gibt einen rechtlichen Schutz für den Einsatz humanoider Serviceroboter.
RS2	Die Gesetze und Vorschriften für den Einsatz von humanoiden Servicerobotern sind klar und deutlich definiert.
RS3	Es gibt eine unterstützende regulatorische Umgebung für die Einführung von humanoiden Servicerobotern in der Bankenbranche.
PU1	Unsere Bank ist der Meinung, dass der Einsatz von humanoiden Servicerobotern die Effizienz unserer Bank steigert.
PU2	Unsere Bank ist der Meinung, dass der Einsatz von humanoiden Servicerobotern die Produktivität in unserer Bank erhöht.
PU3	Unsere Bank ist der Meinung, dass der Einsatz von humanoiden Servicerobotern dazu beitragen würde, das Kundenerlebnis zu verbessern.
PU4	Unsere Bank ist der Meinung, dass der Einsatz von humanoiden Servicerobotern das Image unserer Bank verbessern kann.
PEOU1	Unsere Bank ist der Meinung, dass der Prozess zum Einsatz humanoider Serviceroboter leicht verständlich ist.
PEOU2	Unsere Bank ist der Meinung, dass der Einsatz humanoider Serviceroboter einfach ist.
PEOU3	Unsere Bank ist der Meinung, dass alle Mitarbeitenden den Einsatz von humanoiden Servicerobotern schnell erlernen können.
ItA1	Insgesamt ist unsere Bank der Meinung, dass der Einsatz humanoider Serviceroboter von Vorteil ist.
ItA2	Insgesamt befürwortet unsere Bank den Einsatz humanoider Serviceroboter.
ItA3	Insgesamt beabsichtigt unsere Bank, humanoide Serviceroboter einzusetzen
ADOP1	Setzt ihre Bank aktuell humanoide Serviceroboter ein?
ADOP2	Wie viele humanoide Serviceroboter setzt ihre Bank aktuell ein?

TABLE A2
Bootstrapped Heterotrait-Monotrait Ratios with Bias Correction.

The table reports the bootstrapped Heterotrait-Monotrait ratios with bias corrections for each latent construct combination with 10,000 bootstrap samples. It displays the original ratio estimates (column: Original sample), bootstrapped mean ratio estimates (column: Sample mean), bias correction, and the 95% confidence interval (columns: 2.5% CI and 97.5% CI, respectively) as produced by the percentile method. The 97.5% CI should not include 1 to ensure discriminant validity.

Heterotrait-Monotrait Ratios	Original sample	Sample mean	Bias	2.5% CI	97.5% CI
Relative Advantage ↔ Complexity	0.326	0.369	0.043	0.189	0.437
Relative Advantage ↔ Combability	0.728	0.728	-0.001	0.590	0.839
Relative Advantage ↔ Top Management Support	0.541	0.540	-0.001	0.351	0.688
Relative Advantage ↔ Organizational Readiness	0.345	0.361	0.016	0.194	0.529
Relative Advantage ↔ Competitive Pressure	0.569	0.574	0.005	0.389	0.721
Relative Advantage ↔ Customer Acceptance	0.679	0.679	0.000	0.531	0.802
Relative Advantage ↔ Regulatory Support	0.249	0.272	0.023	0.103	0.438
Relative Advantage ↔ Perceived Usefulness	0.847	0.848	0.001	0.693	0.953
Relative Advantage ↔ Perceived Ease of Use	0.469	0.471	0.002	0.276	0.643
Relative Advantage ↔ Intention to Adopt	0.749	0.750	0.001	0.631	0.839
Complexity ↔ Compatibility	0.572	0.585	0.013	0.371	0.750
Complexity ↔ Top Management Support	0.521	0.524	0.003	0.314	0.687
Complexity ↔ Organizational Readiness	0.492	0.510	0.017	0.291	0.677
Complexity ↔ Competitive Pressure	0.486	0.495	0.009	0.287	0.671
Complexity ↔ Customer Acceptance	0.433	0.440	0.007	0.231	0.608
Complexity ↔ Regulatory Support	0.240	0.270	0.030	0.098	0.432
Complexity ↔ Perceived Usefulness	0.391	0.412	0.022	0.215	0.576
Complexity ↔ Perceived Ease of Use	0.489	0.495	0.006	0.254	0.698
Complexity ↔ Intention to Adopt	0.414	0.417	0.004	0.208	0.600
Combability ↔ Top Management Support	0.687	0.686	-0.002	0.514	0.819
Combability ↔ Organizational Readiness	0.534	0.541	0.007	0.363	0.699
Combability ↔ Competitive Pressure	0.752	0.752	0.000	0.560	0.903
Combability ↔ Customer Acceptance	0.675	0.676	0.001	0.481	0.837
Combability ↔ Regulatory Support	0.439	0.450	0.011	0.228	0.653
Combability ↔ Perceived Usefulness	0.696	0.699	0.003	0.516	0.848
Combability ↔ Perceived Ease of Use	0.537	0.541	0.004	0.322	0.741
Combability ↔ Intention to Adopt	0.752	0.751	-0.001	0.608	0.862
Top Management Support ↔ Organizational Readiness	0.586	0.586	-0.000	0.405	0.736
Top Management Support ↔ Competitive Pressure	0.862	0.862	0.000	0.738	0.957
Top Management Support ↔ Customer Acceptance	0.707	0.707	-0.000	0.523	0.848
Top Management Support ↔ Regulatory Support	0.378	0.382	0.005	0.192	0.574
Top Management Support ↔ Perceived Usefulness	0.779	0.779	0.001	0.636	0.880
Top Management Support ↔ Perceived Ease of Use	0.639	0.640	0.001	0.439	0.793
Top Management Support ↔ Intention to Adopt	0.832	0.832	0.000	0.697	0.922
Organizational Readiness ↔ Competitive Pressure	0.459	0.469	0.010	0.278	0.634
Organizational Readiness ↔ Customer Acceptance	0.461	0.468	0.007	0.259	0.647
Organizational Readiness ↔ Regulatory Support	0.340	0.356	0.016	0.169	0.531
Organizational Readiness ↔ Perceived Usefulness	0.289	0.313	0.024	0.140	0.453

Heterotrait-Monotrait Ratios	Original sample	Sample mean	Bias	2.5% CI	97.5% CI
Organizational Readiness ↔ Perceived Ease of Use	0.487	0.494	0.007	0.303	0.653
Organizational Readiness ↔ Intention to Adopt	0.466	0.470	0.004	0.286	0.630
Competitive Pressure ↔ Customer Acceptance	0.714	0.713	-0.001	0.527	0.854
Competitive Pressure ↔ Regulatory Support	0.383	0.394	0.011	0.203	0.576
Competitive Pressure ↔ Perceived Usefulness	0.804	0.807	0.003	0.686	0.901
Competitive Pressure ↔ Perceived Ease of Use	0.678	0.679	0.000	0.446	0.847
Competitive Pressure ↔ Intention to Adopt	0.881	0.882	0.002	0.772	0.966
Customer Acceptance ↔ Regulatory Support	0.325	0.330	0.004	0.135	0.516
Customer Acceptance ↔ Perceived Usefulness	0.821	0.822	0.001	0.683	0.918
Customer Acceptance ↔ Perceived Ease of Use	0.794	0.793	-0.001	0.667	0.891
Customer Acceptance ↔ Intention to Adopt	0.725	0.726	0.001	0.507	0.868
Regulatory Support ↔ Perceived Usefulness	0.271	0.286	0.015	0.109	0.466
Regulatory Support ↔ Perceived Ease of Use	0.378	0.384	0.006	0.175	0.590
Regulatory Support ↔ Intention to Adopt	0.347	0.352	0.005	0.159	0.543
Perceived Usefulness ↔ Perceived Ease of Use	0.656	0.656	-0.001	0.454	0.812
Perceived Usefulness ↔ Intention to Adopt	0.878	0.879	0.001	0.807	0.933
Perceived Ease of Use ↔ Intention to Adopt	0.650	0.649	-0.000	0.462	0.800

TABLE A3
Quadratic Effects Bootstrapping Results.

The table reports the results of the structural model bootstrapping, including a quadratic term for every hypothesized path. Using 10,000 bootstrap samples in SmartPLS 4.0, the table displays the original path estimates (column: Original sample), bootstrapped mean path estimates (column: Sample mean), standard deviation, the *t*-statistics, and the *p*-value. The computation of results uses the two-stage approach. This approach uses the latent variable scores of the latent predictor variable from the main effects model (without the quadratic effect term). These latent variable scores are saved and used to calculate the squared indicator for the second stage analysis involving the quadratic effect term and the predictor variable (cf. Ringle et al., 2024).

Hypothesized Path	Original sample	Sample mean	Standard deviation	<i>t</i> -statistic	<i>p</i> -value
Relative Advantage → Perceived Usefulness	0.414	0.410	0.083	5.010	<0.001
Relative Advantage → Perceived Ease of Use	0.014	0.011	0.109	0.127	0.899
Complexity → Perceived Usefulness	-0.013	-0.013	0.079	0.160	0.873
Complexity → Perceived Ease of Use	-0.162	-0.170	0.088	1.853	0.064
Compatibility → Perceived Usefulness	0.016	0.008	0.094	0.171	0.864
Compatibility → Perceived Ease of Use	0.008	0.030	0.128	0.064	0.949
Top Management Support → Perceived Usefulness	0.303	0.298	0.103	2.939	0.003
Top Management Support → Perceived Ease of Use	-0.066	-0.090	0.139	0.474	0.635
Organizational Readiness → Perceived Usefulness	-0.196	-0.183	0.070	2.817	0.005
Organizational Readiness → Perceived Ease of Use	0.032	0.047	0.099	0.320	0.749
Competitive Pressure → Perceived Usefulness	0.193	0.191	0.099	1.952	0.051
Competitive Pressure → Perceived Ease of Use	0.186	0.207	0.136	1.370	0.171
Customer Acceptance → Perceived Usefulness	0.152	0.161	0.094	1.606	0.108
Customer Acceptance → Perceived Ease of Use	0.479	0.432	0.123	3.894	<0.001
Regulatory Support → Perceived Usefulness	-0.043	-0.038	0.058	0.744	0.457
Regulatory Support → Perceived Ease of Use	0.123	0.125	0.089	1.385	0.166
Perceived Usefulness → Intention to Adopt	0.705	0.713	0.065	10.887	<0.001
Perceived Ease of Use → Perceived Usefulness	0.066	0.062	0.104	0.628	0.530
Perceived Ease of Use → Intention to Adopt	0.224	0.224	0.081	2.762	0.006
<i>QE</i> Relative Advantage → Perceived Usefulness	-0.025	-0.038	0.064	0.394	0.693
<i>QE</i> Relative Advantage → Perceived Ease of Use	0.080	0.070	0.080	1.011	0.312
<i>QE</i> Complexity → Perceived Usefulness	-0.103	-0.093	0.061	1.678	0.093
<i>QE</i> Complexity → Perceived Ease of Use	0.010	-0.001	0.084	0.114	0.910
<i>QE</i> Compatibility → Perceived Usefulness	0.026	0.012	0.074	0.355	0.723
<i>QE</i> Compatibility → Perceived Ease of Use	-0.344	-0.319	0.097	3.555	<0.001
<i>QE</i> Top Management Support → Perceived Usefulness	0.074	0.070	0.066	1.119	0.263
<i>QE</i> Top Management Support → Perceived Ease of Use	0.011	0.020	0.089	0.119	0.906
<i>QE</i> Organizational Readiness → Perceived Usefulness	-0.032	-0.028	0.053	0.597	0.551
<i>QE</i> Organizational Readiness → Perceived Ease of Use	0.154	0.163	0.069	2.219	0.026
<i>QE</i> Competitive Pressure → Perceived Usefulness	-0.005	0.004	0.056	0.082	0.935
<i>QE</i> Competitive Pressure → Perceived Ease of Use	0.074	0.081	0.077	0.963	0.336
<i>QE</i> Customer Acceptance → Perceived Usefulness	-0.141	-0.121	0.067	2.105	0.035
<i>QE</i> Customer Acceptance → Perceived Ease of Use	-0.010	-0.028	0.081	0.123	0.902
<i>QE</i> Regulatory Support → Perceived Usefulness	0.001	0.007	0.049	0.011	0.991
<i>QE</i> Regulatory Support → Perceived Ease of Use	0.062	0.030	0.098	0.635	0.525
<i>QE</i> Perceived Usefulness → Intention to Adopt	0.077	0.090	0.049	1.588	0.112
<i>QE</i> Perceived Ease of Use → Perceived Usefulness	0.046	0.041	0.066	0.693	0.489
<i>QE</i> Perceived Ease of Use → Intention to Adopt	-0.036	-0.048	0.069	0.521	0.602

TABLE A4
Qualitative Responses on Operations.

The table shows the qualitative responses to the following question: *How do you use humanoid service robots in your bank?*

All responses were provided in German. Consequently, we present both the translated English versions and the original German responses.

Respondent	Comment on Operations
Respondent 1	Service German: Service
Respondent 2	Automation of various business processes of the bank (e.g. operations in core banking system, document processing, ...). NO citizen development. Robotic is integrated in requirements management and we have employed 4 in-house developers for this. NO communication with customers (yet).“ German: Automatisierung von div. Geschäftsprozessen der Bank (zB Operationen in Kernbanksystem, Dokumentverarbeitung, ...). KEIN Citizen Development. Robotic ist im Anforderungsmanagement integriert und wir haben 4 eigene Entwickler dafür beschäftigt. (noch) KEINE Kommunikation mit Kunden.“
Respondent 3	Marketing tool, experimental use in the service sector and at events since 2019 German: Marketinginstrument, experimenteller Einsatz im Servicebereich und auf Veranstaltungen seit 2019
Respondent 4	Chat or clickbot on website and e-banking login page for support on the following topics: e-Banking and mobile banking, cards, customer acquisition. German: Chat- resp. Clickbot auf Website und e-Banking-Loginseite für Support folgender Themen: e-Banking and Mobile Banking, Karten, Kundenakquise
Respondent 5	not at all German: gar nicht

TABLE A5**Qualitative Responses on Humanoid Service Robots in Banks.**

The table presents the qualitative responses to the following question: *Do you have any comments or feedback on humanoid service robots in banks? For example, in terms of improving customer service, increasing process efficiency, or reducing the workload of employees?*

All responses were provided in German. Consequently, we present both the translated English versions and the original German responses.

Respondent	Comments or Feedback on Humanoid Service Robots in Banks
Respondent 1	<p>Robots are not the solution (they are too expensive to repair and break easily). The solution will be bots that are made available on touch screens.</p> <p>German: Roboter sind nicht die Lösung (zu teuer in der Reparatur und gehen auch leicht kaputt). Die Lösung werden Bots sein, die an Touch Screens zur Verfügung gestellt werden.</p>
Respondent 2	<p>Extreme increase in efficiency in the backend and to support employees. No need for customer contact or AI integration yet. Regulatory and technical integration of robots is very complex. Robots should only be built by in-house developers, otherwise rights management, monitoring and stability are very difficult to monitor.</p> <p>German: Extreme Effizienzsteigerung im Backend und zur Unterstützung von Mitarbeitern. Noch kein Bedarf nach Kundenkontakt, bzw. KI Integration. Regulatorisch und technisch ist die Integration von Robotern sehr komplex. Roboter sollten nur von eigenen Entwicklern gebaut werden, ansonsten ist Rechteverwaltung, Überwachung, und Stabilität sehr schwer zu überwachen.</p>
Respondent 3	<p>We have been trialing the use of humanoid robots in various scenarios since 2019. Technical limitations of the robots have meant that their use in stores has only been of very limited benefit. In addition, the technical development of humanoid robots was discontinued by Softbanks in 2021. Alternative scenarios with digital robots (avatars) were therefore prioritized for us.</p> <p>German: Der Einsatz von humanoiden Robotern wurde von uns seit 2019 in verschiedenen Szenarien verprobt. Technische Limitationen der Roboter haben dazu geführt, dass der Einsatz im Filialbereich nur sehr eingeschränkten nutzen gestiftet hat. Darüber hinaus wurde die technische Weiterentwicklung von humanoiden Robotern durch die Firma Softbanks im Jahr 2021 eingestellt. Daher wurden für uns alternative Szenarien mit digitalen Robotern (Avatare) priorisiert.</p>
Respondent 6	<p>We favor avatars instead of humanoid robots. On the 27-inch monitor, the avatar breaks down language barriers and completes simple service processes via case closure, e.g. by displaying a QR code and linking to the Internet branch.</p> <p>German: Wir favorisieren Avatare statt humanoider Roboter. Am 27 Zoll-Monitor löst der Avatar die Sprachbarrieren auf und erledigt einfache Serviceprozesse via Fallabschluss, z. B. durch Anzeige eines QR-Codes und Verlinkung in die Internetfiliale.</p>
Respondent 7	<p>I have narrowly defined the term “humanoid service robot” – analogous to your image in the survey. In our opinion, we are focusing on much more innovative ways of optimizing service and customer management. For example [...] an avatar, is used to guide our customers in the head office, answer simple questions or inform advisors about customer arrivals. In future, chatbots and voicebots will be used in our direct branch service, which will make a significant contribution to the efficiency of the telephone and online channels. We consider service robots such as “Pepper” and the like to be merely a “nice gimmick” in on-site service, which is becoming significantly less important overall.</p> <p>German: Ich habe den Begriff „humanoider Serviceroboter“ – analog zu Ihrem Bild in der Umfrage eng definiert. Wir setzen auf u. E. deutlich innovativere Wege der Optimierung im Service und auch der Kundenleitung. So kommt [...] ein Avatar zum Einsatz, um unsere Kunden in der Zentrale zu leiten, einfache Fragen zu beantworten oder auch Berater über die Kundenankunft zu informieren. Im Service unserer Direktfiliale kommen künftig Chat- und Voicebots zum Einsatz, welche erheblich auf die Effizienz des Telefon- und Onlinekanals einzahlen. Serviceroboter wie „Pepper“ und Co. Halten wir lediglich für eine „nette Spielerei“ im Service vor Ort, welcher aber insgesamt deutlich an Bedeutung verliert.</p>
Respondent 8	<p>Regional credit institutions do not have sufficient budgets and technological resources. The banking associations are therefore required to provide appropriate financial and technological support.</p> <p>German: Regionale Kreditinstitute verfügen über keine ausreichenden Budgets und technologischen Ressourcen. Hierfür sind die Dachverbände angehalten entsprechende finanzielle und technologische Unterstützung bereitzustellen.</p>
Respondent 9	<p>I think there are advantages in terms of process efficiency or reducing the workload of employees through the introduction of humanoid service robots. However, as a regional cooperative bank, the introduction is not in line with our general orientation, which is strongly based on personal contact.</p> <p>German: Ich denke es bestehen Vorteile in der Prozesseffizienz oder der Entlastung von Mitarbeitenden durch die Einführung von humanoiden Servicerobotern. Als regionale Genossenschaftsbank entspricht die Einführung allerdings nicht unserer generellen Ausrichtung, die stark über den persönlichen Kontakt kommt.</p>
Respondent 10	<p>As a cooperative bank, we are solely committed to our customers and members. We are convinced that we need to automate many things. AI is an important topic for us. As a bank, we have been using RPA and other digitalization and automation options for a long time. For example, we have also replaced flesh-and-blood people on site at locations with interactive “service desks”. Here, you are served by flesh-and-blood people from the region - not on site but connected life-size via video stele. We have made the experience and are convinced that people prefer to be served by people than by avatars or humanoid service robots. That may change at some point, but at the moment I don’t believe that this technology will significantly change the banking business.</p> <p>German: Als Genossenschaftsbank sind wir einzig unseren Kunden und Mitgliedern verpflichtet. Wir sind davon überzeugt, dass wir ganz vieles automatisieren müssen. KI ist uns dabei ein wichtiges Thema. Wir haben als Haus bereits lange RPA und andere Möglichkeiten der Digitalisierung und Automatisierung im Einsatz. So haben wir auch an Standorten den Menschen aus Fleisch und Blut vor Ort ersetzt durch interaktive „Service-Stelen“. Hier bedienen Sie Menschen aus Fleisch und Blut aus der Region – halt nicht vor Ort sondern lebensgroß per Video-Stele zugeschaltet. Wir haben die Erfahrung gemacht und sind der Überzeugung, dass Menschen lieber von Menschen als von Avataren oder humanoiden Servicerobotern bedient werden.</p>

Respondent	Comments or Feedback on Humanoid Service Robots in Banks
	Noch – mag sich irgendwann ändern, aktuell glaube ich noch nicht, dass genau diese Technologie das Bankgeschäft maßgeblich verändern wird.
Respondent 11	No improvement
	German: keine Verbesserung