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Explanation of time perspectives in adopting AI service robots under different service settings

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ABSTRACT

This study bridges a gap in AI acceptance literature by integrating Time Perspective Theory with the Technology Acceptance Model by examining how time orientations influence AI acceptance in various service settings. The results show that past-positive, present-hedonistic, and future time perspectives impact individuals' privacy concerns and their recognition of AI's utilitarian and hedonic benefits. Conversely, past-negative and present-fatalistic perspectives show negligible effects. The study highlights distinct patterns in credence versus experience services, with future-oriented and present-hedonistic individuals favoring AI's benefits in hospitals over restaurants, and past-positive individuals valuing hedonic benefits more in restaurant settings. These orientations affect perceived usefulness and ease of use, with privacy concerns significantly influencing ease of use. The findings offer significant theoretical and practical implications, underscoring the nuanced role of time perspectives in AI service robot acceptance across different environments.

1. Introduction

The artificial intelligence (AI) service robotics market is projected to achieve a market size of US$ 6.55 billion by 2023, demonstrating an annual growth rate of 13.75% (Statista, 2023). This trajectory is expected to lead to a market volume of US$16.14 billion by the year 2030 (Statista, 2023) highlighting the need to understand what will lead to the adoption of AI service robots. Recent systematic literature reviews identified important factors affecting AI adoption, including user-related characteristics (e.g., demographic, technology readiness), AI-related characteristics (e.g., anthropomorphism, visual attractiveness), usage-related factors (e.g., performance expectancy, effort expectancy), among others, and that AI adoption behaviors are context-contingent (Chi et al., 2020; Goel et al., 2022; Ling et al., 2021). In the service context, users are becoming increasingly impatient and dissatisfied with the time it takes to retrieve information from traditional services, leading them to switch to AI-powered services (McLean and Osei-Frimpong, 2019a). To this end, AI is blurring the time barrier by offering time-saving for customer service such as 24/7 fast and convenient access to customer support (Adamopoulou and Moussiades, 2020; Akhtar et al., 2019) that frees up human agents for more complex inquiries by handling repetitive tasks. Despite the pivotal role of time influencing AI adoption behavior, the current AI literature about time is limited with a focus on the characteristic of AI (i.e., timeliness) (Ling et al., 2021) rather than human perspective on time. Time, a contextual factor, is overlooked by systematic literature reviews of AI and robotics in the hospitality and tourism sector (Goel et al., 2022), conversational agents (Ling et al., 2021), and AI devices in service delivery (Chi et al., 2020). As such, little is known about the influence of time from a human's perspective on AI adoption. Neglecting to address human time perspectives in AI adoption can lead to several critical pitfalls. First, there may be a misalignment with user values, resulting in AI systems that fail to resonate with the intrinsic motivations and expectation of diverse user groups. This misalignment can exacerbate reduced trust and privacy concerns, as users may perceive the technology as invasive or not safeguarding their personal data adequately. Furthermore, poor user experience and satisfaction are likely, as interfaces and functionalities that do not account for users' temporal preferences and may be seen as unintuitive or cumbersome. Ineffective communication and marketing strategies that ignore these time orientations can result in promotional efforts that fail to engage or attract potential users effectively. Additionally, resistance to change may be heightened, particularly among users who feel their long-standing habits and preferences are not being valued or addressed by the new

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technology. Ultimately, these issues can culminate in a failure to achieve the full potential of AI, with underutilized features and impeded innovation due to a lack of alignment with the temporal expectations and behaviors of the user base.

Despite its profound impact on human nature, the significance of time is often underappreciated by the general population, and researchers (Zimbardo and Boyd, 2008). This has prompted research to challenge the often taken-for-granted nature of time (Shipp and Jansen, 2021), and advocate for a more nuanced examination (Feldman et al., 2019). As the tools (e.g., AI robots, conversational agents) individuals employ for temporal thinking and action undergo rapid changes (Nagy et al., 2021), the need to address the mechanism of how the subjective experience of time changes (i.e., time perspectives) influence their adoption behaviors becomes a promising area for investigation (Zambianchi et al., 2019). Specifically, one of the most important concepts in mainstream temporality research is time perspective (TP) (Zambianchi et al., 2019; Zimbardo and Boyd, 2008). TPs have been demonstrated to play an important role in explaining different behaviors, such as ecotourism intention (Pham and Khanh, 2021), impulsive consumption (Unger et al., 2018), self-disclosure during COVID-19 (Fu et al., 2022), information and communication technologies adoption (Zambianchi et al., 2019), and social networking site usage (Lee, 2023), as users with varying TPs shape their cognitive processing in distinct ways (Zimbardo and Boyd, 1999). As AI is becoming pervasive in our daily lives, the influential role of TPs and their impact mechanisms on beliefs, intentions, and adoption behaviors toward AI remains unexplored. This signals the first research question to fill this chasm.

RQ1. How TPs shape AI service robot adoption behaviors and under what mechanism?

Individuals with different TPs exhibit unique psychological traits and tend to process a situation in distinct ways. For example, individuals with open-ended future time perspectives prioritize utility and outcomes over the process, while those with limited future time perspectives prioritize the process, influenced by their emphasized hedonic motivation (Park et al., 2021). In the field of technology acceptance, the two prominent and distinguishable constructs – perceived usefulness (PU) and perceived ease of use (PEOU) in the seminal Technology Acceptance Model (TAM) are notably outcome-oriented and process-oriented in nature (Davis and Wong, 2007; Park et al., 2021). An expected influence of individuals with different TPs funneled towards the acceptance of service robots via different cognitive paths (e.g., outcome- or process-oriented), thus, has a ground to be tested. Similarly, recent studies found that factors influencing service robot acceptance (SRA) vary across different service settings (Li et al., 2023; Liu et al., 2022; Park et al., 2021) and concluded the need to take into account service settings when investigating SRA factors (Li et al., 2023; Liu et al., 2022; Park et al., 2021). For example, customers' PEOU is higher in the experience (vs credence) service setting (Li et al., 2023). To summarize, in service domains with experience attributes, consumers can readily assess the service post-experience, while evaluating the outcome of credence services remains challenging, even after experiencing them. For the mentioned rationale, we argue that the cognitive processing of users with different TPs would also vary under different service settings. The second research question is, thus, established.

RQ2. How and to what extent TPs influence AI service robot adoption behaviors in different service settings?

This paper addresses the identified gaps in AI adoption literature by responding to two research questions and making three contributions in the process. First, empirical findings unveiled the mechanism through which users with different TPs process their AI adoption behaviors via relevant cognitive pathways embedded in the Technology Adoption Model (TAM) – one of the dominant theories employed in AI service robot adoption literature (Goel et al., 2022). TAM facilitated the comparison between the present study and recent AI service robot studies probing into different service settings (Li et al., 2023; Liu et al., 2022; Park et al., 2021), further enriching our understanding about the moderating role of service settings on users with distinctive TPs. The second contribution addresses the call of Park et al. (2021) to further separate the experience service attribute into utilitarian and hedonic aspects, employing both motivations to drive motivations across settings (e.g., restaurant vs. hospital) and how users with varying TPs develop adoption behaviors triggered by compatible motivations. Privacy concerns were considered due to their significance in explaining adoption reluctance (Pitardi and Marriott, 2021; Zhu et al., 2023), consistently across service settings (Park et al., 2021). Yet, it remains unknown if users with varying TPs process their privacy concerns differently, and are potentially influenced by disparities in the perception of costs, consequences, and life goals (Zimbardo and Boyd, 1999). The paper, thus, makes a third contribution in this regard.

The paper is structured as follows: First, we present the theoretical foundation, the service classification scheme, Time Perspective Theory (TPT), and relevant literature. Next, we introduce the hypotheses. Subsequently, the methodology employed is detailed. The results are presented followed by a detailed discussion on the theoretical and practical implications. Finally, the paper concludes with limitations and areas for future research investigations.

2. Literature review and research hypotheses

2.1. Time perspective theory

Time perspective refers to how individuals categorize their personal and social experiences into distinct temporal categories. This categorization influences decision-making by placing the primary set of psychological influences within the temporal frames of the present, past, or future (Zimbardo and Boyd, 2008). Originated from the Field theory (Lewin, 1951), Zimbardo's Time Perspective Inventory (ZTPI) was conceived to address individual differences in the mentioned temporal categories which are divided into five aspects of TPs namely past negative, past positive, present hedonistic, present fatalistic, and future perspectives. The time perspective significantly influences cognitive processes by shaping an individual's interactions with technology through the formation of diverse beliefs, attitudes, and behaviors (Lee, 2023). TPT has been employed as a foundational framework in technology acceptance research, demonstrating successful integration into established mainstream technology acceptance theories (e.g., TAM) (Alexandrakis et al., 2020; Lee, 2023; Zambianchi et al., 2019). This justifies the theoretical appropriateness of TPT for the present study. Additionally, a review of relevant research in technology adoption and service contexts is summarized in Table 1.

2.1.1. Past perspectives: past positive/negative

Zimbardo and Boyd (1999, p. 1275) defined past-positive as "a warm, sentimental attitude toward the past". The past-positive TP captures a subjective record of positive events that people experienced, or a positive mindset even in aversive events which make them resilient and optimistic (Zimbardo and Boyd, 2008). Individuals with past-positive TP are characterized by a glowing, nostalgic, positive construction of the past with low depression, low aggression, low anxiety, high self-esteem and happiness, and a healthy outlook on life. High scorers on the past-positive scale also possess high energy, friendliness, and creativity, moreover, they tend to maintain a healthy life (e.g., less often alcohol consumption) and are risk-averse (Zimbardo and Boyd, 1999). In contrast, individuals with a past-negative TP exhibit a pessimistic, negative, or aversive attitude toward the past, and this orientation is linked to depression, anxiety, unhappiness, and low self-esteem. Such individuals are less inclined to adopt a healthy lifestyle (e.g., regular exercise), but are more prone to risky behaviors (e.g., gambling).

Table 1
A review of research in technology adoption and contexts.

References	Context	Technology	Theory	Antecedents	Dept. var.	Key findings
Yao et al. (2024)	Restaurant/ Insurance	AI Service robot	GT, FT	Service type (credence vs experience) (moderator) Privacy concern Customer data vulnerability	Adoption intention	• Privacy concerns and service type interact to influence willingness to adopt service robots. • High privacy concerns: lower willingness in credence services compared to experience services. • Customer data vulnerability mediates the relationship between privacy concern, service types, and adoption intention.
Bhuiyan et al. (2024)	Hotels/resorts	AI Service Devices	AIDUA	Social influence Hedonic motivation Anthropomorphism Performance expectancy Effort expectancy Emotion	Willingness to use Objection to use	• Consumer willingness and objection to use are influenced by social influence, hedonic motivation, anthropomorphism, performance expectancy, effort expectancy, and emotions. •Hedonic motivation, social influence, and anthropomorphism impact performance and effort expectations, which in turn affect emotions • Emotions determine hotel customers' willingness to use AI devices.
Lee (2023)	General	Social Networking Sites	TAM, TPT	Past positive Past negative Present hedonic Present fatalistic Future Promotion focus Innovativeness Usefulness Ease of use	Attitude	• Past positive TP enhances promotion focus and innovativeness. • Past negative TP diminishes promotion focus and innovativeness. • Present hedonic TP boosts innovativeness. • Present fatalistic TP reduces promotion focus. • Future TP increases promotion focus and innovativeness. • Ease of use and usefulness mediate the relationship. between TP and attitude toward social networking sites, both independently and sequentially.
Li et al. (2023)	Hotel/Hospital	AI Service robot	RT, RC-TAM	Ability Role clarity Anthropomorphism Autonomy Usefulness Ease of use	Attitude Adoption intention	• Customers in experience service settings have stronger positive attitudes toward and a greater intention to use service robots compared to those in credence service settings. • Perceived usefulness is positively influenced by the anthropomorphism of service robots and customer ability in experience but not credence service settings. • Service robot autonomy positively relates to perceived ease of use in credence settings but not experience settings. • Higher customer ability and perceived ease of use, and lower perception of anthropomorphism in experience (vs credence) settings.
Liu et al. (2022)	Café/Insurance	AI Service robot	CT, UT	Service type (credence vs. experience) (moderator) Service component (core vs. peripheral) Perceived uncertainty	Adoption intention	• In credence services, lower adoption intention for core components compared to peripheral components • In experience services, high adoption intention for both core and peripheral components. • Perceived uncertainty mediates the interaction between service type and components on adoption intention.
Chi et al. (2022)	Hospitality/ Airline	AI service devices	AIDUA	Social influence Hedonic motivation Anthropomorphism Performance expectancy Effort expectancy Emotion	Willingness to use Objection to use	• Social influence is a stronger determinant in hospitality services • Higher performance expectancy for AI in airline (vs hospitality) services • Lower willingness to accept AI in hospitality (vs airline) services.
Park et al. (2021)	Café/Hospital	AI Service robot	TAM	Privacy concern Trust Usefulness Ease of use	Attitude Adoption intention	• Consumers' psychological processes are not the same in different service areas. • Usefulness is a significant underlying mechanism affecting attitudes in AI adoption in a credence (vs. experience) service setting. • Privacy concerns and trust are significant across all service settings
Park et al. (2021)	Online grocery	Self-service grocery	SST	Open-ended future TP Limited future TP Expected desirability Expected feasibility	Adoption intention	• Consumers with a limited (vs. open-ended) future TP negatively assess the desirability and feasibility of self-service technology. • Future TP has a stronger impact on evaluation and adoption intention when functional value is emphasized over emotional or social value.
Lin et al. (2020)	Full/limited-service hotels	AI Service robot	AIDUA	Social influence Hedonic motivation Anthropomorphism Performance expectancy Effort expectancy Positive emotion	Willingness to use Objection to use	• Full-service hotel customers rely less on social groups when evaluating AI robotic devices. • Their emotions are less influenced by effort expectancy • Their emotions have a lesser impact on objection to AI device use.
Alexandrakis et al. (2020)	General	Storytelling app	TAM, TPT	Age Future TP Loneliness	Adoption intention	• Future TP positively influences perceived ease of use • Age and loneliness have no statistically significant effects. • Perceived ease of use influences perceived usefulness positively, and both positively impact adoption intention.

(*continued on next page*)

Table 1 (*continued*)

References	Context	Technology	Theory	Antecedents	Dept. var.	Key findings
Zambianchi et al. (2019)	General	ICTs	TPT	Usefulness Ease of use Age Gender Education Living status Nationality Gender x Nationality Past negative Past positive Present fatalistic Present hedonistic Future negative Future positive	Attitude Usage	• Swedish older adults had more positive attitudes and more frequently use of Information and communication technologies (ICTs) than Italian counterparts. • Younger age and higher educational attainment were positively associated with attitudes towards ICTs. • Italian men had higher attitude but gender effect was not observed in Sweden. • Past negative, future negative, and present fatalistic were negatively associated with attitudes. • Future positive, present hedonistic were positively associated with attitude.
This study	Restaurant/ Hospital	AI service robot	TAM, TPT	Past positive Past negative Present hedonistic Present fatalistic Future Utilitarian benefits Hedonic benefits Privacy concerns Usefulness Ease of use	Attitude Adoption intention	• Past positive, present hedonistic, and future TP positively impact privacy concerns and recognition of AI's utilitarian and hedonic benefits. • Past negative and present fatalistic TP show negligible effects • Future and Present-hedonistic individuals prefer AI benefits more in hospitals than restaurants. • Past-positive individuals value hedonic benefits more in restaurants. • Privacy concern significantly influences ease of use.

Note: TAM: Technology Acceptance Model; RC-TAM: Service Robot-Customer Technology Acceptance Model; AIDUA: Artificially Intelligent Device Use Acceptance; TPT: Time Perspective Theory; SST: Socioemotional Selectivity Theory; GT: Gossip Theory; FT: Fairness Theory; RT: Role Theory; CT: Centrality Theory; UT: Uncertainty Theory; TP: Time Perspective.

Moreover, high scorers on past-negative TP typically lack motivation to pursue future rewards and demonstrate lower levels of openness, energy, emotional stability, and impulse control (Zimbardo and Boyd, 1999). Indeed, experts have corroborated an increasing proclivity towards promotion focus as well as innovativeness by past-positive TP; conversely, past-negative TP diminishes such inclinations within the milieu of technology adoption (Lee, 2023).

AI research has elucidated the significance of the perceived benefits concomitant with affective attachment (i.e., hedonic benefits), and pragmatic utility (i.e., utilitarian benefits) (Gursoy et al., 2019; Lin et al., 2020). To formulate how past-positive/negative TPs influence the perceived benefits of AI service robots, it is of utmost importance to lay out what aspects of the perceived benefits are aligned with each type of user. Utilitarian benefits encompass functional, practical, and instrumental advantages (Patrizi et al., 2021). These encompass efficient task completion through autonomous decisions and access to extensive knowledge, leading to time savings and improved life efficiency for customers (Frank et al., 2021). On the other hand, hedonic benefits pertain to aspects of the users' aesthetic and emotional experience, encompassing elements such as enjoyment (Pitardi and Marriott, 2021), excitement, pleasure (Huang et al., 2021), or playfulness (Terzis et al., 2012). With a positive, energetic, and open disposition toward similar past experiences, it is plausible to argue that users with past-positive TPs would naturally be inclined to embrace AI service robots. This inclination stems from the anticipation of both time-saving and enjoyable benefits, aligning with their overall healthy lifestyle. While risk-averse individuals with past-positive TPs might demonstrate increased privacy concerns, leading to heightened anxiety and mistrust (Park et al., 2021), our contention differs. Given their sanguine posture in confronting arduous situations, users with past-positive TP are more proclive to trust AI's safeguard of their data. Conversely, those with past-negative TP may remain cynical about AI's utilitarian and hedonic benefits, impeaching the safeguarding of their private data.

2.1.2. *Present perspective: present hedonic/fatalistic*

Present TP can be broken down into two components: Present-hedonic and present-fatalistic TPs. Present-hedonic individuals prioritize living in the moment rather than overly worrying about their past or future (Merchant et al., 2014). They focus on current enjoyment, pleasure, and excitement, without making sacrifices today for future rewards. High scorers for present-hedonic TP are less inclined to consider future consequences, exhibit a low preference for consistency, possess a low ego or impulse control, and have an emphasis on novelty and sensation seeking (Zimbardo and Boyd, 1999).

Meanwhile, those with present-fatalistic TP often harbor feelings of helplessness and hopelessness toward life (Zimbardo and Boyd, 1999). What distinguishes this type is a belief that the future is predestined and unaffected by individual actions and that humans are subject to the capricious whims of fate. Contrary to present hedonists who prioritize hedonic goals, present fatalists lack a promotion focus (Lee, 2023). This indicates reduced motivation and persistence for performative tasks. Present-fatalistic TP is anticipated to exert a negative impact on perceived benefits, with an opposite effect expected from present-hedonic TP. Though both prioritize the present, it remains arduous to contend individuals with these TPs would be concerned about potential ramifications from inappropriate use of private data. Nonetheless, empirical investigations demonstrate a robust correlation between present-hedonic TP and proclivities for risk-taking behaviors (Chavarria et al., 2015; Zimbardo and Boyd, 1999). Inversely, present-fatalistic TP may instantiate an oppositional relationship to mitigate anxieties from uncontrollable activities. A similar pattern was found in ICT adoption where attitude was negatively associated with present-fatalisitic TP but positively with present-hedonistic TP (Zambianchi et al., 2019).

2.1.3. *Future perspective*

Lewin (1951, p. 75) defined Future TP as "the totality of the individual's views of his psychological future … at a given time" and that our perception of the future not only significantly shapes our behaviors but also reflects a cornerstone in the development process. Specifically, future TP involves the planning and attainment of future goals (Zimbardo and Boyd, 1999). Therefore, individuals with future TP are expected to be future-consequences oriented, conscientious, consistent, and reward-dependent, alongside a lower level of sensation seeking. They also possess a sense of time-use efficiency to reach their high standards in what they do and are willing to sacrifice short-term hedonic pursuits for long-term gains (Sekścińska and Iwanicka, 2021; Zimbardo and Boyd, 2008). Empirical evidence has indicated a positive association between future TP and promotion focus (Baltes et al., 2014; Lee, 2023), as well as innovativeness, both of which are established antecedents to technology acceptance (Lee, 2023). Given their future orientation, future-oriented individuals are expected to prioritize utilitarian over hedonic benefits when adopting AI service robots. Despite obvious gains from using AI, these future-minded users may avoid risks that could hinder goal attainment. Thus, a negative association between future TP and privacy risks surrounding Ai adoption is hypothesized.

2.2. Service classification

Service classification literature classifies service areas along the continuum of search, experience, and credence (SEC) attributes (Girard and Dion, 2010; Mitra et al., 1999). SEC framework relies on the consumer's assessment of risk when evaluating service outcomes. Customers who have limited access to information before a service tend to perceive increased risks, leading to a decreased intention to accept the service (Mitra et al., 1999). A service with a search attribute (e.g., bank deposit, car rentals, hotel accommodations) allows customers to retrieve relevant information and easily evaluate that service before using it. In contrast, a service with experience (e.g., hairdressing, restaurant dining) or credence (e.g., legal, financial advisory, medical diagnosis) attributes can only be evaluated after its use. Hence, customers' perceived risks and uncertainty are higher in experience and credence (vs search) services (Li et al., 2023; Park et al., 2021). Due to the time lag until realized benefits, heightened risks, and service environments (e.g., restaurants, hospitals) where AI service robots are employed, experience and credence service settings are of higher interest from recent studies (Li et al., 2023; Liu et al., 2022; Park et al., 2021). For that reason, we also focus on experience and credence service settings.

Research examining how service scenarios influence the adoption of service robots is still in its early stages (Liu et al., 2022). Among recent studies investigating the difference between service settings, Park et al. (2021) found the moderating role of service type (i.e., experience vs credence) on the relationships between PU, PEOU, and attitudes and intentions to use service robots. Liu et al. (2022) further decomposed service components into core and peripheral and concluded the interaction effect between service component and service type (credence vs. experience) on service robot adoption intention. Additionally, customers have a lower adoption intention in the core (vs. peripheral component) for credence service, whereas no difference was found for experience service. Li et al. (2023) further extend the stream of research by considering customer characteristics (i.e., ability, role clarity) and robot characteristics (i.e., anthropomorphism, autonomy) guided by TAM. Their results reinforce the variance of SRA factors in different service settings. Specifically, PU is influenced by anthropomorphism and customer ability in experience but not credence settings. Conversely, service robot autonomy correlates with PEOU in the credence but not experience settings. Customer ability and PEOU are higher, while anthropomorphism is lower in the experience setting.

While prior research has explored antecedents of technology adoption across service contexts, a gap remains in understanding the heterogeneous motivations of different user groups. Motivations for utilizing service robots are multidimensional, driven by both utilitarian and hedonic factors contingent on the environment. This study not only accounts for these disparate motivations but also examines how individual differences in TPs influence the mechanism underlying AI service robot adoption motivations.

2.2.1. Cross-service differences

To address the second research question, we examined the psychological pathways of users with different TPs across credence (i.e., hospital) and experience (i.e., restaurant) service settings. Regarding privacy concerns, we expected the influence of risk-averse TPs (present-fatalistic and future) to be more pronounced in experience than credence services compared to risk-taking TPs (past-positive, past-negative, present-hedonistic). Unlike experience services, credence services lack standardization, necessitating higher service capabilities and involving lower customer knowledge (Liu et al., 2022; Mitra et al., 1999), potentially explaining lower perceived risks in experience settings (Liu et al., 2022; Park et al., 2021). Moreover, the high knowledge barrier in credence contexts (Li et al., 2023) suggests that additional information may not influence present-fatalistic users' perceived benefits across settings. However, for past-negative, past-positive, present-hedonistic, and future TPs, the impact might differ between experience (i.e., lower risk and knowledge barrier) and credence settings.

H1. Past positive (vs. negative) TPs influences (a) utilitarian benefits, (b) hedonic benefits, and (c) privacy concerns positively and (d) those effects are stronger in experience than credence service settings.

H2. Present hedonistic- (vs. fatalistic) TP influences (a) utilitarian benefits, (b) hedonic benefits positively and negatively for (c) privacy concerns and (d) those effects are stronger in experience than credence service settings for present-h22hedonistic TP but (e) there is no difference for present-fatalistic TP.

H3. Future TP influences (a) hedonic benefits and (c) privacy concerns negatively, and (b) utilitarian benefits positively and (d) those effects are stronger in experience than credence service settings.

2.2.2. Utilitarian and hedonic benefits of AI

Depending on the expected value from the service, customers tend to emphasize the hedonic value when their usage objective is entertainment-related (Foroughi et al., 2023; Rese et al., 2020; Zhang and Wang, 2023), evaluating the service outcome based on enjoyment and emotional satisfaction. Conversely, when the usage goal is task-oriented, the emphasis shifts to utilitarian value (Ling et al., 2021; Zhang and Wang, 2023), with the evaluation of outcomes based on the fulfillment of utilitarian needs (Rese et al., 2020). For instance, recent empirical investigations have elucidated that consumers exhibit a predilection for hedonic benefits when procuring hospitality services (i.e., hotels, restaurants), in contrast to airline services (Chi et al., 2022). Moreover, hedonic motivation was found to be associated with performance expectancy and effort expectancy (Bhuiyan et al., 2024; Gursoy et al., 2019). Customers who find using AI enjoyable and appealing are likely to perceive AI as more useful and require less effort to utilize. Aligned with the utility-driven nature of the credence setting and hedonic-driven nature of the experience setting, the effect of hedonic motivation would be stronger in the experience than credence setting.

On the other hand, customers would weigh more focus on the utilitarian aspect of the credence service and are more inclined to evaluate the usefulness of AI service positively (Chi et al., 2022). The notion of AI's utilitarian benefits already implies the ability to interact effortlessly without the need to even look at or interact physically (e.g., via voice command) (Patrizi et al., 2021). This could create a synergistic effect that triggers the positive influence of utilitarian benefits on perceived ease of use. In other words, utilitarian-oriented users would also perceive AI service robots easy to use. The following hypotheses are postulated.

H4. The utilitarian benefits enhance customers' (a) PU and (b) PEOU. (c) The effects are more in credence than experience service settings.

H5. Hedonic benefits influence customers' (a) PU and (b) PEOU positively and (c) the effects are stronger in experience than credence service settings.

2.2.3. Privacy concerns about AI

The negative role of privacy concerns has been highlighted in mainstream AI research recently (Kamoonpuri and Sengar, 2023; McLean and Osei-Frimpong, 2019b; Pitardi and Marriott, 2021; Rese et al., 2020). Privacy concerns arise when personal data is collected, used, or controlled without proper authorization (Malhotra et al., 2004). The adverse impacts of inadequate privacy protection are recognized for reducing customer attitudes and, consequently, their willingness to adopt AI (Pitardi and Marriott, 2021; Zhu et al., 2023). This perception also contributes to AI service robots being perceived as less valuable. Moreover, the effort to investigate in understanding, using and accepting AI service robots may be diminished by unauthorized access or mishandling of data. This is in line with the findings of Park et al. (2021). These authors further affirmed no notable difference between experience and credence settings for privacy concerns. We, therefore, hypothesize the following.

H6. A lower privacy concern will enhance customers' (a) PU and (b) PEOU and (c) there is no significant differences between experience and credence service settings.

3. Method

3.1. Data collection and sampling

We utilized Prolific – a widely employed online recruitment and data collection platform to conduct an online survey in February 2024. Respondents, compensated at a minimum hourly wage, were recruited from the United States. The choice of the USA as the survey sample aligns with the country's leading market size of US$2479 million in 2023 (Statista, 2023). This justifies the extensive adoption of AI service robots and rationale behind selecting respondents from this region.

A pilot test of 10 U.S. respondents was conducted to further revise and simplify the language of the questionnaire. Respondents were randomly assigned to the restaurant and hospital groups relatively equal. To calculate our minimum sample size, we calculated by considering the number of latent constructs, observed items, probability level, desired effect size, and desired statistical power. Used the calculator of Soper (2023), the probability level of 0.05, statistical power of 0.9, and effect size of 0.3 yielded a minimum sample size of 210. 33 records were removed due to excessively long or short response times. The remaining sample size of 287 (approximately 51%) for the restaurant cohort, and 271 (approximately 49%) for the hospital cohort are appropriate, summing a total of 558 completed questionnaires.

3.2. Research design

Following Park, Tung, et al. (2021), a scenario-based online survey was employed. This method was proven to succeed in elaborating the differences in multiple service settings (Li et al., 2023; Park et al., 2021). The questionnaire consisted of three parts. In the first section, the definition of service robot according to The International Organization for Standardization (ISO 8373:2012) as a "robot that performs useful tasks for humans or equipment excluding industrial automation applications" was introduced. This ensured a uniform understanding of service robots among all respondents.

Using Qualtrics randomization feature, respondents were assigned a scenario randomly, each accompanied by a brief description outlining relevant tasks for a service robot between a hospital (credence setting) and a restaurant (experience setting). Specifically, respondents were instructed to envision themselves within the given scenario and pay close attention to all the details of the situation. To facilitate their elaboration an illustration generated by Stablediffusion – a free and open-source platform was offered (see **Appendix 2**). Similar to Park et al. (2021), confounding variables were controlled by mentioning that respondents could experience the same quality of service through the use of service robots in a hospital or café, with no additional cost or time compared to current services. The five-point Likert scales (strongly disagree to strongly agree) were adapted from Sun et al. (2012) and Liu et al. (2022), with two confound checks included. The first assessed respondents' confidence in evaluating the service setting with the item "I am confident that I can accurately evaluate the service of the restaurant/hospital" (M = 4.03). The second assessed the perceived realism of the scenario with the item "the scenario described in the material is realistic" (M = 4.05). The results indicated that respondents were confident in their judgment and perceived the stimuli as highly realistic. However, both had no significant impact on their intention to use, suggesting that the scenario analysis was not confounded by differences in perceived realism and confidence levels.

The second part of the study included the adapted measurement of 12 latent constructs: past-positive, past-negative, present-hedonic, present-fatalistic, future TPs (Peng et al., 2021; Zimbardo and Boyd, 2008), utilitarian and hedonic benefits (McLean and Osei-Frimpong, 2019b; Yuan et al., 2022), privacy concerns (Park et al., 2021), PU and PEOU (Park et al., 2021), attitude (Park et al., 2021), and intention to use AI service robot (Venkatesh et al., 2012) (see **Appendix 1**). All items were measured on a five-point Likert-type scale ranging from 1 "strongly disagree" to 5 "strongly agree". For the time perspective constructs, we adopted the most robust and short version proposed by Peng et al. (2021), acknowledged for its enhanced internal consistency, improved psychometric properties compared to the original scale, and potential to mitigate boredom and fatigue among respondents. The five-point Likert-type of these constructs ranged from 1 "very untrue" to 5 "very true".

The third part contained demographic characteristics of the respondents including age, gender, education, occupation and marital status. Prior experience was included as a covariate in the model due to its potential impact (McLean and Osei-Frimpong, 2019a; Wang and Qiu, 2024). Similar to the finding of Park et al. (2021), the overall results remain unchanged with(out) the covariate. In addition, no group differences were found in terms of prior experience in service robot usage.

3.3. Common method bias

To mitigate potential common method bias, several procedural remedies outlined by MacKenzie and Podsakoff (2012) were implemented. Our pilot test sought to overcome limitations related to respondents' verbal ability, education, or cognitive sophistication by ensuring questionnaire clarity and simplicity. We provided a concise definition of service robots, supported by scenario descriptions and visual aids, to promote uniform understanding among respondents. Additionally, rigorous attention was given to question clarity, with scrutiny to eliminate double-barreled inquiries, complex syntax, and ambiguous terms. Response options were meticulously labelled to prevent item ambiguity. Recognizing that impulsiveness may hinder comprehension and information accuracy, we emphasized the importance of conscientiousness and encouraged respondents to read each question thoroughly. To maintain data integrity, responses with excessively long or short durations were excluded. Moreover, to streamline the assessment process, we opted for a condensed version of the ZTPI, utilizing a 16-item scale instead of the original 56-item scale.

4. Data analysis and results

Data were analyzed using a structural equation model by Smart-PLS 3.33. Due to the model's complexity and prediction orientation by aiming to explain the cause-effect mechanism postulated, PLS-SEM deems appropriate in its ability to handle highly complex models with many indicators, and constructs (Hair et al., 2019; Sarstedt et al., 2022). The predictive nature of technology acceptance models fits well with PLS-SEM approach which makes the method highly valuable, particularly in marketing discipline (Li et al., 2023; Sarstedt et al., 2022). Additionally, recent studies in this research stream have successfully applied PLS-SEM for similar analyses (Bhuiyan et al., 2024; Li et al., 2023; Rese et al., 2020).

4.1. Demographic characteristics

The demographic characteristics of the respondents suggest potential generalizability. The sample consisted of 54.7% females (n = 305). Age distribution was as follows: 18–25 (6.3%, n = 35), 26–34 (24.7%, n = 138), 35–54 (45.5%, n = 254), 55–64 (12.2%, n = 68), 65+(11.3%, n = 63). Educationally, 51.4% were university graduates (n = 287), 19.4% had postgraduate degrees (n = 108), and 29.2% had a high school diploma or less (n = 163). Regarding occupation, the majority were professionals (35.1%, n = 196) or managers (18.8%, n = 105), with others (25.4%, n = 142) in varied roles, followed by homemakers (9.5%, n = 53), salespersons (7.7%, n = 43), and student (3.4%, n = 19). Marital status distribution was: married (50.2%, n = 280), single (28%, n = 156), live together (10.8%, n = 60), divorced (9%, n = 50), and widowed (2.2%, n = 12). Notably, 62.4% (n = 348) had no prior experience with AI service robots. The demographic spread across age, education, occupation, and marital status provides a balanced view, supporting the external validity of the study.

4.2. Measurement model

The reliability and validity of the measurement model were assessed using Cronbach's alpha, composite reliability, and average variance extracted (see Table 2). Cronbach's alpha and composite reliability exceeded 0.7, while the average variance extracted surpassed 0.5, confirming internal consistency (Fornell and Larcker, 1981). Subsequent to eliminating ATT1, ATT2, INT1, INT3, HB3, UB3, PU2, PU3, PC2, and PN1 with VIFs exceeding 3, the remaining VIF values were within the acceptable limit (Hair et al., 2019). PH2 and PH3 were retained to uphold internal reliability above 0.7, while PF3 was omitted due to a loading below 0.5. All remaining indicator loadings exceeded the threshold, confirming acceptable item reliability.

The values of the square root of the average variance extracted values on the diagonal were higher than all inter-construct correlations in the same column, proving sufficient discriminant validity (see Table 3). Additionally, the HTMT statistics are below 0.9, thereby confirming discriminant validity (see Table 4). We also tested common method bias by performing Harman's single-factor analysis detailed by Podsakoff et al. (2003). The results showed that a single factor explained 32.210% of the maximum covariance (less than 50%). Hence, the common method bias was not established.

4.3. Structural model

We followed guidelines from Hair et al. (2019) for the structural model analysis. Since collinearity was not an issue, R^2 values were examined. The model fit indicated that the adjusted R^2 values of latent constructs were significantly lower than the 0.05 level, except for privacy concerns. Specifically, these latent constructs were intention (adj. $R^2 = 0.658$, $p < 0.001$), attitude (adj. $R^2 = 0.626$, $p < 0.001$), hedonic benefits (adj. $R^2 = 0.089$, $p < 0.001$), utilitarian benefits (adj. $R^2 = 0.058$, $p < 0.05$), privacy concerns (adj. $R^2 = 0.039$, $p > 0.05$), PU (adj. $R^2 = 0.617$, $p < 0.001$), and PEOU (adj. $R^2 = 0.332$, $p < 0.001$). To assess the model's predictive accuracy, Stone-Geisser's Q^2, based on the blindfolding procedure. The Q^2 values obtained were as follows: intention (0.582), attitude (0.620), PU (0.539), PEOU (0.233), hedonic benefits (0.065), utilitarian benefits (0.046), privacy concerns (0.033). As a rule of thumb, Q^2 values higher than 0, 0.25, and 0.5 indicate small, medium, and large predictive relevance of the PLS-path model (Hair et al., 2019). Additionally, the PLSpredict procedure was utilized to conduct a 2-fold with 10-repetitions cross-validation to access the out-of-sample prediction (Shmueli et al., 2016). Due to the highly non-symmetric prediction error, the mean absolute error (MAE) was deemed more appropriate than the root mean squared error (RMSE) (Hair et al., 2019; Shmueli et al., 2019). After comparing the MAE values with the linear regression (LM) values, only a minority of the dependent construct indicators in the PLS-SEM model exhibited higher prediction errors relative to the naïve LM benchmark, denoting a medium predictive power (Table 5).

Table 2
Loadings, Cronbach's alpha (CA), Composite reliability (CR), average variance extracted (AVE), and variance inflation (VIF).

Constructs	Item loadings[c]	VIF	Mean (Std. Deviation)	CA	CR	AVE
Hedonic benefits[a]	HB1: 0.791	1.58	3.287 (1.061)	0.833	0.848	0.900
	HB2: 0.919	2.72	3.539 (1.056)			
	HB4: 0.886	2.39	3.478 (1.111)			
Utilitarian benefits[a]	UB1: 0.944	2.50	3.588 (0.966)	0.873	0.940	0.887
	UB2: 0.940	2.50	3.584 (0.942)			
Perceived ease of use	PE1: 0.758	1.64	3.419 (1.057)	0.864	0.907	0.711
	PE2: 0.883	2.64	3.527 (0.996)			
	PE3: 0.824	1.97	3.043 (1.152)			
	PE4: 0.900	2.71	3.659 (0.953)			
Perceived usefulness[a]	PU1: 0.944	2.37	3.656 (1.096)	0.864	0.936	0.880
	PU4: 0.932	2.37	3.604 (1.136)			
Privacy concerns[a]	PC1: 0.906	2.52	2.921 (1.066)	0.890	0.932	0.819
	PC3: 0.889	2.50	2.808 (1.091)			
	PC4: 0.921	2.87	2.943 (1.063)			
Attitude[a]	ATT3: 1.000	1.00	3.563 (1.119)	1.000	1.000	1.000
Intention[a]	INT3: 0.950	2.64	3.615 (1.152)	0.882	0.944	0.894
	INT4: 0.941	2.64	3.866 (1.093)			
Past negative[a]	PN2: 0.995	2.02	2.715 (1.295)	0.831	0.886	0.798
	PN3: 0.779	2.02	3.163 (1.182)			
Past positive	PP1: 0.823	2.07	3.633 (1.150)	0.868	0.916	0.785
	PP2: 0.922	2.45	3.597 (1.081)			
	PP3: 0.911	2.39	3.206 (1.074)			
Present fatalistic[b]	PF1: 0.937	1.43	2.643 (1.086)	0.709	0.865	0.764
	PF2: 0.806	1.43	2.529 (1.080)			
Present hedonistic	PH1: 0.770	1.37	3.663 (1.072)	0.826	0.898	0.746
	PH2: 0.905	3.58	2.717 (1.165)			
	PH3: 0.909	3.57	2.581 (1.181)			
Future	FU1: 0.703	1.319	3.711 (0.988)	0.774	0.854	0.595
	FU2: 0.711	1.535	4.118 (0.792)			
	FU3: 0.856	2.004	4.084 (0.841)			
	FU4: 0.806	1.619	3.833 (0.957)			

[a] ATT1, ATT2, INT1, INT3, HB3, UB3, PU2, PU3, PC2, PN1 were eliminated due to VIFs >3.
[b] PF3 was eliminated due to loading less than 0.5.
[c] All loadings were significant at $p < 0.001$.

Table 3
Discriminant validity (Fornell-Larcker criterion).

	ATT	HB	PEOU	PU	PN	PP	PF	PC	FU	INT	PH	PAU	UB
Attitude (ATT)	**1.000**												
Hedonic benefits (HB)	0.714	**0.867**											
PEOU	0.590	0.500	**0.843**										
PU	0.744	0.657	0.473	**0.938**									
Past negative (PN)	−0.089	−0.008	−0.147	0.009	**0.893**								
Past positive (PP)	0.127	0.188	0.052	0.116	−0.198	**0.886**							
Present fatalistic (PF)	−0.115	−0.029	−0.066	−0.08	0.384	−0.152	**0.874**						
Privacy concerns (PC)	0.574	0.563	0.456	0.475	−0.128	0.097	−0.053	**0.905**					
Future (FU)	0.157	0.193	0.18	0.215	−0.074	0.169	−0.198	0.127	**0.772**				
Intention (INT)	0.811	0.711	0.546	0.757	−0.051	0.131	−0.129	0.544	0.182	**0.946**			
Present hedonistic	0.117	0.209	0.079	0.184	0.048	0.201	0.018	0.12	−0.021	0.135	**0.864**		
Past usage (PAU)	0.126	0.144	0.096	0.162	−0.068	0.083	−0.049	0.098	0.022	0.129	0.157	**1.000**	
Utilitarian benefits (UB)	0.706	0.66	0.505	0.755	0.013	0.081	−0.08	0.464	0.21	0.705	0.13	0.148	**0.942**

Table 4
HTMT statistics.

	ATT	HB	PEOU	PU	PN	PP	PF	PC	FU	INT	PH	PAU	UB
Attitude (ATT)													
Hedonic benefits (HB)	0.779												
PEOU	0.628	0.579											
PU	0.800	0.769	0.537										
Past negative (PN)	0.094	0.057	0.163	0.025									
Past positive (PP)	0.127	0.207	0.066	0.121	0.297								
Present fatalistic (PF)	0.130	0.044	0.091	0.094	0.495	0.192							
Privacy concerns (PC)	0.606	0.653	0.514	0.538	0.102	0.109	0.066						
Future (FU)	0.177	0.237	0.207	0.257	0.123	0.203	0.258	0.144					
Intention (INT)	0.863	0.824	0.615	0.865	0.046	0.141	0.159	0.611	0.220				
Present hedonistic (PH)	0.129	0.253	0.09	0.219	0.056	0.231	0.099	0.140	0.076	0.158			
Past usage (PAU)	0.126	0.159	0.106	0.174	0.055	0.089	0.067	0.102	0.055	0.138	0.174		
Utilitarian benefits (UB)	0.755	0.771	0.577	0.866	0.029	0.085	0.095	0.524	0.251	0.803	0.154	0.158	

Table 5
Out-of-sample prediction.

Indicators	MAE		PLS-LM
	PLS data	LM data	
ATT2	0.850	0.854	−0.004
HB4	0.871	0.869	0.002
HB1	0.850	0.840	0.010
HB2	0.820	0.824	−0.004
PE2	0.830	0.833	−0.003
PE3	0.946	0.949	−0.003
PE4	0.752	0.754	−0.002
PE1	0.895	0.907	−0.012
PU1	0.842	0.855	−0.013
PU4	0.887	0.898	−0.011
PC3	0.881	0.898	−0.017
PC4	0.827	0.852	−0.025
PC1	0.840	0.862	−0.022
INT4	0.787	0.825	−0.038
INT1	0.907	0.900	0.007
UB2	0.736	0.742	−0.006
UB1	0.761	0.764	−0.003

4.4. Multigroup analysis

A multigroup analysis (MGA) was performed to evaluate the proposed hypotheses. Before MGA, we employed the MICOM procedure (Henseler et al., 2016) to assess the measurement invariance of composite models (MICOM). MICOM is the three-step approach analyzing: (1) configural invariance, (2) compositional invariance, and (3) the equality of composite mean values and variances. The configuration invariance assessment was confirmed due to the same configuration across both groups (i.e., restaurant and hospital). To verify composite variance, the original correlation c is compared with the 5% quantile of c_u. Table 6 demonstrates that all c were equal or greater than the 5%-quantile, thus, the composite invariance was verified. For the next step, the equality of means and the equality of variances were all confirmed using the non-parametric permutations test. The results concluded the full measurement invariance.

After considering the measurement invariance, Henseler's MGA (Henseler et al., 2016) was applied using bias-corrected and bootstrapping with 5000 sub-samples to explore the differences between the two service settings. Although Henseler's MGA did not yield any significant path differences between settings, the bootstrap's results of each group indicated noticeable differences. These results are presented in Table 7 and illustrated in Fig. 1. The impact of past-positive TP was found significant on hedonic benefits ($b = 0.137$, $p < 0.05$) in the restaurant setting only, supporting **H1d** partially. The influence of present-hedonistic TP on hedonic benefits ($b_{restaurant} = 0.201$, $p < 0.01$; $b_{hospital} = 0.184$, $p < 0.01$) was only slightly higher for the restaurant setting, whereas the influences on utilitarian benefits ($b = 0.137$, $p < 0.05$) and privacy concerns ($b = 0.163$, $p < 0.05$) were significant in the hospital setting only, rejecting **H2d**. No significant differences for present-fatalistic TP were found, supporting **H2e**. The influence of future TP was found to be significantly higher in hospital (vs. restaurant) settings for utilitarian benefits ($b_{restaurant} = 0.213$, $p < 0.01$; $b_{hospital} = 0.200$, $p < 0.01$), hedonic benefits ($b_{restaurant} = 0.103$, *n.s.*; $b_{hospital} = 0.256$, $p < 0.001$) suggesting a reverse pattern of impact from hypothesized ones (**H3d**). The impact of utilitarian benefits was found to be higher in credence than experience service settings for PU ($b_{restaurant} = 0.549$, $p < 0.001$; $b_{hospital} = 0.536$, $p < 0.001$), and PEOU ($b_{restaurant} = 0.207$, $p < 0.05$; $b_{hospital} = 0.353$, $p < 0.001$), supporting **H4a,b,c**. The positive associations between hedonic benefits, PU, and PEOU, supported **H5a,b**. The impacts of hedonic benefits on PU ($b_{restaurant} = 0.190$, $p < 0.01$; $b_{hospital} = 0.298$, $p < 0.001$) and PEOU ($b_{restaurant} = 0.183$, $p < 0.05$; $b_{hospital} = 0.212$, $p < 0.01$) were found to be higher in the hospital setting, thus rejecting **H5c**. **H6a** was rejected due to the insignificant impact of privacy concerns on PU, whereas its influence on PEOU

Table 6
Results of invariance measurement testing using permutation.

Constructs	Configural invariance	Compositional invariance (Correlation = 1)		Compositional invariance	Equal mean assessment			Equal variance assessment			Measurement invariance
		C = 1	5% quantile of C_u		Differences	Confidence interval	Equal mean value	Differences	Confidence interval	Equal variance	
ATT	Yes	1.000	1.000	Yes	0.008	[-0.175; 0.163]	Yes	0.051	[-0.227; 0.229]	Yes	Full
HB	Yes	1.000	0.999	Yes	0.080	[-0.164; 0.169]	Yes	0.097	[-0.258; 0.238]	Yes	Full
PEOU	Yes	1.000	0.998	Yes	0.142	[-0.175; 0.162]	Yes	−0.145	[-0.232; 0.228]	Yes	Full
PU	Yes	1.000	1.000	Yes	−0.099	[-0.178; 0.169]	Yes	−0.089	[-0.260; 0.245]	Yes	Full
PN	Yes	0.996	0.530	Yes	0.026	[-0.157; 0.160]	Yes	0.017	[-0.174; 0.166]	Yes	Full
PP	Yes	0.996	0.975	Yes	−0.102	[-0.173; 0.171]	Yes	−0.015	[-0.221; 0.232]	Yes	Full
PF	Yes	0.811	0.461	Yes	0.002	[-0.164; 0.168]	Yes	0.050	[-0.199; 0.191]	Yes	Full
PC	Yes	1.000	0.999	Yes	−0.070	[-0.169; 0.163]	Yes	−0.187	[-0.217; 0.220]	Yes	Full
FU	Yes	0.997	0.948	Yes	0.021	[-0.166; 0.177]	Yes	−0.161	[-0.284; 0.288]	Yes	Full
INT	Yes	1.000	1.000	Yes	−0.027	[-0.178; 0.169]	Yes	0.002	[-0.271; 0.261]	Yes	Full
PH	Yes	0.999	0.970	Yes	−0.130	[-0.169; 0.173]	Yes	0.103	[-0.180; 0.183]	Yes	Full
UB	Yes	1.000	1.000	Yes	−0.094	[-0.169; 0.166]	Yes	0.001	[-0.300; 0.274]	Yes	Full

Note: ATT: attitude; HB: hedonic benefits; PEOU: Perceived ease of use; PU: perceived usefulness; PC: privacy concerns; FU: future; INT: intention; PN: past negative; PP: past positive; PF: present fatalistic; PH: present hedonistic; UB: utilitarian benefits.

supported **H6b**. **H6c** was partially supported due to the insignificant impact of privacy concerns on PU, while its positive impacts on PEOU ($b_{restaurant} = 0.181$, $p < 0.01$; $b_{hospital} = 0.235$, $p < 0.001$) were not significantly different across settings, consistent as hypothesized. We further conducted indirect effect analysis. The majority of future TP's indirect effects on intention via both utilitarian and hedonic benefits were significant in the hospital context but not the restaurant one. The indirect effects of present-hedonistic TP highlighted that these users were mainly motivated to seek pleasure or enjoyment of using AI service robots consistent as postulated in the TPT.

5. Discussion

5.1. Theoretical implications

Based on TPT and TAM, this study contributes to time, marketing, and technology acceptance literature by addressing two research questions about role of time perspectives on shaping AI service robot adoption behaviors, and how the patterns of impact vary across service settings. Several theoretical contributions can be made from our findings.

First, empirical evidence suggested that individuals with distinct time perspectives approach the adoption of AI service robots through disparate cognitive routes, influenced by privacy issues, as well as utilitarian and hedonic gains. Specifically, both present-hedonistic and future-oriented individuals processed these factors similarly, appreciating the pragmatic and enjoyable advantages of AI service robots while exhibiting diminished privacy concerns. However, future-oriented users favored the hospital setting, whereas present-hedonistic preferences were inconsistent across contexts. In the credence settings, present-hedonistic users prioritized utilitarian benefits and exhibit reduced privacy concerns, but in experience settings, they were more inclined towards hedonic benefits. This variation may be imputed to their propensities for risk-taking (Zambianchi et al., 2019; Zimbardo and Boyd, 1999) and pleasure-seeking attitudes (Zimbardo and Boyd, 2008). In credence services requiring elevated trust, such as those requiring personal, financial, or medical details, sharing such sensitive data typically engenders privacy and misuse concerns (Yao et al., 2024). However, individuals with a present-hedonic orientation, who prioritize immediate gratification without much consideration for future consequences (Fu et al., 2022; Zimbardo and Boyd, 1999) may overlook these risks. On the other hand, future-oriented customers, especially those with an open-ended view, tend to have fewer privacy concerns in these settings. According to Park et al. (2021), this is because people with a broad future perspective focus more on the desired outcomes than the processes involved, unlike those with a more limited view of the future, who emphasize the process and practicality. Thus, future-oriented individuals with open-ended future perspective might see sharing personal data as a necessary step to achieve their goals in high-trust services. The influence of both past-positive and present-hedonistic TPs, but not future TP on hedonic benefits in the experience setting reinforce the central role of considering users' emotional experience gains in technology acceptance, for example in the recently proposed theoretical model of artificially intelligent device use acceptance (AIDUA) (Gursoy et al., 2019). While Park et al. (2021) suggested a more pronounced influence of future TP on adoption intention when functional value is accentuated over emotional value, our findings elucidate their conclusions within varying service contexts. Specifically, their assertion is corroborated in experience settings, whereas a more substantial impact on hedonic rather than utilitarian benefits was observed in credence settings. Our findings contribute to the understanding of how individuals with different TPs process input information prior to making adoption decisions, thus, also enrich TPT.

Second, this study answered to the call of Park et al. (2021) for the consideration of the utilitarian and hedonic aspects in service settings. The findings revealed a pronounced impact of both utilitarian and hedonic benefits on PU and PEOU in credence (as opposed to experience) service contexts, suggesting that a credence service (such as a hospital)

Table 7
SEM results across both groups.

Hypotheses		Path coefficients				Support
		Pooled	Restaurant	Hospital	Differences	
H1a	PP → UB	0.022	0.063	−0.022	0.085	No
	PN → UB	0.048	0.049	0.062	−0.014	
H1b	PP → HB	0.126[b]	0.137[*]	0.112	0.024	Partial
	PN → HB	0.015	0.053	−0.002	0.055	
H1c	PP → PC	0.031	0.077	−0.016	0.093	No
	PN → PC	−0.128	−0.098	−0.144	0.046	
H2a	PH → UB	0.129[b]	0.116	0.137[*]	−0.022	Partial
	PF → UB	−0.057	−0.071	−0.079	0.008	
H2b	PH → HB	0.187[a]	0.201[b]	0.184[b]	0.017	Partial
	PF → HB	0.017	−0.080	0.050	−0.130	
H2c	PH → PC	0.122[b]	0.083	0.163[*]	−0.081	Partial
	PF → PC	0.022	−0.013	0.024	−0.037	
H3a	FU → UB	0.201[a]	0.200[b]	0.213[b]	−0.012	Yes
H3b	FU → HB	0.180[a]	0.103	0.256[a]	−0.153	No
H3c	FU → PC	0.119[b]	0.071	0.164[*]	−0.093	Yes
H4a	UB → PU	0.542[a]	0.549[a]	0.536[a]	0.013	Yes
H4b	UB → PEOU	0.275[a]	0.207[*]	0.353[b]	−0.147	Yes
H5a	HB → PU	0.235[a]	0.190[b]	0.298[a]	−0.108	Yes
H5b	HB → PEOU	0.195[b]	0.183[c]	0.212[b]	−0.029	Yes
H6a	PC → PU	0.067	0.086	0.031	0.054	No
H6b	PC → PEOU	0.219[a]	0.181[b]	0.235[a]	−0.054	Yes
Indirect effects						
FU → UB → PU → ATT → INT		0.053[a]	0.053[b]	0.057[b]		
FU → UB → PEOU → ATT → INT		0.014[b]	0.010	0.018[c]		
FU → HB → PU → ATT → INT		0.020[b]	0.009	0.038[b]		
FU → HB → PEOU → ATT → INT		0.009[c]	0.005	0.013[c]		
PH → UB → PU → ATT → INT		0.034[b]	0.030	0.037		
PH → HB → PU → ATT → INT		0.021[b]	0.018	0.027[c]		
PH → HB → PEOU → ATT → INT		0.009[c]	0.009	0.010[c]		
PP → HB → PEOU → ATT → INT		0.006[c]	0.006	0.006		
UB → PEOU → ATT → INT		0.068[a]	0.052[b]	0.086[b]		
HB → PEOU → ATT → INT		0.048[b]	0.046[c]	0.052[b]		
PC → PEOU → ATT → INT		0.054[a]	0.046[c]	0.057[b]		

Note.
[a] $p < 0.001$.
[b] $p < 0.01$.
[c] $p < 0.05$.

can provide both utilitarian and hedonic values consistent with earlier studies (Babin et al., 1994). The positive effect of hedonic benefits on ease of use, despite insignificant in experience settings, supports findings of Gursoy et al. (2019) and Bhuiyan et al. (2024); Lin et al. (2020) in the United States, whereas contrasting the finding of Bhuiyan et al. (2024) in Bangladesh's hotel context. A higher degree of hedonic benefits (e.g., novelty, fun, entertainment) can motivate consumers in terms of both sensory satisfaction and utility. Furthermore, this study provides evidence to counter the argument of Chi et al. (2022) that customers are more likely to focus on hedonic benefits in hospitality services whereas utilitarian benefits are favored in utility-oriented services (i.e., airline). On the contrary, both utilitarian and hedonic benefits in our study exerted consistently robust influences on PU and PEOU. The effects were stronger in the hospital (vs. restaurant) settings. This highlighted the imperative of deliberate integration of both types of benefits in design attempts aimed at enhancing the meaningfulness and seamlessness of customer experience across varied contexts. Additionally, the discrepancy in findings from existing studies was addressed by highlighting the potential root cause in individual differences. Noticeably, the indirect effects of future and present-hedonistic TPs toward intention to use were channeled via utilitarian and hedonic benefits, subsequently influencing PU and PEOU, while no substantial impacts were discerned for alternative TPs. Given the cognitive-motivational malleability of TPs like future TP (Kooij et al., 2018), the consistent indirect effects in the hospital setting, but not in the restaurant setting, highlight the need to consider alternative TPs to better explain the mechanisms driving shifts in technology adoption behaviors. In other words, a shift in TP induced by external factors such as marketing interventions or educational initiatives will subsequently alter individuals' evaluation and adoption of AI technologies.

Taking into account the variations among individuals, especially between those with present-hedonistic and future TPs, this study enriches the ongoing body of research on service variations (for instance, J. Park et al., 2021; Li et al., 2023; Liu et al., 2022) demonstrating that individuals with different time-orientation are likely to have differing views on credence (vs. experience) service environments for AI service robots. Moreover, traditional technology acceptance models such as TAM and UTAUT focus on the cognitive perspective, highlighting utilitarian motivation (extrinsic motivation), whereas others, including UTATU2 and AIDUA, are grounded in the emotional, irrational perspective, emphasizing hedonic value (intrinsic motivation). Scholars, such as Yuan et al. (2022), contended that both dimensions play a vital role in human cognitive processes and, as such, should not be considered in isolation. Our research not only supports this view but also underscores the importance of assessing the impact of these influences across various contexts, particularly concerning time orientation and service settings. Accordingly, our discoveries furnish substantiation to fortify the theoretical positioning of TPs within TPT, advocating its potential as a supplementary framework to established technology acceptance theories.

Third, this study contributes to AI literature by incorporating privacy concerns into TAM in AI service robot contexts. Privacy concerns manifested as a significant antecedent of PEOU, but not PU, diverging from Park et al. (2021), who identified a significant link between privacy concerns and PU in South Korea. This discrepancy allows for a comparative analysis with the U.S. population. Nevertheless, the insignificant differences regarding the impact of privacy concerns on PU and PEOU across settings aligns with Park et al. (2021), corroborating the consistent importance of privacy concerns in the adoption of AI service robots in both settings. On the contrary, Kelly et al. (2022) found that Australian consumers might adjust their privacy concerns based on the specific context in which they are considering using AI chatbots including mental healthcare, online shopping, and online banking. However, no justification was given for the positive effect of privacy concerns in their study. Perhaps, in certain contexts, accentuated privacy concerns might imply a circumspect utilization at a rational cost, rather than a direct repudiation or evasion, as discovered in the qualitative research of Menon and Shilpa (2023). Another sensible reason for the discrepancy could be imputed to the intricate mechanism through which privacy concerns exert its influence, rather than a direct impact. The indirect effect, though marginal, from privacy concerns to usage intention via perceived ease and attitude in both contexts suggested mitigating privacy concerns could incite customers to explore the process, fostering a positive attitude and, eventually, augmenting usage intention.

5.2. Practical implications

Several managerial implications can be drawn from this research for

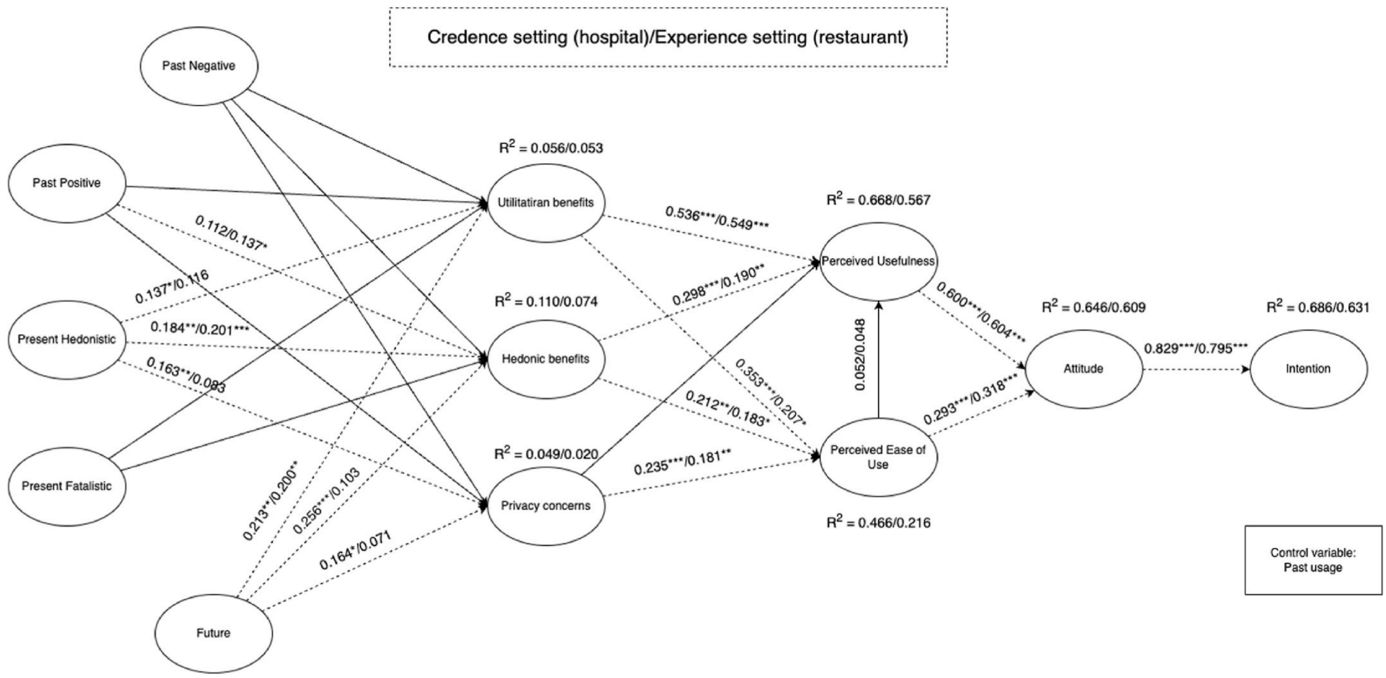

Fig. 1. The results of SEM in both settings. Notes: The dotted lines indicate the differences across settings. Unreported paths are not significant in both settings. R^2 values in the figure are adjusted R^2 values; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

the development, marketing, and deployment of AI service robots in service settings. First, marketing campaigns for AI service robots can be tailored to match the individual differences in terms of time orientation, empowering marketers to target varied audiences effectively. For future-oriented individuals, emphasizing both the long-term benefits as well as the hedonic aspect of using AI service robots in credence service settings (e.g., hospital) can be more appealing. In contrast, for present-hedonistic individuals, highlighting the immediate pleasure, convenience, and fund aspects of using AI service robots in experience-based settings (e.g., restaurant) might be more effective. This targeted approach can help in addressing the specific motivations and concerns of different user segments.

Second, AI developers and product managers should implement appropriate design and features to address users' preferences. For service settings that require high trust, such as hospitals, it is crucial to design AI service robots with features that address privacy concerns and emphasize the utility and safety of sharing personal data. This is particularly important for future-oriented users who are more likely to pay heed to the outcomes rather than the process. On the other hand, in experience settings, focusing on enhancing the hedonic aspects of the AI service robots – such as user interaction, entertainment value, and user experience – can cater to the preferences of present-hedonistic individuals. Also, understanding that present-hedonistic individuals may downplay privacy risks in favor of immediate gratification, service providers should implement additional safeguards and consent processes for data sharing, especially in credence contexts. This could help mitigate potential privacy risks and protect users from possible data misuse. Given the varying impact of privacy concerns across different time perspectives, it is important for companies to develop clear, transparent privacy policies and communicate them effectively to users. For present-hedonistic individuals, simplifying the communication about how their data is protected might reduce any lingering concerns. For future-oriented individuals, detailing how privacy protections align with long-term benefits could be reassuring.

Third, for customer service specialists, it is essential to customize services based on time orientation and service settings. The development of AI service robots can benefit from customization options that allow users to adjust settings based on their time orientation and the specific service context. For instance, in credence services, offering options that allow for more controlled sharing of personal data might appeal to future-oriented users. Conversely, providing features that enhance the enjoyment and interactive experience such as intuitive user interfaces, or social interaction (e.g., small talk, jokes) could attract present-hedonistic users in experience settings. Practical data from service encounters could offer valuable insights for regulatory compliance officials to navigate legal and regulatory frameworks governing the deployment of service robots, ensuring compliance with relevant laws and standards.

6. Limitations and future research directions

This study only invested the proposed model in the U.S. context, thus lack a consideration of the cross-country and cross-cultural differences, particularly for time-orientation. Notably, Zimbardo and Boyd (1999) emphasize that the development of an individual's time perspective is influenced by personal factors as well as the characteristics of their socio-cultural context. Echoing this view, Sircova et al. (2014) advocated the need to examine cross-cultural similarities and differences alongside time perspective profiles. For this reason, future research conducted with a cross-cultural comparison between countries to understand the analogy and discrepancy in time orientation perceived is needed. Also, the AI acceptance process highlighting individual differences could further benefit from an in-depth examination of the underlying mechanisms of the relationships tested in this study using different moderators such as the big five personality traits.

Incorporating time dimension into the technology acceptance model using ZTPI has shown its value across various studies on technology adoption (Fasbender et al., 2023; Lee, 2023; Merchant et al., 2014; Miceli et al., 2022). Nonetheless, our research suggests a nuanced approach is necessary, particularly the segmentation of future TP into distinct profiles for a more tailored explanation across service settings. The socioemotional selectivity theory presents a useful framework, distinguishing individuals by their orientation towards an open-ended or limited future TP, which correlates with their focus on outcomes or processes (Carstensen et al., 1999). Furthermore, Carelli et al. (2011) posited that future TP encompasses both negative and positive aspects, advocating for its division into separate dimensions to achieve a healthier equilibrium between pursuing future goals and appreciating the present moment. This led to the introduction of future-positive and future-negative TPs in the Swedish adaptation of the ZTPI (S-ZTPI). Future studies should consider more time dimensions to better capture the mechanism underpinning the influence of time orientation in different service setting. The variables investigated are limited to the scope of the study. Further examinations into the interplay between time and other context-specific factors such as cultural differences (e.g., religion, customs, traditions), and relational (e.g., social influence) could add value to advance our results. Despite efforts to mitigate method bias, random measurement error may persist due to the model complexity potentially engendering respondent fatigue (MacKenzie and Podsakoff, 2012). A prospective solution entails conducting pairwise comparisons among salient TPs on technology adoption, such as future, present-hedonistic, and past-positive TPs, across multiple studies to maintain respondent motivation and ensure robust results.

Data availability statement

Data are available upon reasonable request from the corresponding author.

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CRediT authorship contribution statement

Simon Dang: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Sara Quach:** Writing – review & editing, Supervision, Conceptualization. **Robin E. Roberts:** Writing – review & editing, Supervision, Conceptualization.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the first author used ChatGPT to improve readability and language. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Declaration of competing interest

The authors declare no conflict of interest.

Data availability

Data will be made available on request.

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Appendix 1

Measurement items

Code	Statement
Past Negative	
PN1	I think about the bad things that have happened to me in the past
PN2	Painful past experiences keep being replayed in my mind
PN3	It's hard for me to forget unpleasant images of my youth
Past Positive	
PP1	It gives me pleasure to think about the past
PP2	Familiar childhood sights, sounds, and smells often bring back a flood of wonderful memories
PP3	Happy memories of good times spring readily to mind
Present Hedonistic	
PH1	It is important to put excitement in my life
PH2	Taking risks keeps my life from becoming boring
PH3	I take risks to put excitement in my life
Present Fatalistic	
PF1	You can't really plan for the future because things change so much
PF2	My life path is controlled by forces I cannot influence
PF3	It doesn't make sense to worry about the future, since there is nothing that I can do about it anyway
Future	
FU1	Meeting tomorrow's deadlines and doing other necessary work come before tonight's play
FU2	I meet my obligation to friends and authorities on time
FU3	I complete projects on time by making steady progress
FU4	I am able to resist temptations when I know that there is work to be done
Utilitarian Benefits	
UB1	Completing tasks with AI robot makes my life easier
UB2	Completing tasks with AI robot fits with my schedule
UB3	Completing tasks with AI robot is an efficient use of my time
Hedonic Benefits	
HB1	I was able to immerse myself in AI service

(*continued on next page*)

(*continued*)

Code	Statement
HB2	I find using AI robot could be enjoyable
HB3	I have fun using AI robot to complete tasks
HB4	The actual process of using AI robot is entertaining
Privacy Concerns	
PC1	I think my personal information is safe when using the AI robot
PC2	My data will be kept secured in using the AI robot
PC3	The AI robot will not transmit my information to a third party
PC4	The AI robot will protect my financial-transaction records
Perceived Usefulness	
PU1	Using AI robot would increase my productivity
PU2	Using AI robot would enhance my effectiveness on the job
PU3	Using AI robot make it easier to do my job
PU4	I would find AI useful in my job
Perceived Ease of Use	
PE1	Using the AI robot will not require a lot of effort
PE2	Learning to operate the AI robot will be easy
PE3	I will not experience any difficulties using the AI robot
PE4	Overall, I think the AI robot will be easy to use
Attitude	
ATT1	Using the AI robot is positive for me
ATT2	It is good to use the AI robot
ATT3	Using the AI robot is a pleasant experience for me
Intention	
INT1	I plan to continue to use AI robot
INT2	I intend to continue to use AI robot
INT3	I predict I would continue to use AI robot in the future
INT4	I think I would be willing to interact with AI robot

Appendix 2

Scenario illustrations

Hospital scenario

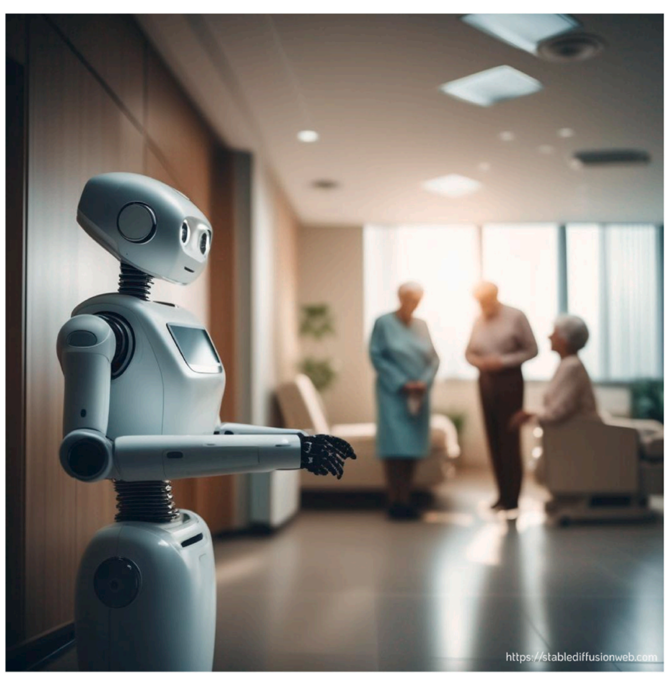

Image created by Stablediffusion – a free and open-source model.

Restaurant scenario

Image created by Stablediffusion – a free and open-source model.

References

Adamopoulou, E., Moussiades, L., 2020. Chatbots: history, technology, and applications. Machine Learning with Applications 2, 100006.

Akhtar, M., Neidhardt, J., Werthner, H., 2019. The Potential of Chatbots: Analysis of Chatbot Conversations. 2019 IEEE 21st Conference on Business Informatics (CBI),.

Alexandrakis, D., Chorianopoulos, K., Tselios, N., 2020. Older adults and web 2.0 storytelling technologies: probing the technology acceptance model through an age-related perspective. Int. J. Hum. Comput. Interact. 36 (17), 1623–1635.

Babin, B.J., Darden, W.R., Griffin, M., 1994. Work and/or fun: measuring hedonic and utilitarian shopping value. J. Consum. Res. 20 (4), 644–656.

Baltes, B.B., Wynne, K., Sirabian, M., Krenn, D., de Lange, A., 2014. Future time perspective, regulatory focus, and selection, optimization, and compensation: testing a longitudinal model. J. Organ. Behav. 35 (8), 1120–1133.

Bhuiyan, K.H., Ahmed, S., Jahan, I., 2024. Consumer attitude toward using artificial intelligence (AI) devices in hospitality services. J. Hospit. Tour. Insights 7 (2), 968–985.

Carelli, M.G., Wiberg, B., Wiberg, M., 2011. Development and construct validation of the Swedish Zimbardo time perspective inventory. Eur. J. Psychol. Assess. 27 (4), 220–227.

Carstensen, L.L., Isaacowitz, D.M., Charles, S.T., 1999. Taking time seriously: a theory of socioemotional selectivity. Am. Psychol. 54 (3), 165–181.

Chavarria, J., Allan, N.P., Moltisanti, A., Taylor, J., 2015. The effects of present hedonistic time perspective and past negative time perspective on substance use consequences. Drug Alcohol Depend. 152, 39–46.

Chi, O.H., Denton, G., Gursoy, D., 2020. Artificially intelligent device use in service delivery: a systematic review, synthesis, and research agenda. J. Hospit. Market. Manag. 29 (7), 757–786.

Chi, O.H., Gursoy, D., Chi, C.G., 2022. Tourists' attitudes toward the use of artificially intelligent (AI) devices in tourism service delivery: moderating role of service value seeking. J. Trav. Res. 61 (1), 170–185.

Davis, R., Wong, D., 2007. Conceptualizing and measuring the optimal experience of the eLearning environment. Decis. Sci. J. Innovat. Educ. 5 (1), 97–126.

Fasbender, U., Gerpott, F.H., Rinker, L., 2023. Getting ready for the future, is it worth it? A dual pathway model of age and technology acceptance at work. Work, Aging and Retirement 9 (4), 358–375.

Feldman, E., Reid, E.M., Mazmanian, M., 2019. Signs of our time: time-use as dedication, performance, identity, and power in contemporary workplaces. Acad. Manag. Ann. 14 (2), 598–626.

Fornell, C., Larcker, D.F., 1981. Evaluating structural equation models with unobservable variables and measurement error. J. Market. Res. 18 (1), 39–50.

Foroughi, B., Nhan, P.V., Iranmanesh, M., Ghobakhloo, M., Nilashi, M., Yadegaridehkordi, E., 2023. Determinants of intention to use autonomous vehicles: findings from PLS-SEM and ANFIS. J. Retailing Consum. Serv. 70, 103158.

Frank, B., Herbas-Torrico, B., Schvaneveldt, S.J., 2021. The AI-extended consumer: technology, consumer, country differences in the formation of demand for AI-empowered consumer products. Technol. Forecast. Soc. Change 172.

Fu, Q., Rodríguez-Ardura, I., Meseguer-Artola, A., Wu, P., 2022. Self-disclosure during the COVID-19 emergency: effects of narcissism traits, time perspective, virtual presence, and hedonic gratification. Comput. Hum. Behav. 130, 107154.

Girard, T., Dion, P., 2010. Validating the search, experience, and credence product classification framework. J. Bus. Res. 63 (9), 1079–1087.

Goel, P., Kaushik, N., Sivathanu, B., Pillai, R., Vikas, J., 2022. Consumers' adoption of artificial intelligence and robotics in hospitality and tourism sector: literature review and future research agenda. Tourism Rev. 77 (4), 1081–1096.

Gursoy, D., Chi, O.H., Lu, L., Nunkoo, R., 2019. Consumers acceptance of artificially intelligent (AI) device use in service delivery. Int. J. Inf. Manag. 49, 157–169.

Hair, J.F., Risher, J.J., Sarstedt, M., Ringle, C.M., 2019. When to use and how to report the results of PLS-SEM. Eur. Bus. Rev. 31 (1), 2–24.

Henseler, J., Ringle, C.M., Sarstedt, M., 2016. Testing measurement invariance of composites using partial least squares. Int. Market. Rev. 33 (3), 405–431.

Huang, S.Y.B., Lee, C.J., Lee, S.C., 2021. Toward a unified theory of customer continuance model for financial technology chatbots. Sensors 21 (17). Article 5687.

Kamoonpuri, S.Z., Sengar, A., 2023. Hi, May AI help you? An analysis of the barriers impeding the implementation and use of artificial intelligence-enabled virtual assistants in retail. J. Retailing Consum. Serv. 72, 103258.

Kelly, S., Kaye, S.-A., Oviedo-Trespalacios, O., 2022. A multi-industry analysis of the future use of AI chatbots. Human Behavior and Emerging Technologies 2022, 2552099.

Kooij, D.T.A.M., Kanfer, R., Betts, M., Rudolph, C.W., 2018. Future time perspective: a systematic review and meta-analysis. J. Appl. Psychol. 103 (8), 867–893.

Lee, J.K., 2023. The roles of individual differences in time perspective, promotion focus, and innovativeness: testing technology acceptance model. Curr. Psychol. 42 (33), 29448–29460.

Lewin, K., 1951. Field theory in social science: selected theoretical papers. In: Cartwright, Dorwin (Ed.), Harpers.

Li, Y., Wang, C., Song, B., 2023. Customer acceptance of service robots under different service settings. Journal of Service Theory and Practice 33 (1), 46–71.

Lin, H., Chi, O.H., Gursoy, D., 2020. Antecedents of customers' acceptance of artificially intelligent robotic device use in hospitality services. J. Hospit. Market. Manag. 29 (5), 530–549.

Ling, E.C., Tussyadiah, I., Tuomi, A., Stienmetz, J., Ioannou, A., 2021. Factors influencing users' adoption and use of conversational agents: a systematic review. Psychol. Market. 38 (7), 1031–1051.

Ling, H.-C., Chen, H.-R., Ho, K.K.W., Hsiao, K.-L., 2021. Exploring the factors affecting customers' intention to purchase a smart speaker. J. Retailing Consum. Serv. 59, 102331.

Liu, Y., Wang, X., Wang, S., 2022. Research on service robot adoption under different service scenarios. Technol. Soc. 68, 101810.

MacKenzie, S.B., Podsakoff, P.M., 2012. Common method bias in marketing: causes, mechanisms, and procedural remedies. J. Retailing 88 (4), 542–555.

Malhotra, N.K., Kim, S.S., Agarwal, J., 2004. Internet users' information privacy concerns (IUIPC): the construct, the scale, and a causal model. Inf. Syst. Res. 15 (4), 336–355.
McLean, G., Osei-Frimpong, K., 2019a. Chat now… Examining the variables influencing the use of online live chat. Technol. Forecast. Soc. Change 146, 55–67.
McLean, G., Osei-Frimpong, K., 2019b. Hey Alexa … examine the variables influencing the use of artificial intelligent in-home voice assistants. Comput. Hum. Behav. 99, 28–37.
Menon, D., Shilpa, K., 2023. "Chatting with ChatGPT": analyzing the factors influencing users' intention to Use the Open AI's ChatGPT using the UTAUT model. Heliyon 9 (11), e20962.
Merchant, A., Rose, G., Rose, M., 2014. The impact of time orientation on consumer innovativeness in the United States and India. J. Market. Theor. Pract. 22 (3), 325–338.
Miceli, S., Cardaci, M., Scrima, F., Caci, B., 2022. Time perspective and Facebook addiction: the moderating role of neuroticism. Curr. Psychol. 41 (12), 8811–8820.
Mitra, K., Reiss, M.C., Capella, L.M., 1999. An examination of perceived risk, information search and behavioral intentions in search, experience and credence services. J. Serv. Market. 13 (3), 208–228.
Nagy, P., Eschrich, J., Finn, E., 2021. Time hacking: how technologies mediate time. Inf. Commun. Soc. 24 (15), 2229–2243.
Park, J., Hong, E., Le, H.T.P.M., 2021. Adopting autonomous vehicles: the moderating effects of demographic variables. J. Retailing Consum. Serv. 63, 102687.
Park, J., Kim, D., Hyun, H., 2021. Understanding self-service technology adoption by "older" consumers. J. Serv. Market. 35 (1), 78–97.
Park, S.S., Tung, C.D., Lee, H., 2021. The adoption of AI service robots: a comparison between credence and experience service settings. Psychol. Market. 38 (4), 691–703.
Patrizi, M., Vernuccio, M., Pastore, A., 2021. "Hey, voice assistant!" How do users perceive you? An exploratory study. Sinergie Italian Journal of Management 39 (1), 173–192.
Peng, C., Yue, C., Avitt, A., Chen, Y., 2021. A systematic review approach to find robust items of the Zimbardo time perspective inventory [brief research report]. Front. Psychol. 12.
Pham, H.S.T., Khanh, C.N.T., 2021. Ecotourism intention: the roles of environmental concern, time perspective and destination image. Tourism Rev. 76 (5), 1141–1153.
Pitardi, V., Marriott, H.R., 2021. Alexa, she's not human but… Unveiling the drivers of consumers' trust in voice-based artificial intelligence. Psychol. Market. 38 (4), 626–642.
Podsakoff, P.M., MacKenzie, S.B., Lee, J.-Y., Podsakoff, N.P., 2003. Common method biases in behavioral research: a critical review of the literature and recommended remedies. J. Appl. Psychol. 88 (5), 879–903.
Rese, A., Ganster, L., Baier, D., 2020. Chatbots in retailers' customer communication: how to measure their acceptance? J. Retailing Consum. Serv. 56, 102176.
Sarstedt, M., Hair, J.F., Pick, M., Liengaard, B.D., Radomir, L., Ringle, C.M., 2022. Progress in partial least squares structural equation modeling use in marketing research in the last decade. Psychol. Market. 39 (5), 1035–1064.
Sekścińska, K., Iwanicka, K., 2021. Purchasing insurance – the roles of individual differences in time perspectives and regulatory foci. Aust. J. Psychol. 73 (3), 357–367.
Shipp, A.J., Jansen, K.J., 2021. The "other" time: a review of the subjective experience of time in organizations. Acad. Manag. Ann. 15 (1), 299–334.
Shmueli, G., Ray, S., Velasquez Estrada, J.M., Shatla, S.B., 2016. The elephant in the room: evaluating the predictive performance of PLS models. J. Bus. Res. 69 (10), 4552–4564.
Shmueli, G., Sarstedt, M., Hair, J.F., Cheah, J.-H., Ting, H., Vaithilingam, S., Ringle, C. M., 2019. Predictive model assessment in PLS-SEM: guidelines for using PLSpredict. Eur. J. Market. 53 (11), 2322–2347.
Sircova, A., van de Vijver, F.J.R., Osin, E., Milfont, T.L., Fieulaine, N., Kislali-Erginbilgic, A., Zimbardo, P.G., Djarallah, S., Chorfi, M.S., Leite, U.d.R., Lin, H., Lv, H., Bunjevac, T., Tomaš, T., Punek, J., Vrlec, A., Matić, J., Bokulić, M., Klicperová-Baker, M., Boyd, J.N., 2014. A global look at time: a 24-country study of the equivalence of the Zimbardo time perspective inventory. Sage Open 4 (1), 2158244013515686.
Soper, D.S., 2023. A-priori sample size calculator for structural equation models. https://www.danielsoper.com/statcalc/default.aspx.
Statista, 2023. AI service robotics - worldwide. Retrieved 27/11/2023 from. https://www.statista.com/outlook/tmo/artificial-intelligence/ai-robotics/ai-service-robotics/worldwide.
Sun, J., Keh, H.T., Lee, A.Y., 2012. The effect of attribute alignability on service evaluation: the moderating role of uncertainty. J. Consum. Res. 39 (4), 831–847.
Terzis, V., Moridis, C.N., Economides, A.A., 2012. The effect of emotional feedback on behavioral intention to use computer based assessment. Comput. Educ. 59 (2), 710–721.
Unger, A., Lyu, H., Zimbardo, P.G., 2018. How compulsive buying is influenced by time perspective—cross-cultural evidence from Germany, Ukraine, and China. Int. J. Ment. Health Addiction 16 (3), 525–544.
Venkatesh, Thong, Xu, 2012. Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. MIS Q. 36 (1), 157.
Wang, X., Qiu, X., 2024. The positive effect of artificial intelligence technology transparency on digital endorsers: based on the theory of mind perception. J. Retailing Consum. Serv. 78, 103777.
Yao, Q., Hu, C., Zhou, W., 2024. The impact of customer privacy concerns on service robot adoption intentions: a credence/experience service typology perspective. Technol. Forecast. Soc. Change 198, 122948.
Yuan, C.L., Zhang, C.L., Wang, S.M., 2022. Social anxiety as a moderator in consumer willingness to accept AI assistants based on utilitarian and hedonic values. J. Retailing Consum. Serv. (65), 102878
Zambianchi, M., Rönnlund, M., Carelli, M.G., 2019. Attitudes towards and use of information and communication technologies (ICTs) among older adults in Italy and Sweden: the influence of cultural context, socio-demographic factors, and time perspective. J. Cross Cult. Gerontol. 34 (3), 291–306.
Zhang, Y., Wang, S., 2023. The influence of anthropomorphic appearance of artificial intelligence products on consumer behavior and brand evaluation under different product types. J. Retailing Consum. Serv. 74, 103432.
Zhu, Y.T., Lu, Y.B., Gupta, S., Wang, J.Q., Hu, P., 2023. Promoting smart wearable devices in the health-AI market: the role of health consciousness and privacy protection. J. Res. Indian Med.
Zimbardo, P.G., Boyd, J.N., 1999. Putting time in perspective: a valid, reliable, individual differences metric. J. Pers. Soc. Psychol. 6, 1271–1288.
Zimbardo, P.G., Boyd, J.N., 2008. The Time Paradox: the New Psychology of Time that Will Change Your Life. Free Press.