International Journal of E-Business Research
Volume 19 • Issue 1

A Study of Customer Acceptance of Artificial Intelligence Technology

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ABSTRACT

This research aims to investigate the acceptance of artificial intelligence (AI) technology-enabled services by customers during front-line service meetings. The study collected data from 412 Korean individuals through an online survey and utilized hierarchical regression analysis to test the hypotheses. The results of the study show that the clarity of the roles of both the customer and the AI, the customer's motivation to adopt AI-based technology, and the customer's ability to use AI devices increase the likelihood of acceptance of AI devices. However, concerns related to privacy weaken the relationship between role clarity and customer acceptance, while trust in AI technology strengthens the relationship between ability and customer acceptance.

KEYWORDS

Artificial Intelligence, Technology Acceptance, Willingness to Accept the Use of AI Device

INTRODUCTION

AI is a technology that has gained considerable global attention across various domains such as media, academia, and politics (Enholm et al., 2022). Numerous resources, such as reports, articles, books, and webcasts, have been published on the subject of AI and its impact on business strategies (Gibbs et al., 2017). While there have been many reports and books written about AI, academic articles focusing on the impact of AI on customers or end-users are still limited in number (Tegmark, 2017). Many of the current works on AI are focused on technological advancements and do not consider the impact on human or customer acceptance, as well as broader ethical concerns (Huang & Rust, 2018; Juma, 2016). However, international attitudes towards AI vary from positive evaluations of its potential to improve human physical labor and create new business opportunities (Frank et al., 2017) to concerns about its potential to render humans irrelevant in a society fully operated by robots (Leonhard, 2016). As a result, it is crucial to comprehend the benefits of adopting AI-based ESS to increase the likelihood of successful implementation. Nonetheless, there has been limited research into how customers embrace AI-based ESS.

To address the existing research gap, this study aims to examine how and why customers are adopting business-focused AI applications in their service touchpoints. This paper is structured as

DOI: 10.4018/IJEBR.323796
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follows: the next section presents to propose a conceptual framework based on previous reviews, examples, and theories to identify the role of AI in service encounters and to describe customer acceptance of AI in service studies. In addition, this study proposes a process model constituting the main variables that contribute to customer response to technology introduction at the service interface and develops a hypothesis to test the relationship between these variables. Second, this study aims to explain the methodology of the survey process and variable measurement items in order to verify the hypothesis. Third, this study presents validity of variables, multiple fairness issues, relationships between variables, and hypothesis test results for hypothesis verification. Fourth, this study provides the discussion on the research results. Finally, this study presents the contributions and practical implications of the study, the limitations of the study, and the direction of future research. This study is significant in that the framework of this study expanded the existing technology acceptance theory to include AI-related variables such as privacy issues and trust. In addition, this study is meaningful in that it is the first study to explore the role of AI at the front-line service interface and its effect on user acceptance of AI technology-based services from the customer's point of view.

THEORETICAL BACKGROUND AND HYPOTHESIS DEVELOPMENT

Artificial intelligence (AI) is a broad field of computer science that is concerned with creating intelligent machines capable of performing tasks that typically require human intelligence, such as learning, reasoning, problem-solving, perception, and natural language processing (Enholm et al., 2022). AI can be categorized into two main types: narrow or weak AI, which is designed to perform specific tasks, and general or strong AI, which can perform any intellectual task that a human can do. Some of the key techniques used in AI include machine learning, deep learning, natural language processing, computer vision, and robotics. AI has a wide range of applications in various fields, including healthcare, finance, transportation, education, and entertainment, among others. However, AI also raises ethical and societal concerns, such as the potential impact on employment and privacy, and the need for transparent and responsible development and use of AI technologies.

This study specifically focuses on comprehending and theoretically justifying customer acceptance of AI in the service industry. Previous research has examined the precursor to SST (Self-Service Technology) adoption and integrated significant variables into the theoretical framework of the model. Meuter et al. established that the customer adoption of SST relies on customer clarity (whether the customer understands how to use SST), motivation (why customers should use SST), and capabilities (whether customers have the resources and skills to use SST). This core structure is influenced by the nature of the technology itself and customer disparities. Subsequently, a meta-analysis of SST acceptance revealed the intricacy of the variables affecting SST acceptance (Blut et al., 2016). This study proposes that the acceptance of AI in service contexts depends on additional AI-specific variables beyond those traditionally investigated in SST studies. This set of variables comprises privacy concerns, technology and trust in the company, and awareness of the frightening aspects of the technology. The aim is to reduce plagiarism in academic writing.

Core Construct

AI-based technology differs from SST in that it can function independently, regardless of user awareness of AI behavior (Hoffman & Novak, 2017). For instance, Google's initial AI application, its spam filter, detects and blocks 99.9 percent of spam and phishing messages without user intervention (Lardinois, 2017). Recently, Facebook introduced an AI-based suicide prevention tool that proposes support to users expressing suicidal thoughts, including contacting friends or family members, helplines, and providing information on available help resources (Rosen, 2017). The notion of role clarity should extend to customers and AI's roles in the service process. Customers accessing AI support technology must comprehend that both parties contribute to the co-production of services.

Role clarity is vital from two perspectives: (1) establishing accountability sharing in joint services and (2) increasing customer trust in technology through transparency.

To achieve the desired service results, the customer and AI must both understand and perform their respective roles as designed. It is important to establish role clarity to ensure successful integration of AI inputs with customers. This clarity ensures that customers understand the steps AI takes in designing service delivery and providing seamless service performance. Without role clarity, misunderstandings can lead to tragic consequences, as seen in the 2013 Asiana Airlines crash in San Francisco where insufficient role clarity resulted in disaster. As a result of the accident investigation, the problem was that the crew did not receive sufficient education and training, and the cooperation and communication between the crew members was not smooth. In addition, most of the flight attendants were new and lacked previous experience performing takeoff and landing procedures. As a result, the roles and responsibilities of the flight attendants were ambiguous, and they were unable to carry out an accurate division of duties. Customers can also lack role clarity when AI appears in the same context as self-driving cars, which can lead to confusion about the actions carried out by an AI-enabled vehicle and what the customer should do. Role clarity also contributes to transparency, which builds trust between customers and service providers. Transparency in AI roles during meetings is particularly important as failure to fully disclose the role of AI and its behavior can erode customer confidence in the technology and service providers.

Therefore, the concept of role clarity can encompass inquiries about the data that AI gathers during its interactions, as well as how it employs this information both during and after the process. For example, Amazon made headlines when it was ordered to provide audio recordings made by personal Echo devices as evidence during a criminal investigation (Heater, 2017). This revelation surprised numerous customers who were unaware that their Alexa device was recording and storing audio even when they were not using it. Unroll.me, a no-cost service designed to assist customers in unsubscribing from email distribution lists, is another illustration of a lack of transparency that resulted in customer dissatisfaction. Unroll.me was scanning its users' emails and selling insights to third parties, a revelation that angered customers (Isaac & Lohr, 2017). Instances where customers are unaware of AI's role raise concerns about data privacy and impede the adoption of AI-based technologies.

Hypothesis 1: Clarity of customer and AI's roles is positively associated with the customer's willingness to accept the use of AI devices.

AI-driven technology enhances convenience, efficiency, and service speed, delivering immense value to customers and motivating them to embrace and use these technologies. By leveraging interaction data collected from customers, these products continuously learn and adapt to meet individual needs. For instance, Nest can optimize energy efficiency while adhering to temperature preferences by fine-tuning initial schedules based on behavioral patterns. In addition to being functional, AI-based technology also has the potential to provide users with enjoyment and pleasure, as exemplified by Microsoft's XiaoIce chatbot. This friendly chatbot imitates human interaction and has gained popularity among millions of Chinese users, with perceived absorption being a crucial variable of intrinsic motivation for users. According to Agarwal and Karahanna (2000) and Lowry et al. (2013), this hedonic technique explains why XiaoIce attracts so many users.

Hypothesis 2: The customer's motivation to adopt AI-based technology is positively associated with the customer's willingness to accept the use of AI devices.

The term "customer self-service" (SST) refers to the ability of customers to perform actions related to their interaction with an SST system. This concept should be expanded within the context of an AI support service meeting. For instance, AI-powered devices with voice assistance can eliminate technological barriers and facilitate interaction with technology for customers regardless of their technical expertise. At the same time, customers can evaluate whether AI or technology plays a customer-centric role in their service experience or to what extent it enhances or restricts their capabilities. Customers can view AI as an extension of their abilities or physical capacity and integrate human and AI capabilities to improve service performance (Wilson & Daugherty, 2018). Although AI has the potential to democratize services by making them more user-friendly, a lack of technical know-how or financial resources could hinder customers from adopting AI-based technologies. For example, a recent survey conducted by PwC's Global Consumer Insights revealed that early adopters of AI tend to be more technologically adept and less sensitive to price than non-adopters (PwC's Global Consumer Insights Survey 2018).

Hypothesis 3: The customer's ability in the context of the adoption of AI-based technology is positively associated with the customer's willingness to accept the use of AI devices.

AI-Specific Moderators

The contrasting performance of Microsoft's chatbots, XiaoIce and Tay, demonstrates the significance of high-quality training data in achieving AI success. While Tay failed due to its controversial interactions on Twitter, XiaoIce succeeded in part due to the willingness of users to share personal information for personalization. However, there is a paradox between personalization and privacy, with many customers feeling uncomfortable with companies accessing their personal data for AI-based solutions. Privacy concerns are a significant obstacle to customer adoption of AI-based technologies, with over 50 percent of survey respondents feeling uneasy about companies using AI to access personal data. Nevertheless, studies have shown that the value of personalized services may be more important to customers than privacy concerns, and increasing confidence in service providers can help alleviate customer awareness of privacy risks. Overall, privacy concern is a crucial factor affecting customer acceptance of AI-based technologies.

Hypothesis 4: Privacy concerns related to the use of AI-based technology weaken the relationship between core constructs and customers' willingness to accept the use of AI devices.

Previous research on automation and human interaction can provide insights into customers' confidence in AI-based technology. Lee and See (2004) define trust as an attitude that assists individuals in achieving personal goals in situations that are uncertain and vulnerable. Uncertainty and vulnerability are recognized as important factors in both socio-psychology and marketing literature. When a service provider's actions are beyond control, uncertainty creates vulnerability, and the outcomes directly impact the customer, leading to the activation of trust in relationships and organizational interactions. Trust is particularly crucial in the initial stages of a relationship when the adoption of new technology is uncertain. According to Lee and See (2004), trust bridges the gap between the nature of automation and an individual's belief in its function, as well as their intention to utilize and rely on it. In the context of e-commerce, Pavlou (2003) distinguishes between trust in the supplier and trust in the trading medium. This distinction also applies to AI support service interactions.

The confidence customers have in AI support services will be influenced by their trust in service providers and specific AI technologies. According to Mayer et al. (1995), three crucial factors that determine the trustworthiness of an organization are competence, integrity, and benevolence. Competence refers to the expertise, skills, and capabilities specific to the domain and associated with service interactions. Integrity assesses whether the customer can accept and find the principles that the provider adheres to. Benevolence is related to how well the supplier coordinates with the customer's intentions and motivations. Recent events involving Facebook and Cambridge Analytica have demonstrated a lack of integrity and benevolence in the eyes of Facebook users as data was collected without disclosing or acknowledging Facebook's business model (Rosenberg & Frenkel 2018), leading to a significant decline in public trust in Facebook (Weisbaum, 2018). In the context of automation, Lee and See (2004) define trust as being based on performance, processes, and objectives. Performance, similar to ability, reflects how well technology functions in a reliable, predictable, and competent manner. AI-enabled technologies can be effective in service meetings and help customers achieve their goals. The objective of the technology determines its intended purpose and whether it aligns with the designer's intentions. Customers evaluate service providers based on their capabilities, integrity, philanthropy, and overall experience, including the performance, processes, and objectives of AI-enabled technologies. The level of confidence in new AI support services depends on the reliability and number of contributors that customers recognize. To increase confidence in the adoption of AI-based solutions in B2B services, transparency in the development process and gradual introduction of technology are important strategies. Companies can introduce new capabilities gradually to engage customers' curiosity and desire for novelty rather than doing it all at once, which may alarm customers and deviate too much from traditional service delivery alternatives.

Hypothesis 5: Customer's trust in AI-based technology strengthens the relationship between core constructs and the customer's willingness to accept the use of AI devices.

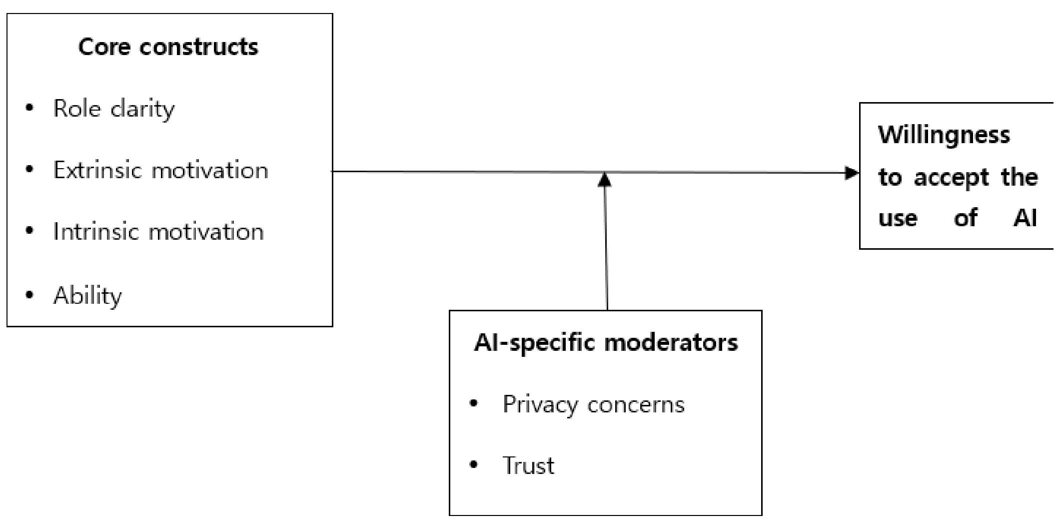
The model of this study is shown in Figure 1.

METHODOLOGY

Sample and Data Collection

In this research, an online survey method was employed, utilizing convenience sampling to gather data. This method was selected due to its ability to gather data from a large number of individuals in a relatively short amount of time and at a lower cost. The survey was commissioned and paid for by a professional survey company. To increase response rates and reduce non-response bias, participants

Figure 1. Research model



were offered a small monetary incentive to complete the survey online. To ensure the accuracy and reliability of the data, several validation and attention check questions were incorporated into the survey, which were used to detect any completed surveys that were randomly answered. Surveys that did not pass any of the validation and/or attention check questions were discarded, resulting in a sample size of 412.

The participants are Korean and consist of men (42.4%) and women (58.6%). The age of them includes 20s (22.1%), 30s (27.7%), 40s (21.4%) and 50s (28.8%). The marital status includes unmarried (40.9%) and married (49.1%). The occupation includes office work (62.3%), research and development (37.7%). The level of their education includes middle school (0.5%), high school (16.4%), community college (28.0%), undergraduate (44.3%) and graduate school (10.6%). The income includes under 30,000 USD (24.1%), 30,000–50,000 USD (49.1%) and 50,000–100,000 USD (26.8%).

Survey Instrument

The survey used in this research was divided into two parts: demographic information and primary questions. The demographic information section included questions pertaining to gender, age, marital status, occupation, education, and income. The main questions section included five items on role clarity, adapted from Rizzo, House, and Lirtzman's (1970) research, three expectancy items on extrinsic motivation, adapted from Tyagi's (1985) work, as well as four instrumentality and four valence items created for the research's context. Intrinsic motivation also had three expectancy items adapted from Tyagi (1985), as well as five instrumentality and five valence items created for the context. Six items on ability, adapted from Jones (1986) and Oliver and Bearden (1985), were also included. The privacy risk measures were based on six questions from Chellappa and Sin's (2005) and Xu et al.'s (2011) research on perceived risks from providing personal information for the use of AI. Additionally, trust was measured with three items adapted from Jarvenpaa et al. (1999), and the willingness to accept the use of AI devices was measured using three items adapted from Venkatesh et al. (2012) and Lu et al. (2019).

ANALYSIS RESULT

Verification of Reliability and Validity

Gefen et al. (2011) suggested that the validity and reliability of the measures were assessed prior to hypothesis testing. First, tests were conducted to evaluate the convergent and discriminant validity and the reliability of reflective measures. Factor loadings were used to establish convergent validity. Loadings in excess of 0.70 on their respective factors are interpreted to indicate convergent validity (Straub et al., 2004). The second indicator of convergence was also employed. Here, a value above 0.50 for each construct's average variance extracted (AVE) is assumed to indicate sufficient convergence. Tests results indicate that both of these conditions have been met. Discriminant validity is demonstrated when the square root of the AVE is greater than the correlations between constructs (Henseler et al., 2014). In table 2, the square rooted AVEs for privacy concern, trust and willingness to accept the use of AI devices are 0.777, 0.758 and 0.769, respectively. Their inter-construct correlation is 0.201, 0.214, 0.213. For the second test of discriminant validity, individual items may be assumed to possess sufficient discriminant validity if they load higher on their respective construct than on any other latent variable (Gefen et al., 2011; Straub et al., 2004). It was true for all items. Based on both tests, the measures possess sufficient discriminant validity. Reliability is established by examining the internal consistency measure for each construct. Constructs that exceed the 0.70 level are judged to possess sufficient reliability (Fornell et al., 1982).

Second, Alternative validity and reliability tests were conducted on the formative constructs: role clarity, extrinsic motivation, intrinsic motivation and ability (Bass & Avolio, 1995). To assess convergent and discriminant validity, correlation patterns between items and latent variables are depicted in a modified multi-trait, multi-method (MTMM) matrix (Loch et al., 2003). Convergent validity is assessed via examining item construct correlations (Chin, 1995). If items load significantly on their corresponding constructs, convergent validity is demonstrated. The results indicate that item weights are significant at a 0.05 level of significance, except for six indicators. The six non-significant items were further analyzed according to prescriptions for interpreting formatively measured construct results (Cenfetelli & Bassellier, 2009). The prescriptions developed by Cenfetelli & Bassellier (2009) distinguish between an indicator's relative and absolute contribution to its construct. Relative contribution is the relation between an indicator and a criterion while holding other predictors constant. It is the importance of an indicator compared to other indicators of the same construct. Absolute contribution is the relation between an indicator and a criterion, ignoring other predictors. In some instances, it is necessary to consider both perspectives to develop a more accurate picture of an indicator's influence. For example, an indicator may have a low or non-significant relative contribution to the construct. Despite this, it may still have an important absolute contribution. Therefore, it is recommended that when relative contribution (measured in terms of indicator weights) is low, absolute contribution (represented by item loadings) should also be considered.. The absolute contributions for four items are significant. Their values are 0.723, 0.712, 0.722, and 0.722, respectively. Thus, although the contributions of the indicators are relatively low compared to other indicators, they have a strong, bivariate relation to their respective constructs (Nunnally & Burnstein, 1994). Furthermore, there did not appear to be any patterns in wording, polarity, or content among the items that would account for the differences, and no conceptual issues regarding the construct definitions were salient. Thus, there was no theoretical justification for removing the items and rather than discarding the items and changing the meaning of the constructs. It was determined that the items should be retained. Finally, discriminant validity evidence is presented when items correlate higher with their respective construct measures than other measures and composite values (Loch et al., 2003).

Common Method Bias

To minimize the risk of common method bias, which is a potential issue with self-reported data (MacKenzie & Podsakoff, 2012; Podsakoff et al., 2003), this study implemented various procedural and statistical remedies recommended by Podsakoff et al. (2003) to evaluate the extent of this bias. First, anonymity and confidentiality were guaranteed to respondents during the survey to decrease evaluation apprehension. Additionally, the questionnaire was carefully developed and worded to reduce ambiguity, making it less likely for respondents to modify their answers to be socially desirable, acquiescent, or consistent with the researcher's expectations (Podsakoff et al., 2003). Second, Harman's one-factor test was performed on all items in this study. A principle components factor analysis revealed that no single factor emerged, and the first factor explained only 34.1 percent of the variance, indicating that no one factor accounted for most of the variance. Furthermore, the measurement model was reevaluated by adding a latent common method variance factor (Podsakoff et al., 2003), and all indicator variables in the model were loaded on this factor. However, the addition of the common variance factor did not improve the fit over the measurement model without that factor, and all indicators remained significant. Therefore, common method bias was not a major concern in this study based on these findings.

Relationship Between Variables

Table 1 summarizes the Pearson correlation test results between variables and reports the degree of multi-collinearity between independent variables. The minimum tolerance of 0.812 and the maximum variance inflation factor of 1.231 shows that the statistical significance of the data analysis was not compromised by multi-collinearity.

Table 1. Variables' correlation coefficient

	1	2	3	4	5	6
1. Role clarity	1					
2. Extrinsic motivation	.012	1				
3. Intrinsic motivation	.032	.022	1			
4. Ability	.026	.102	.011	1		
5. Privacy concerns	-.042	.013	-.031	.012	1	
6.Trust	.015	.062	.021	.017	-.035	1
7. Willingness to accept the use of AI devices	.029**	.021**	.042**	.022**	-.102**	.022**

*$p < .05$, **$p < .01$

Hypothesis Testing

This study used hierarchical multiple regression analyses of SPSS 24.0 with three steps to test the hypotheses. In the first step, demographic variables were controlled. Independents were entered in the second step. In the final step, the multiplicative interaction terms between independent factors and moderating variables were entered to directly test the current hypothesis about the moderating effect. Table 2 shows the results. First, among demographic variables, men are more willing to accept the use of AI devices than women, and younger people are more willing to accept the use of AI devices than older people. Second, to analyze the relationship between independent variables and willingness to accept the use of AI devices, model 2 in Table 2 shows that some of the independent variables have statistical significance with game engagement. Role clarity ($\beta = .033$, $p < .01$) is positively related to willingness to accept the use of AI devices. Extrinsic motivation ($\beta = .022$, $p < .01$) and intrinsic motivation ($\beta = .009$, $p < .01$) have positive relationships with the willingness to accept the use of AI devices. Ability ($\beta = .019$, $p < .01$) shows a positive association with willingness to accept the use of AI devices. Therefore, hypotheses 1, 2, and 3 are supported.

Lastly, model 3, consisting of moderators, shows the interactions between independent variables and moderating variables on game engagement. Privacy concerns were found to harm the relationship between role clarity and willingness to accept the use of AI devices. ($\beta = -.099$, $p < .05$). Privacy concerns were found to have no significance in the relationship between other independent variables and willingness to accept the use of AI devices. Trust was found to have a positive effect on the relationship between the ability and willingness to accept the use of AI devices. ($\beta = .042$, $p < .05$). Trust was found to have no significance in the relationship between other independent variables and willingness to accept the use of AI devices. Therefore, hypotheses 4 and 5 are partially supported (see Figure 1).

DISCUSSION

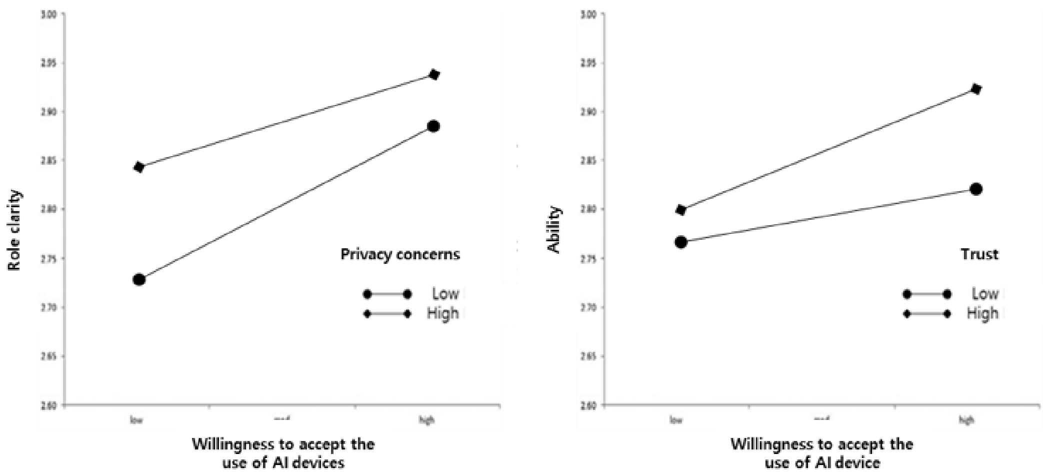
The aim of this research was to investigate how customers perceive and accept the use of AI, and to identify the factors that can moderate this process. The study found that customers' understanding of their own and AI's roles, their motivation to use AI-based technology, and their ability to use it positively affect their willingness to adopt AI devices. On the other hand, privacy concerns related to the use of AI-based technology negatively impact the relationship between role clarity and customers' acceptance of AI devices. In contrast, trust in AI-based technology enhances the relationship between ability and customers' willingness to adopt AI devices. Previous research has shown that

Table 2. Analysis 1

	Willingness to Accept the Use of AI Devices		
	Model 1	**Model 2**	**Model 3**
Gender	.045*	.041*	.037*
Age	-.042*	-.036*	-.029*
Marital status	.012	.009	.006
Occupation	.024	.021	.019
Education	-.040	-.033	-.028
Income	.010	.006	.004
Role clarity		.033**	.029**
Extrinsic motivation		.022**	.019**
Intrinsic motivation		.009*	.007*
Ability		.019**	.013**
Privacy concerns			-.010*
Trust			.014*
Role clarity * Privacy concerns			-.099**
Extrinsic motivation * Privacy concerns			.017
Intrinsic motivation * Privacy concerns			-.015
Ability * Privacy conserns			.100
Role clarity * Trust			.035
Extrinsic motivation * Trust			.109
Intrinsic motivation * Trust			.013
Ability * Trust			.042**
Adj. R^2	.104	.179	.197
F	4.611**	10.992**	15.991**

*$p < .05$, **$p < .01$

Figure 2. Interaction effect



privacy concerns can undermine customers' willingness to use personalized services, but the value of personalized services can outweigh these concerns. In addition, customer confidence in service providers can alleviate privacy concerns related to location-based mobile commerce. Therefore, this study concluded that privacy concerns are a critical factor affecting customer acceptance of AI-based technologies. The findings suggest that privacy concerns may have a more significant impact on the relationship between role clarity and customers' acceptance of AI devices compared to other factors, as privacy concerns are directly related to the functional process of using AI devices and the roles of both customers and AI in this process.

Lee and See (2004) state that trust plays a critical role in bridging the gap between the functionality of automation and an individual's belief in its purpose, as well as their intention to use and depend on it. In the context of e-commerce, Pavlou (2003) distinguishes between two forms of trust: trust in the trading medium and trust in the supplier. This distinction can also be applied to AI support service encounters. This research indicates that trust in both service providers and specific AI technologies can enhance customer confidence in AI support services. The findings reveal that trust regarding the use of AI-based technology strengthens the relationship between only the ability and the customer's willingness to accept the use of AI devices, whereas privacy concerns do not affect the relationship between other independent variables and the customer's willingness to accept the use of AI devices. Therefore, because trust is linked to the psychological evaluation of AI device usage, and a customer's ability in the context of AI-based technology adoption is also based on psychological judgment, it may have a more significant impact on this relationship than any other factor.

CONCLUSION

Research Contributions and Practical Implications

This study has made a novel contribution by shedding light on the role of artificial intelligence in frontline service meetings, specifically in terms of how customers perceive and accept AI-enabled services. While the practical importance of AI is increasing, there are limited quantitative studies on the individual factors that impact customers' willingness to use AI devices. This study has therefore focused on individual factors and proposed a model that integrates them rather than identifying fragmented factors. The study has shown that individual factors such as role, motivation, and ability can coexist in the context of AI use, despite potential conflicts. Additionally, the study has explored

AI-specific moderators, revealing that privacy concerns and trust have a significant impact on customers' perceptions of AI devices. Privacy concerns may affect the functional process of using AI devices, while trust may impact the psychological judgment of using such devices, particularly in the context of customers' ability to adopt AI-based technology. Overall, this study provides valuable insights into the individual and contextual factors that influence customers' acceptance of AI-enabled services in frontline service meetings.

The study highlights the importance of individual factors such as role, motivation, and ability in enhancing the acceptance of AI. This implies that AI device developers should strive to create user interfaces that enable AI customers to perceive a high level of role clarity, motivation, and ability. In addition, privacy concerns appear to have a significant impact on the relationship between customers and AI devices due to the functional process of using them. Consequently, AI device operators need to prioritize privacy protection and establish a privacy process in the role-play between customers and AIs. Finally, trust plays a critical role in the psychological judgment of using AI devices and the customer's ability to adopt AI-based technology. Therefore, AI device operators should take measures to foster trust, such as allowing various forms of communication (e.g., text, pictures, voice, video, etc.) between customers and AIs.

Limitations and Future Research Directions

The current study provides valuable insights into customers' acceptance of AI, but it is important to acknowledge its limitations. Firstly, the study only collected responses from customers in South Korea, which may have cultural implications that could affect the generalizability of the results. To ensure the reliability of the findings, future studies should replicate the study in other countries. Secondly, as all variables were measured simultaneously, it is uncertain whether the relationships between them are consistent over time. Despite taking measures to avoid this issue, such as asking survey questions in reverse order of the analysis model, the possibility of causal relationships between variables cannot be ruled out. Therefore, longitudinal studies should be considered in future research. Lastly, this study focused on individual factors such as role clarity, motivation, and ability, and explored privacy concerns and trust as AI-specific moderators. However, other individual factors such as locus of control and interaction with AI may also be relevant as moderators, given the unique characteristics of AI. Further research should take these factors into account to gain a more comprehensive understanding of customers' acceptance of AI.

COMPETING INTERESTS

The authors of this publication declare there are no competing interests.

FUNDING AGENCY

This study was supported by 2022 Sangmyung University Research Fund.

REFERENCES

Agarwal, R., & Karahanna, E. (2000). Time flies when you're having fun: Cognitive absorption and beliefs about information technology usage. *Management Information Systems Quarterly*, *24*(4), 665. doi:10.2307/3250951

Bass, B. M., & Avolio, B. J. (1995). *Multifactor Leadership Questionnaire: Manual leader form, rater, and scoring key for MLQ, Form 5x-Short*. Mind Garden.

Blut, M., Wang, C., & Schoefer, K. (2016). Factors influencing the acceptance of self-service technologies: A meta-analysis. *Journal of Service Research*, *19*(4), 396–416. doi:10.1177/1094670516662352

Cenfetelli, R., & Basselier, G. (2009). Interpretation of formative measurement in IS research. *Management Information Systems Quarterly*, *33*(4), 689–707. doi:10.2307/20650323

Chellappa, R. K., & Sin, R. G. (2005). Personalization versus privacy: An empirical examination of the online Consumer's dilemma. *Information Technology and Management*, *6*(2), 181–202. doi:10.1007/s10799-005-5879-y

Chin, W. (1995). Partial least squares is to LISREL as principal components analysis is to common factor analysis. *Technology Studies*, *2*, 315–319.

Ellenberg, J. (2014). *What's even creepier than Target guessing that you're pregnant?* Slate. Retrieved from http://www.slate.com/blogs/how_not_to_be_wrong/2014/06/09/big_ data_what_s_even_creepier_than_target_guessing_that_you_re_pregnant.html

Enholm, I. M., Papagiannidis, E., Mikalef, P., & Krogstie, J. (2022). Artificial Intelligence and Business Value: A Literature Review. *Information Systems Frontiers*, *24*(5), 1709–1734. doi:10.1007/s10796-021-10186-w

Fornell, C., & Bookstein, F. (1982). Two structural equation models: LISREL and PLS applied to consumer exit-voice theory. *JMR, Journal of Marketing Research*, *19*(4), 440–452. doi:10.1177/002224378201900406

Frank, M., Roehring, P., & Pring, B. (2017). *What to Do when Machines Do Everything: How to Get Ahead in a World of AI, Algorithms, Bots and Big Data*. John Wiley & Sons.

Gefen, D., Rigdon, E. E., & Straub, D. (2011). An Update and Extension to SEM Guidelines for Administrative and Social Science Research. *Management Information Systems Quarterly*, *35*(2), 3–14. doi:10.2307/23044042

Genpact. (2017). *The consumer: Sees AI benefits but still prefers the human touch*. Retrieved May 12, 2018, from https://www.genpact.com/lp/ai-research-consumer

Gibbs, N., Pine, D. W., & Pollack, K. (2017). *Artificial intelligence: The future of humankind*. Time Books.

Heater, B. (2017). *After pushing back,Amazon hands over Echodata in Arkansas murder case*. Retrieved June 7, 2018, from http://social.techcrunch.com/2017/03/07/amazon-echomurder

Hengstler, M., Enkel, E., & Duelli, S. (2016). Applied artificial intelligence and trust—The case of autonomous vehicles and medical assistance devices. *Technological Forecasting and Social Change*, *105*, 105–120. doi:10.1016/j.techfore.2015.12.014

Henseler, J., Ringle, C. M., & Sarstedt, M. (2014). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135. doi:10.1007/s11747-014-0403-8

Hoffman, D. L., & Novak, T. P. (2017). Consumer and object experience in the Internet of Things: An assemblage theory approach. *The Journal of Consumer Research*, *44*(6), 1178–1204. doi:10.1093/jcr/ucx105

Huang, M. H., & Rust, R. T. (2018). Artificial intelligence in service. *Journal of Service Research*, *21*(2), 155–172. doi:10.1177/1094670517752459

Hunt, E. (2016). Tay, Microsoft's AI chatbot, gets acrash course in racism from Twitter. *The Guardian.* Retrieved from https://www.theguardian.com/technology/2016/mar/24/taymicrosofts-ai-chatbot-gets-a-crash-course-in-racism-from-twitter

Isaac, M., & Lohr, S. (2017).Unroll.meservicefacesbacklashoverawidespreadpractice: Selling user data. *The New York Times*. Retrieved June7,2018,fromhttps://www.nytimes.com/ 2017/04/24/technology/personal-data-firm-slice-unroll-me-backlash-uber.html

Jarvenpaa, S. L., Tractinsky, N., & Vitale, M. (1999). Consumer trust in an Internet store. *Information Technology Management*, *1*(12), 45–71.

Jones, G. R. (1986). Socialization Tactics, Self-Efficacy, and Newcomers' Adjustments to Organizations. *Academy of Management Journal*, *29*(2), 262–279. doi:10.2307/256188

Juma, C. (2016). *Innovation and its enemies: Why people resist new technologies*. Oxford University Press. doi:10.1093/acprof:oso/9780190467036.001.0001

Lardinois, F. (2017, May 31). *Google says its machine learning tech now blocks 99.9% of Gmail spam and phishing messages*. Retrieved June 7, 2018, from https://techcrunch.com/2017/05/31/ google-says-its-machine-learning-tech-now-blocks-99-9-of-gmail-spam-and-phishingmessages/

Lee, J. D., & See, K. A. (2004). Trust in automation: Designing for appropriate reliance. *Human Factors*, *46*(1), 50–80. doi:10.1518/hfes.46.1.50.30392 PMID:15151155

Lee, J. M., & Rha, J. Y. (2016). Personalization–privacy paradox and consumer conflict with the use of location-based mobile commerce. *Computers in Human Behavior*, *63*, 453–462. doi:10.1016/j.chb.2016.05.056

Leonhard, G. (2016). *Technology vs. Humanity: The Coming Clash Between Man and Machine*. Fast Future Publishing.

Loch, K., Straub, D., & Kamel, S. (2003). Diffusing the internet in the Arab world: The role of social norms and technological culturation. *IEEE Transactions on Engineering Management*, *50*(1), 45–64. doi:10.1109/TEM.2002.808257

Loewy, R. (1951). *Never leave well enough alone*. Simon and Schuster.

Loewy, R. (1979). *Industrial design*. Overlook Press.

Lowry, P. B., Gaskin, J. E., Twyman, N. W., Hammer, B., & Roberts, T. L. (2013). Taking "funand games" seriously: Proposing the hedonic-motivation system adoption model (HMSAM). *Journal of the Association for Information Systems*, *14*(11), 617–671. doi:10.17705/1jais.00347

Lu, L., Cai, R., & Gursoy, D. (2019). Developing and validating a service robot integration willingness scale. *International Journal of Hospitality Management*, *80*, 36–51. doi:10.1016/j.ijhm.2019.01.005

MacKenzie, S. B., & Podsakoff, P. M. (2012). Common method bias in marketing: Causes, mechanisms, and procedural remedies. *Journal of Retailing*, *88*(4), 542–555. doi:10.1016/j.jretai.2012.08.001

Mayer, R. C., Davis, J. H., & Schoorman, F. D. (1995). An integrative model of organizational trust. *Academy of Management Review*, *20*(3), 709–734. doi:10.2307/258792

McKnight, D. H., Cummings, L. L., & Chervany, N. L. (1998). Initial trust formation in new organizational relationships. *Academy of Management Review*, *23*(3), 473. doi:10.2307/259290

Nunnally, J. C., & Bernstein, I. H. (1994). *Psychometric Theory*. McGraw-Hill.

Oliver, R. L., & Bearden, W. O. (1985). Crossover Effects in the Theory of Reasoned Action: A Moderating Influence Attempt. *The Journal of Consumer Research*, *12*(December), 324–340. doi:10.1086/208519

Pavlou, P. A. (2003). Consumer acceptance of electronic commerce: Integrating trust and risk with the technology acceptance model. *International Journal of Electronic Commerce*, *7*(3), 101–134. doi:10.1080/10864415.2003.11044275

Podsakoff, P. M., MacKensie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *The Journal of Applied Psychology*, *88*(5), 879–903. doi:10.1037/0021-9010.88.5.879 PMID:14516251

PwC's Global Consumer Insights Survey. (2018). *Artificial intelligence: Touchpoints with consumers*. Retrieved June 7, 2018, from https://www.pwc.com/gx/en/retail-consumer/assets/artificial-intelligence-global-consumer-insights-survey.pdf

Rizzo, J. R., House, R. J., & Lirtzman, S. I. (1970). Role Conflict and Ambiguity in Complex Organizations. *Administrative Science Quarterly*, *15*(2), 150–163. doi:10.2307/2391486

Rosen, G. (2017, November 27). *Getting our community help in real time*. Facebook Newsroom. Retrieved June 7, 2018, from https://newsroom.fb.com/news/2017/11/getting-our-communityhelp-in-real-time/

Rosenberg, M., & Frenkel, S. (2018,April 3). Facebook's role in data misuse sets off storms on two continents. *The New York Times*. Retrieved from https://www.nytimes.com/2018/03/18/us/ cambridge-analytica-facebook-privacy-data.html

Straub, D. W., Boudreau, M. C., & Gefen, D. (2004). Validation guidelines for IS positivist research. *Communications of AIS*, *13*(63), 380–427.

Tegmark, M. (2017). *Life 3.0: Being Human in the Age of Artificial Intelligence*. Alfred A. Knopf.

Tene, O., & Polonetsky, J. (2014). A theory of creepy: Technology, privacy, and shifting social norms. *Yale Journal of Law and Technology*, *16*(1), 2.

Tyagi, P. K. (1985). Relative Importance of Key Job Dimensions and Leadership Behaviors in Motivating Salesperson Work Performance. *Journal of Marketing*, *49*(Summer), 76–86. doi:10.1177/002224298504900307

Venkatesh, V., Thong, J., & Xu, X. (2012). Consumer acceptance and user of information technology: Extending the unified theory of acceptance and use of technology. *Management Information Systems Quarterly*, *36*(1), 157–178. doi:10.2307/41410412

Weisbaum, H. (2018). *Trust in Facebook has dropped by 66 percent since the Cambridge Analytica scandal*. Retrieved May 28, 2018, from https://www.nbcnews.com/business/con sumer/trust-facebook-has-dropped-51-percent-cambridge-analytica-scandal-n867011

Wilson, H. J., & Daugherty, P. (2018). AI will change health care jobs for the better. *Harvard Business Review*. Retrieved from https://hbr.org/2018/03/ai-will-change-health-carejobs-for-the-better

Xu, H., Luo, X. R., Carroll, J. M., & Rosson, M. B. (2011). The personalization privacy paradox: An exploratory study of decision making process for location-aware marketing. *Decision Support Systems*, *51*(1), 42–52. doi:10.1016/j.dss.2010.11.017

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