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The search for AI value: The role of complexity in human-AI engagement in the financial industry

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ABSTRACT

The banking industry is infusing AI systems into service encounters while dissolving some traditional services. This study aims to empirically test an exploratory framework to identify how human-AI interactions differ when engaged in basic or advanced virtual agent usage contexts. A conceptual framework was developed to examine consumer perceptions of basic and advanced virtual agent usage intentions. Five independent variables of trust in AI, perceived security in AI, perceived AI expertise, comfort in using AI technologies, and need for social presence were explored. Data was collected from 322 respondents and analyzed using multivariate regression. The findings suggest that consumers do not perceive service encounters with virtual agents from a "one size fits all" approach. Consumers perceive different value-in-use perceptions based on the complexity of the usage contexts. Our results suggest that success in advanced virtual agent encounters may require social presence for robust human-AI interaction. Additionally, this study extends the digital servitization and service robot acceptance model (sRAM) literature by evaluating consumer value-in-use perceptions with empirical evidence.

1. Introduction

Artificial intelligence (AI) is a disruptive service innovation that has the ability to transform the banking industry by offering personalized, customer-centric processes (Fernandes & Oliveira, 2021). Customers increasingly demand more powerful self-service technologies. Recent advances in generative AI (GenAI) use sophisticated language models to mimic conversational answers to complex questions. Unlike earlier self-service technologies, artificial intelligence can interpret complex data, converse and react to consumer needs, and potentially replace traditional human-human service encounters (Huang & Rust, 2018).

Of importance to banking customers in the human-AI service encounter is for AI to "do the right thing," whether to perform simple deposit transactions or provide complex personalized advice for debt reduction. AI is "a system's ability to interpret external data correctly, to learn from such data, and to use these learnings to achieve specific goals and tasks through flexible adaption" (Haenlein & Kaplan, 2019, p.5).

Central to human-AI service encounters are the digital platforms used for service exchange. Integrating AI technologies into virtual agents in the banking industry provides an effective digital platform, especially when delivered via the mobile channel (Manser Payne et al., 2018). The diverse applications of AI-enabled virtual agents (hereafter called virtual agents) allow customers to conduct banking activities, engage with customer service 24/7, and receive expert advice and collaboration concerning their financial portfolios (Jang et al., 2021) quickly and conveniently. However, AI technologies have the potential to be more than a new feature to virtual agents. AI can leverage business models from selling bank services to engaging in complex problem-solving, such as supporting customers' personal wealth goals.

Despite the heightened interest in incorporating virtual agents into customer-facing services, research exploring the contexts of the service exchange when using virtual agents is sparse (Fernandes & Oliveira, 2021). Previous studies suggest that the consumer usage context influences their perceptions of technology (Aljukhadar et al., 2014; Lu et al., 2020). Our framework decouples virtual agent usage intentions by separating basic and advanced service contexts. Basic virtual agent contexts tend to be more transactional and utilitarian, where human-AI service encounters are limited to routine tasks, such as depositing checks or paying bills. Conversely, advanced virtual agent usage requires problem-solving abilities for complex tasks, such as retirement planning or debt consolidation advice. Additionally, the advanced virtual agent usage context may require a demonstration of social-emotional needs by

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the virtual agent (Pelau et al., 2021; Lin et al., 2020; Xu et al., 2020). Our research question for this study seeks to answer how consumer attitudes may vary based on the complexity of the task asked of the AI virtual agent.

We support our exploratory framework with the service robot acceptance model (sRAM) and digital servitization. An emerging theoretical domain of interest for AI literature is sRAM (Wirtz et al., 2018). Building upon the technology acceptance model (Davis, 1989) and role theory (Soloman et al., 1985), Wirtz et al. (2018) suggest that consumer acceptance of AI-enabled robots in service encounters varies by the degree of the robot's ability to deliver fundamental service needs as well as social-emotional needs. Furthermore, the financial industry places considerable importance on digital servitization as consumers move from traditional bank branches to digital channels for their banking needs. Digital servitization transforms business models from product-centric to customer-centric approaches, creating new revenue opportunities and value propositions for the customer by co-creating value with human-AI interactions (Wirtz et al., 2023). Accordingly, our research question examines the new value propositions in AI virtual agent service encounters.

Our study responds to calls to advance our understanding of AI-human service encounters and investigate customer attitudes toward those interactions (Larivière et al., 2017; Lu et al., 2020). We extend the literature by empirically testing a novel framework to examine how consumer attitudes influence consumer basic and advanced virtual agent usage intentions. Most service-related studies on virtual agents tend to be conceptual (Lu et al., 2020) or generally measure virtual agents (Pitardi & Marriott, 2021), thus limiting our ability to understand virtual agent usage intentions more precisely in the financial industry. Our framework fills this gap and provides insight into understanding consumer perceptions and how the need for social presence may influence consumer interactions with virtual agents.

2. Theoretical framework and hypotheses

2.1. Chatbots to virtual agents

Consumers do not interact with AI per se; instead, they use an AI-enabled digital platform. Innovative computer systems designed to interact with humans have their roots in Eliza (Weizenbaum, 1966), the first chatbot launched in 1966. Early chatbots engaged in scripted small talk and were based on the Turing test (Riikkinen et al., 2018) within limited domains. Essentially, early chatbots could not truly understand a conversation. Instead, they responded to human text-based or audio-based input. Technological advances in the 1990s led to task-completion chatbots with natural language and machine learning. Although more advanced than the first generation, task-completion chatbots were limited to a narrow scope of tasks.

The introduction of Siri in 2011 provided the ability to converse in quick conversations with an artificial agent. After Siri, other intelligent personal assistants (IPAs) have since been available to consumers, such as Google Assistant, Alexa (Amazon), and Cortana (Microsoft). Of current interest to researchers and industry is AI's ability to have a social presence. Chatbot innovation now includes systems that can hold long conversations with their human counterparts and address human social and emotional needs (Lin et al., 2020; Zhou et al., 2020) in a broad spectrum of domains. For example, Microsoft's XiaoIce, a social chatbot that exhibits empathy with over 600 million active users, can create an emotional connection by conversing with human-like tendencies, recognizing and reacting appropriately when its human counterpart feels sad, and by initiating new topics into the conversation (Zhou et al., 2020).

Generative AI can quickly learn and adjust to a user's language (Korzynski et al., 2023) and engage in extended conversations that reflect a human expert (Dwivedi et al., 2023). Generative AI, such as ChatGPT-4, is slowly being integrated into customer service roles. Its natural language capabilities and personalized financial content offer a human-like touch to customer-bank engagement (Harley, 2023). However, back-office concerns remain. Cybersecurity, third-party AI software regulatory requirements, and how generative AI may fit into a bank's business strategy have made banks proceed cautiously (Harley, 2023; Jackson, 2023).

Nowadays, the financial industry incorporates task-completion chatbots, IPAs, and generative AI into customer-facing virtual agent systems. The findings from Sarbabidya and Saha (2020) suggest that the impact of virtual agents on customer-bank relationships may reflect not only utilitarian but also hedonic values. Virtual agents may increase engagement and relationships with the customer, thus contributing to hedonic value. Riikkinen et al. (2018) made similar observations in their study pertaining to chatbots and value creation.

Human-virtual agent engagement has changed the customer journey in the fintech industry (Lăzăroiu et al., 2023). In back-office operations, the computing power of the Internet of Things-based fintechs makes the customer journey more streamlined with cybersecurity and cloud-based personalized services (Andronie et al., 2023). Generative AI-enabled virtual agents in fintech have innovated customer-facing operations with anthropomorphic algorithms (Priya & Sharma, 2023). Admittedly, still in the developmental stages, consumers now have the choice to bank with a virtual agent who can converse with them as if they were talking to a human customer service representative.

Despite the rapid pace of integrating AI into the financial industry, consumers are still cautious about AI's impact on daily life (Kennedy et al., 2023). Recent research by the Pew Research Center (Anderson & Rainie, 2023) suggests that consumers are more concerned than excited about AI. Regarding consumers' financial lives, a lack of confidence in AI may significantly affect the successful future implementation of virtual agents in the financial industry.

2.2. Theories

2.2.1. Service robot acceptance model

The service robot acceptance model (sRAM) (Wirtz et al., 2018) is a promising theory that seeks to understand consumer adoption of service robots. sRAM examines functional, social-emotional, and relational adoption attributes (Lu et al., 2020; Pitardi & Marriott, 2021). Lu et al. (2020, p. 909) define service robots as "system-based autonomous and adaptive interfaces that interact, communicate, and deliver service to an organization's customers." The sRAM model provides researchers with a comprehensive model to examine multiple facets of human-computer interactions (Fernandes & Oliveira, 2021) and value co-creation in service encounters (Čaić et al., 2019).

2.2.2. Digital servitization

Digital servitization refers to incorporating digital tools into transformational processes, business models, and company resources that lead to a service-centric mindset and value-creating opportunities (Sklyar et al., 2019). Digital technology has the potential to evolve the service ecosystem into one that is more dependent on multiple actors and responsive to consumer needs (Kohtamäki et al., 2019). However, transforming business models from a basic product-oriented service (e.g., standard financial services) to an advanced service-based orientation (individualized financial solutions) calls for a cultural shift and new capabilities to align back-office and customer-facing operations (Parida et al., 2019). Digital innovations, such as artificial intelligence, offer promising revenue growth potential for eco-service systems (Gebauer et al., 2021), especially in the banking industry, where information and knowledge dispersion drive consumer needs for financial solutions.

2.3. Model development

The growing influence of artificial intelligence on service encounters has generated a need to understand how customers may perceive virtual agents in the financial industry. Advances in AI technologies have created situations where consumers may view the human-AI interactions based on the service encounter context. We propose an exploratory model (Fig. 1) to investigate how consumer attitudes and the need for social presence in human-AI interactions influence the context of virtual agent usage intentions.

2.4. *Attitudes toward AI-enabled technologies*

2.4.1. *Trust*

Trust-building is a dynamic process. Typically, trust is gained gradually due to multiple interactions and is contingent on the willingness to assume risk (Gefen & Straub, 2003). Trust plays a significant role in service encounters, especially in digital banking (Ngoc Phan & Ghantous, 2013) and AI-based services and products (Siau & Wang, 2018). Trust has been found to be influential in digital channels (Eren, 2021; Lee & Chen, 2022). Drawing from banking literature for trust and AI usage associations (Manser Payne et al., 2018; Northey et al., 2022), we expect trust will impact both basic and advanced virtual agent usage intentions.

H1. Propensity to trust AI positively influences (a) basic virtual agent usage intentions and (b) advanced virtual agent usage intentions.

2.4.2. *Perceived security in AI technology*

Consumer decisions to use technology-based banking services heavily depend on the bank's security systems (Chaouali & Souiden, 2019). Security threats potentially hinder the adoption of innovative technology (Laukkanen & Kiviniemi, 2010). Previous literature suggests that positive attitudes toward security systems have an influential role in increasing digital channel usage (Lin et al., 2020) and may enhance the value of the service encounter (Parida et al., 2019). Perceived security in AI technology refers to user attitudes to perceived and actual security threats toward their financial information while using AI technologies.

AI-enabled digital platforms, such as virtual agents accessed through mobile banking, offer a faster means to respond against security threats by monitoring, reasoning, and acting autonomously of human input (Srivastava, 2018). Similarly, Mhlanga (2020) argued that AI improves cybersecurity protection and fraud detection for financial institutions. Mhlanga (2020) further argued that virtual agents with AI security systems may reduce risks associated with digital financial services. As a result, consumers may perceive security in AI technology as a value-added benefit in digital service encounters with virtual agents.

H2. Perceived security in AI technology positively influences (a) basic virtual agent usage intentions and (b) advanced virtual agent usage intentions.

2.4.3. *Perception of AI expertise*

One of AI's most significant successes has been its power in back-office processing and synthesizing big data in multiple industries, including banking. Huang and Rust (2018) suggest that AI expertise may overtake human know-how in data analysis in knowledge-based services, such as financial planning. Back-office AI knowledge is transferred and integrated within the financial industry with customer-facing virtual agents, creating opportunities for the customer to experience AI expertise personally. This has the potential to transform and positively influence service encounter expectations (Northey et al., 2022; Manser Payne et al., 2021).

Perception of AI expertise refers to the user's perception of AI technology's knowledge, competency, and capabilities. We theorize that customers will perceive AI expertise as beneficial and valuable in conducting their banking activities through virtual agents. Furthermore, we may expect customers to value AI expertise in more complex knowledge-based situations, such as advice for real-time investment portfolios. Customers may perceive AI as more knowledgeable than a human financial agent (Huang & Rust, 2018). Additionally, as customers spend more time in human-AI interactions, they may experience satisfaction with the analytical abilities that the infusion of AI expertise brings to the service encounter, leading to higher usage intention behaviors (Bitner et al., 2000).

H3. Perception of AI expertise positively influences (a) basic virtual agent usage intentions and (b) advanced virtual agent usage intentions.

2.4.4. *Comfort in using AI technology*

Comfort in using AI technology refers to the users' perceived confidence in using AI technology and is critical to consumer acceptance of innovative technologies. (Rogers, 1995; Parasuraman & Colby, 2015). Self-service technology and e-banking research have consistently

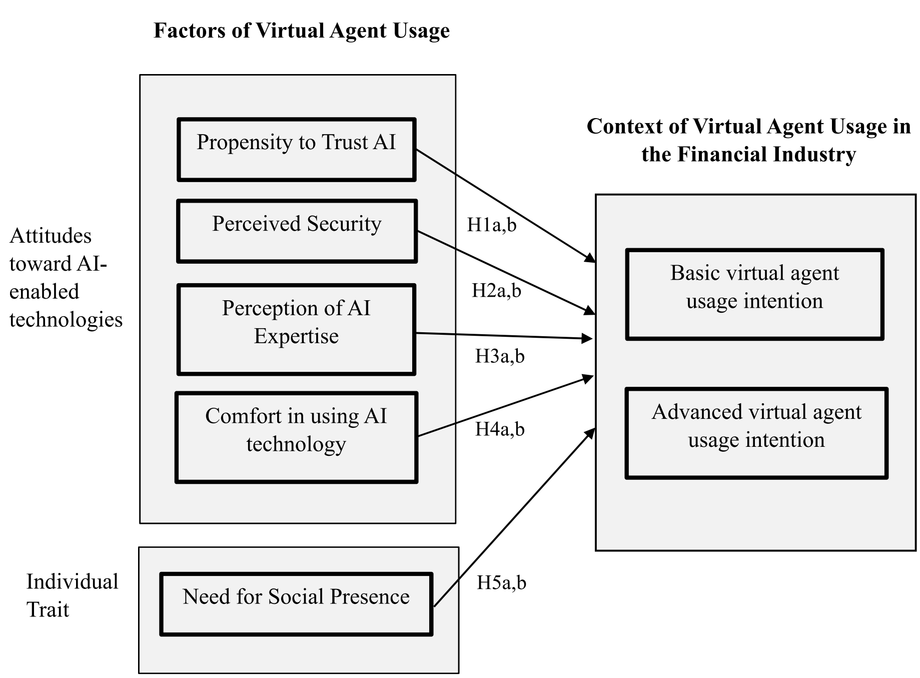

Fig. 1. Exploratory model.

demonstrated that increased consumer comfort levels led to higher technology usage behaviors (Akhter, 2015; Lee & Chen, 2022; van Pinxteren et al., 2019) and positive perceptions in digital service encounters (Lin & Hsieh, 2007). Van Pinxteren et al. (2019) suggest that the nature of the service encounter may make customers uncomfortable with a service robot. Akhter (2015) argued that the feeling of comfort might impact transactional activities conducted on the Internet. Chen et al. (2016) determined that comfort with technology encourages its use, resulting in higher usage and even higher comfort levels. Therefore, we may expect similar results with AI technology. Accordingly, as consumers gain more experience with virtual agents, comfort in using AI technology may aid in increasing basic and advanced virtual agent usage behaviors (Lee & Chen, 2022; Lee et al., 2021).

H4. Comfort in using AI technology positively influences (a) basic virtual agent usage intentions and (b) advanced virtual agent usage intentions.

2.5. Individual trait

2.5.1. Need for social presence

Social presence (Short et al., 1976) is rooted in interpersonal communication in non-mediated interactions, such as face-to-face exchanges. Nowadays, social presence (Grosso & Forza, 2020) is discussed predominantly in mediated communication, such as engaging with a virtual agent. Social presence reflects the degree to which an individual perceives a 'human' on the other side of technology interaction. For some customers, the human connection is critical in service encounters as self-service technologies tend to lose the social experience (Dabholkar et al., 2003).

Following the work of Lee et al. (2021) and Jin and Youn (2023), we suggest that consumers are more likely to engage with a virtual agent if they feel a copresence, psychological involvement, and behavioral engagement in the service encounter. For example, copresence in a virtual environment includes cues that indicate you are not alone, such as a feeling of human warmth or sensitivity.

While social presence is an important factor in technology usage, it is necessary to determine whether its impact may vary based on the usage situation. Basic virtual agent usage typically incorporates utilitarian value perceptions of the task-oriented interaction. There may be little need for social chatbot skills due to limited psychological involvement with the task. Conversely, virtual agent interactions in more advanced contexts may require extended conversations to solve more complex financial problems. We can expect that consumers will require high levels of behavioral engagement and a copresence to be engaged with advanced virtual agents (Fernandes & Oliveira, 2021).

H5. Need for social presence positively influences (a) basic virtual agent usage intentions, and (b) social presence has a positive effect on advanced virtual agent usage intentions.

3. Methods

3.1. Sample and data collection

Data were collected from 337 respondents with a bank or a credit union account, resulting in 322 useable responses. We obtained our sample from undergraduate students, mainly Generation Z, who agreed to participate and complete an online survey for extra credit. Generation Z is the first generational cohort that has not known a world without the Internet, and they are receptive to new innovative technologies for financial services and products (Target, 2019). However, individuals in the Generation Z cohort vary in their perceptions of managing their finances (Mondres, 2019).

3.2. Measure development

We identified key factors that may impact consumer usage of virtual agents and adapted established scales from the literature. Our dependent variables, basic virtual agent usage intention and advanced virtual agent usage intention, were measured with original items developed after reviewing artificial intelligence and banking literature (Baabdullah et al., 2019; Belanche et al., 2019; Kaya, 2019). All items were measured using a 5-point Likert scale.

We verified construct dimensionality by running an exploratory factor analysis with Varimax rotation on 33 items. Our final measurement model consisted of 30 items. The reliability scores for all factors (Cronbach's α ranged from 0.84 to 0.93) were well above 0.70 (Nunnally, 1978). Additionally, we used confirmatory factor analysis to assess model fit, reliability, and validity. The constructs' composite reliability (CR) value ranged between 0.84 and 0.93, above the 0.70 cutoff suggested by Hair et al. (2009). The model fit statistics exceeded thresholds recommended by Hu and Bentler (1999) and Hair et al. (2006), indicating an excellent overall fit of the data (CMIN = 576.463, d.f. = 373, CMIN/d.f. = 1.545, $p = 0.00$; GFI = 0.90; CFI = 0.97; NFI = 0.92; TLI = 0.97; RMSEA = 0.04; SRMR = 0.046.) Regarding convergent validity, item loadings for 28 of the 30 items meet or exceed the ideal 0.70 convergent validity threshold (Hair et al., 2009). The other items (0.60 and 0.61) were well above the baseline value of 0.50, as suggested by Hair et al. (2009). Discriminant validity was established by testing the average variance extracted (AVE). Each construct achieved an AVE above 0.50 with MSV < AVE and ASV < AVE. The square root of the AVE exceeded all paired correlations, as shown in the correlations matrix in Table I, satisfying the Fornell and Larcker (1981) test. We also used the heterotrait-monotrait (HTMT) criterion to further assess discriminant validity. As shown in Table II, the HTMT indicates that our measurement model achieved discriminate validity with all values below the 0.85 threshold (Henseler et al., 2015). Appendix A presents the measures for the constructs and items, the standardized factor loadings, and the scale reliability/validity statistics.

Finally, we tested for common method bias. Proactively, attention was given to the research design to reduce common method variance (CMV) effects (Podsakoff et al., 2003). Then, two post-measurement procedures were taken. First, a diagnostic test using Harman's single-factor method indicated that the total percentage of the variance explained was only 27.6 %, suggesting no common method bias (Podsakoff et al., 2003). Second, the common latent factor (CLF) method was employed (Gaskin, 2012). Our squared regression weights resulted in 19 % CMV. Although a total elimination of common method bias is not possible, it appears that the measurement model is not strongly impacted by common method bias.

4. Results

Using factor scores, we employed a multivariate regression and two separate regressions to examine how the factors may impact our dependent variables. Table III shows the results of the multivariate regression analysis. All factors were highly significant in the joint explanation of the dependent variables. However, major differences in factor influence are seen when examining the context of virtual agent usage intention. In the basic virtual agent usage intention model ($F = 7.981$, $p < 0.001$, $R^2 = 0.112$), three factors were significant and in the hypothesized direction. The most decisive influence was seen from trust in AI technology (H1a, $\beta = 0\ 0.236$, $p = 0.000$) followed by comfort in using AI technology (H4a, $\beta = 0.184$, $p = 0.001$), then perceived security in AI technology (H2a, $\beta = 0.164$, $p = 0.003$). However, the perception of AI expertise and the need for social presence did not significantly impact basic virtual agent usage intentions. Therefore, H3a and H5a were not supported.

In our advanced virtual agent usage intention model ($F = 12.397$, $p < 0.001$, $R^2 = 0.164$), four factors were determined to be significant

Table 1
Descriptive statistics.

	Mean	SD	1	2	3	4	5	6	7
1. Basic virtual agent usage intentions	3.72	1.03	**.826**						
2. Adv. virtual agent usage intentions	2.97	1.07	.357**	**.878**					
3. Need for social presence	3.60	1.00	.003	.159**	**.814**				
4. Perceived security in AI technology	3.23	0.91	.233**	.320**	.065	**.859**			
5. Comfort in using AI technology	3.71	0.80	.258**	.220**	−.111*	.313**	**.723**		
6. Perception of AI expertise	3.86	0.84	.136*	.308**	.117*	.405**	.429**	**.805**	
7. Trust in AI technology	3.45	0.82	.305**	.207**	−.018	.459**	.559**	.382**	**.799**

Notes. SD = standard deviation; AI = artificial intelligence; **Bold** values are the squared root of the AVE; AVE = average variance extracted.
**Significant at p < 0.01; *Significant at p < 0.05 (2-tailed).

Table 2
Heterotrait-monotrait analysis for discriminant validity.

	1	2	3	4	5	6	7
1. Need for Social Presence							
2. Comfort in using AI technology	0.125						
3. Trust in AI technology	0.021	0.645					
4. Security in AI technology	0.072	0.36	0.51				
5. Perceived AI Expertise	0.135	0.503	0.431	0.452			
6. Basic VA Usage Intention	0.005	0.296	0.343	0.259	0.155		
7. Advanced VA Usage Intention	0.175	0.248	0.226	0.346	0.34	0.391	

predictors and in the hypothesized direction. Perceived security in AI technology (H2b, β = 0 0.272, p = 0.000) had the most substantial impact on the model. Interestingly, in this model, the perception of AI expertise (H3b, β = 0 0.245, p = 0.000) and the need for social presence (H5b, β = 0 0.160, p = 0.004) have a significant impact; neither were significant predictors in the basic virtual agent model. Comfort in using AI technologies (H4b, β = 0 0.146, p = 0.009) was also a significant predictor. Trust in AI technology, the strongest influencing factor in the basic virtual agent model, was not statistically significant in the advanced virtual agent model. Therefore, H1b was not supported.

5. Discussion

The primary objective of this current study was to investigate how consumer perceptions, attitudes, and need for social presence in human-AI service encounters may differ based on the context of basic versus advanced virtual agent usage intentions. The results suggest that consumers do not perceive service encounters with virtual agents in a "one size fits all" approach. Instead, consumers change their value-in-use perceptions based on usage contexts.

Our results for trust are mixed. Trust is the most influential factor for basic virtual agent usage intentions and is consistent with trust studies for e-banking adoption (Manser Payne et al., 2018; Tam & Oliveira, 2017). With routine banking activities, consumers may feel confident that a virtual agent can perform this type of transaction. However, our findings for trust in advanced virtual agent contexts were insignificant. These findings are consistent with Northey et al. (2022). Their study suggests that consumers in high-involvement situations are less likely to believe financial advice from a robo-advisor. As such, this lack of support may result in consumers needing more experience interacting with virtual agents for complex financial problem-solving services to gain consumers' confidence that the virtual agent will perform as expected (Ferrario et al., 2020). Furthermore, advanced financial services tend to be more personal to the consumer and may require time with the virtual agent to build stronger relational bonds (Wirtz et al., 2018; Fernandes & Oliveira, 2021). Gefen and Straub (2003) found that social presence is an enabler for building trust. Our study suggests that banks may need to increase their virtual agent's social skills so consumers may come to trust virtual agents for complex financial services.

Some pre-AI application studies in e-banking (Akturan & Tezcan, 2012; Chau & Ngai, 2010) have argued that security issues are limited in consumer attitudes and usage behaviors due to comfortability in everyday digital banking transactions. Today, security risks are rapidly evolving, with the ability to disrupt the consumer digital experience and modify consumer attitudes. Our research suggests a change in consumer attitudes in that perceived security in AI technology significantly impacts the intention to use virtual agents in basic and advanced contexts. While fraud detection and risk prevention are back-office operations, consumers may perceive AI to have a faster response time to an increasing level of security threats in comparison to an employee (e.g., human) (Lăzăroiu et al., 2023; Rahman et al., 2023). Interestingly, our basic model reflects previous banking studies (Chau & Ngai, 2010; Sharma & Sharma, 2019) suggesting that other factors, such as comfort and trust in technologies, may be more important for routine digital banking activities. Unlike the basic usage context, AI security is the most critical factor associated with advanced virtual agent usage. Consumers

Table 3
Multivariate regression results for basic virtual agent usage intentions and advanced virtual agent usage intentions.

Variables	Multivariate	Basic Virtual Agent Usage Intention			Advanced Virtual Agent Usage Intention		
	Test: Wilk's Lambda	Standard β	t-value	p-value	Standard β	t-value	p-value
Intercept	Λ = .051, p = 0.000	3.718	68.151	0.000	2.972	54.032	0.000
H1: Trust in AI technology	Λ = .944, p = 0.000	**0.236**	4.316	0.000	0.085	1.551	n.s
H2: Perceived security in AI technology	Λ = .922, p = 0.000	0.164	3.004	0.003	**0.272**	4.935	0.000
H3: Perception of AI expertise	Λ = .941, p = 0.000	0.052	0.951	n.s.	**0.245**	4.444	0.000
H4: Comfort in using AI technology	Λ = .957, p = 0.001	**0.184**	3.366	0.001	0.146	2.648	0.009
H5: Need for social presence	Λ = .972, p = 0.012	0.007	0.134	n.s.	0.160	2.909	0.004

Notes: AI = artificial intelligence; Λ = Lambda; Basic virtual agent usage intention (F = 7.981, p < 0.001, $R^{2=}$0.112); Advanced virtual agent usage intention (F = 12.397, p < 0.001, $R^{2=}$0.164); **bold** values indicate the most significant predictors.

may perceive greater security risks with more complex financial services not regularly used. Our results support AI studies (Königstorfer & Thalmann, 2020) that argue that AI-enabled technologies are critical for more complicated banking processes. The study suggests that the greater the risk, the greater the need for security measures in banking activities.

We also examined how perceptions of AI expertise may differ between basic and advanced contexts. Our results show that consumers rate AI expertise as valuable only when conducting more complex banking activities. One explanation may be that today's consumers demand new innovative means to access knowledge (Wirtz et al., 2023). Our study supports Ashta and Herrmann (2021) and Königstorfer and Thalmann (2020), who argue that artificial intelligence's machine learning and data mining capabilities may help solve the consumer's complex financial needs. Additionally, consumers may feel empowered to make personalized financial decisions using an advanced virtual agent embedded with AI capabilities. Conversely, for more routine task-oriented banking activities, consumers may not value the knowledge processes (occurring out of sight in back-office operations) that AI brings to routine financial activities as being innovative or even as needed while depositing a check.

We hypothesized that comfort in using AI technology would positively impact the intentions to use basic and advanced virtual agents. Our results show that consumer level of comfort is impactful for both contexts. This supports previous technology studies (Chen et al., 2016; Hameed & Nigam, 2022; Lee et al., 2021). Consumers frequently access AI technology in multiple situations, such as Siri, Alexa, and ChatGPT. The transfer of comfort in AI technology into the financial industry through basic virtual agent interactions is conceivable. Furthermore, as AI technology improves for advanced contexts, we can expect to see even higher comfort levels, thus strengthening its usage (Lee & Chen, 2022).

Finally, we examined the need for social presence. While previous studies indicated that consumers might require some human warmth in any virtual encounter regardless of task context (Dabholkar et al., 2003; Lee et al., 2021), our novel results indicate that consumers do not need to feel a need for social presence when engaging in basic virtual agent contexts. Social presence may be influenced by the interactivity and vividness of the task being performed (Lee e*t al.*, 2021). It is reasonable that consumers consider social interaction during routine virtual agent usage unnecessary and, therefore, may have little or no need for social presence. As a result, consumers likely just want the task done. Interestingly, in advanced virtual contexts, the consumer expects to perceive a 'human' on the other side of the transaction. Our findings indicate that social presence has a positive impact in advanced contexts. Thus, incorporating social chatbot skills into virtual agents may motivate consumers to engage in service exchanges previously limited to human-to-human (Korzynski et al., 2023; van Pinxteren et al., 2019). Supporting the work of Fernandes and Oliveira (2021), our study indicates that consumers do not associate strong anthropomorphic qualities with advanced virtual agent interactions. This could explain why financial institutions such as Bank of America developed strategies for customer service recovery when interactions between a virtual agent and the customer fail. Bank of America's virtual agent, Erica, will direct the conversation to a human employee when the customer needs more help. It is feasible that with virtual agent technology enhancements, such as GenAI, virtual agents may soon provide stronger, meaningful quasi-social relationships and human-like responses, creating a stronger social presence in virtual agent interactions.

6. Conclusion

The banking industry is creating new value propositions and business models to capitalize on digital servitization trends. Concurrently, banks are infusing services with AI systems and dissolving more traditional services.

Technological advances in AI technology, including generative AI, will continue to shape service encounters (Shahsavar & Choudhury, 2023). What may be seen as unobtainable (e.g., human-like engagement with virtual agents to problem-solve complex financial situations) may someday be viewed as normal interactions with the bank. AI will continue to be a significant driver of digital servitization efforts in the financial industry. Social-emotional and rapport-building AI virtual agents will be needed to expand digital servitization strategies.

6.1. Theoretical implications

Wirtz et al. (2018) propose that consumer acceptance of AI-enabled service robots is based on the bot's ability to address fundamental service needs as well as the social-emotional needs of the consumer. However, our results suggest that the need for social presence is only expected in complex service robot encounters to allow the consumer to perceive a positive psychological experience that will positively influence service robot adoption. Accordingly, our results suggest extending sRAM into complex service encounters. As AI becomes more human-like, it necessitates examining consumer expectations with the interaction and in digital eco-service systems (Pelau et al., 2021).

6.2. Managerial implications

First, banks should consider promoting the trustworthiness of AI and the fact that virtual agents can "get it right" for routine banking needs. While the respondents are comfortable using AI technologies, they still have some security concerns with AI. Banks must invest in enhanced security AI systems. For example, Ally Bank has invested heavily in generative AI with Ally.ai. Partnering with Open AI and other GenAI companies, Ally.ai is an in-house GenAI system that holds customer data internally. Customer information and data are not shared with ChatGPT. Additionally, Ally.ai works in conjunction with employees to refine its capabilities.

Second, advanced service encounters with virtual agents will need AI systems with social skills to empathize with the individual. This point may be critical as social presence enables building trust. As a result, achieving outstanding advanced digital service encounters may be challenging if the bank's AI technology is limited to task-completion chatbots. Significant AI investments may be necessary to ensure an outstanding service experience and to remain competitive in a digital servitization environment.

6.3. Limitations and future research

First, the participants' demographics were primarily comprised of Generation Z from an American university. Future studies with a broader demographic base would enhance our understanding of virtual agent usage contexts. Second, our model is exploratory. As one of the first studies to examine the context of virtual agent usage intentions, there are still many antecedent factors that our paper did not explore. Our model would benefit from including other potentially influencing sRAM dimensional factors, such as rapport and role congruency. Finally, we believe expanding our model to assess and identify the consequences of basic and advanced virtual agent adoption contexts is important. Virtual agents, especially for more complicated and personalized financial services, offer financial institutions new revenue opportunities and a means to differentiate themselves from the competition.

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CRediT authorship contribution statement

Elizabeth H. Manser Payne: Conceptualization, Data curation, Formal analysis, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Colleen A. O'Brien:** Conceptualization, Data curation, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Summary of the measurement model

Construct and Measurement Item	Loadings	Reference
Basic virtual agent usage intentions α = .89; CR = .90; AVE = .68		
In the future, it is likely that I will use my bank's AI-enabled virtual agent to assist me with …		Original scale items
Transferring funds	0.89	
Depositing checks	0.87	
Checking my account balances	0.80	
Paying bills	0.80	
Advanced virtual agent usage intentions α = .93; CR = .93; AVE = .77		
In the future, it is likely that I will use my bank's AI-enabled virtual agent for personalized advice with …		Original scale items
Retirement planning	0.91	
Financial goal setting	0.88	
My investment portfolios	0.88	
Consolidating my debts	0.83	
Perceived security in AI technologies α = .91; CR = .92; AVE = .74		
I believe that my financial data is secure with AI.	0.91	Akturan and Tezcan (2012) and Balapour et al. (2020)
I am confident that my financial data will not get hacked when I used AI technologies	0.87	
I am confident in the security of the financial data if AI technology is used.	0.86	
AI helps to keep my financial information safe.	0.70	
Perception of AI expertise α = .87; CR = .88; AVE = .65		
I think that artificial intelligence …		Nordheim et al. (2019)
Can deliver expert solutions	0.85	
Is competent enough to provide expert recommendations	0.84	
Is capable of providing expert advise	0.81	
Is knowledgeable	0.70	
Comfort in using AI technologies α = .84; CR = .84; AVE = .52		
I feel comfortable using AI technology.	0.83	Manser Payne et al. *(2018)*
I am confident that I can use AI technology	0.83	
Overall, I would be comfortable interacting with AI technology	0.77	
AI technology is exciting	0.61	
I would enjoy using AI technology	0.60	
Need for social presence α = .90; CR = .91; AVE = .66		
How important is each of the following when interacting with a virtual agent?		Gefen and Straub (2003)
A sense of human sensitivity	0.91	
A sense of human warmth	0.89	
A sense of empathy	0.86	
A sense of human conversation	0.78	
A sense of personalization	0.77	
Propensity to trust AI α = .89; CR = .88; AVE = .64		
I generally trust AI	0.84	Nordheim et al. (2019)
I think that AI is trustworthy	0.83	
My tendency to trust AI is high	0.77	
I trust that AI will do what is right for me	0.71	

Notes: CR = composite reliability; AVE = average variance extracted. The sample consisted of 322 respondents.

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