Aslib Journal of Information Management

Artificial intelligence (AI) powered chatbots: factors in uptake among early adopters

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Received 23 December 2024
Revised 17 March 2025
5 May 2025
Accepted 10 May 2025

Abstract

Purpose – The purpose of this paper is to examine factors that influence early adopters' intention to use AI chatbots, emphasizing diverse factors such as personalization, conversational ability, social influence and trust.

Design/methodology/approach – Data collected from 323 US adults were analyzed using structural equation modeling (SEM) to examine the relationships between interaction factors and early adopters' attitudes and intentions toward AI chatbot adoption.

Findings – Users' attitude toward adopting AI chatbots is influenced by system affordances such as conversational ability, personalization, as well as users' trust in AI chatbots. Social influence does not significantly impact usage intentions, but it positively affects users' belief in the perceived usefulness of AI chatbots.

Practical implications – System designers and developers must enhance features related to conversational ability while simultaneously ensuring that AI chatbots have user-friendly interfaces that afford users low barriers of entry. Additionally, efforts should be made to enhance training data quality and optimize interaction models to support more effective and adaptive communication between users and AI-powered systems.

Originality/value – The rapid adoption of large language models will undoubtedly have a transformative effect on modern life and society. Therefore, a comprehensive understanding of the phenomenon is needed. The current study proposes a novel information model situated on the determinants that influence user acceptance of AI-powered chatbots. We extend the technology acceptance model by assessing interaction factors offered by this new technology, as well as users' beliefs about intended use and resulting outcomes in the context of seeking information.

Keywords ChatGPT, AI-powered chatbots, Technology use and adoption, Personalization, Conversational ability, Social influence, Trust

Paper type Research paper

1. Introduction

In an era shaped by digital interactions, chatbots represent a transformative shift in communication, information-seeking and workflow. Chatbots are widely used in health (Kim *et al.*, 2022), libraries (Lappalainen and Narayanan, 2023; Lund and Wang, 2023) and business, where they enhance customer service and social media engagement (Sheehan *et al.*, 2020; Jiang *et al.*, 2022). Early chatbots relied on scripted responses, but advances in artificial intelligence (AI) have introduced a new category: Large-Scale Language Models (LLMs) or generative artificial intelligence (AI). Introduced in late 2022 with groundbreaking models like ChatGPT, and further developed by platforms like BingChat, Bard, Ernie, Plutchik and WebGPT, LLMs have revolutionized digital communication (see Figures 1 and 2).

Aslib Journal of Information Management

e-ISSN: 2050-3814
p-ISSN: 2050-3806
DOI 10.1108/AJIM-12-2024-0994

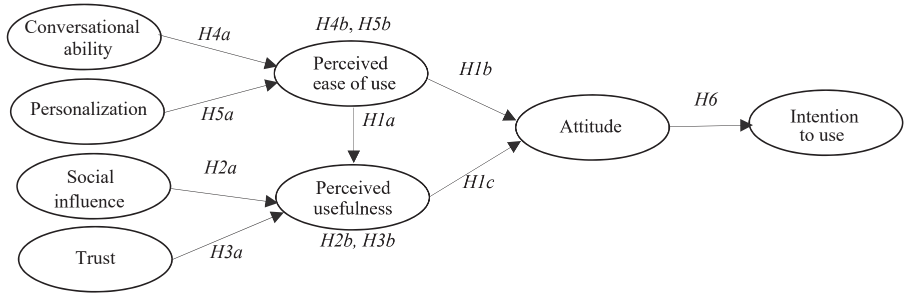

Figure 1. Proposed research model. Source: Authors' own work

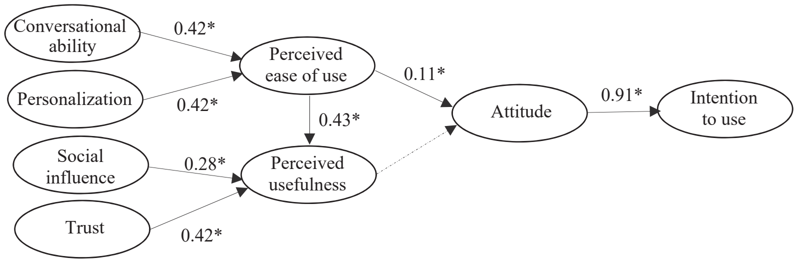

Figure 2. Hypothesized results (*$p < 0.05$). Source: Authors' own work

The chatbot's prowess lies in its capacity to process and produce text from enormous data sets, making them adept at diverse tasks, from summarizing articles to even coding. The potential of LLMs is vast and quickly evolving. A study by Eloundou *et al*. (2023), for example, suggests that LLMs could have a profound impact on many sectors of the United States' labor market, noting at least a 10% impact on work tasks due to the integration of LLMs. Furthermore, LLMs have the potential to accelerate approximately 15% of all work tasks in the United States while maintaining the same level of quality. However, like all technological advancements, LLMs come with their own set of challenges and despite its recent emergence, researchers have already highlighted ethical and legal considerations (Paranjape *et al*., 2019), effects on libraries and information professionals (Lund and Wang, 2023; Lund *et al*., 2023), limitations with information temporality (Komeili *et al*., 2021), as well as racial biases (Biddle, 2022; Cave and Dihal, 2020; Schlesinger *et al*., 2018).

Despite these challenges, the emergence of AI chatbots marks a pivotal paradigm shift in technology. Understanding the evolution from traditional chatbots to AI-powered chatbots requires focusing on a distinct group: early adopters. According to Brandtzaeg and Følstad (2017), "early adopters are usually more risk-oriented and curious about new technologies" compared to those who adopt technology later. These individuals, positioned at the forefront of technological exploration, offer unique insights into the opportunities, challenges and perceptions surrounding AI chatbot technologies (Gkinko and Elbanna, 2022). For instance, a recent Pew Research report highlights that only "about 18% of US adults" have used the most prominent AI chatbot, ChatGPT (Park and Gelles-Watnick, 2023). In this study, we define early adopters as individuals who have sought information using AI-powered chatbots, such as ChatGPT, BingChat or similar technologies within the past 6 months of our research survey's launch.

While research is emerging on factors that spur use intentions among users of AI powered chatbots, much of this literature focuses on narrow, task-specific domains such as banking and retail (Lin and Lee, 2023; Chang and Hsiao, 2024), education (Gayashan and Samarasinghe, 2024; Esiyok *et al.*, 2024), healthcare (Shahsavar and Choudhury, 2023; Gamble, 2020; Li *et al.*, 2024), research science (Chen *et al.*, 2024), mobility and transportation (Kilian *et al.*, 2019; Kuberkar and Singhal, 2020) and tourism (Zhang *et al.*, 2023; Liu *et al.*, 2024). The rapid adoption of large language models will undoubtedly have a transformative effect on modern life and society. Therefore, a comprehensive understanding of the phenomenon is needed. The current study proposes a novel information model situated on the determinants that influence user acceptance of AI-powered chatbots. We extend the technology acceptance model by assessing interaction factors offered by this new technology, as well as users' beliefs about intended use and resulting outcomes in the context of seeking information.

Specifically, this study explores:

RQ1. What relationships exist between human factors, such as social influence and trust, and the behavioral intention of early adopters to use AI-powered chatbots for information-seeking?

RQ2. What relationships exist between AI chatbots' system features, such as personalization and conversational ability, and the behavioral intention of early adopters to use them for information-seeking?

2. Related literature and corresponding hypotheses

2.1 Users' intention to adopt and use AI chatbots

Researchers in information science and related fields have long examined users' intentions to accept and use new technologies, particularly over the past several decades of rapid technological development. A series of technology acceptance models (TAM1, TAM2 and TAM3), which were introduced and empirically tested by Davis (1989), Venkatesh and Davis (2000) and Venkatesh and Bala (2008), respectively, have provided a foundation for understanding technology adoption. Additionally, the unified theory of acceptance and use of technology (UTAUT) model, developed by Venkatesh *et al.* (2003), offers a framework for explaining technology use based on key factors including performance expectancy and effort expectancy.

The current study employed the technology acceptance models as our theoretical framework to identify users' perceived usefulness and perceived ease of use as core factors. The original TAM (1989) was derived from the theories of reasoned action (TRA) (Fishbein, 1975; Ajzen and Fishbein, 1980) and planned behavior (TPB) (Ajzen, 1985, 1991). TAM is an empirically supported model that predicts and explains the relationships between individuals' intentions and the resulting behavior associated with technology use mediated through ease of use and usefulness. TAM and the extended versions (e.g. TAM2 and TAM3) have evolved by incorporating and validating additional variables for continuous improvement. However, three core variables – perceived usefulness, perceived ease of use and intention to use – remain consistent across the three versions and form the focus of our study. This study emphasizes the usability aspects of a system, which are fundamental to the system's success. These two variables have consistently proven to be strong determinants that influence users' adoption and continued usage of systems. Therefore, TAM provides an appropriate theoretical framework to examine whether a newly introduced system is perceived as useable and useful from the user's perspective. Additionally, we introduced two new variables reflecting distinctive features of large language models (LLMs): personalization (Arslan, 2023; Harahap *et al.*, 2023) and conversational ability (Cai *et al.*, 2022; Haleem *et al.*, 2022). Although these system features have been conceptually recognized in previous studies, we have operationalized them specifically to explore users' perceptions of LLMs.

TAM and the extended versions have been applied across a wide range of technology acceptance and usage scenarios to predict and explain users' technology adoption and behaviors. The extensive empirical testing of these models has demonstrated that they are some of the most robust and adaptable frameworks for research (Rahimi *et al.*, 2018; Booker *et al.*, 2012; King and He, 2006). Specifically, they explain users' motivations and determinants for adoption across various user populations, including early adopters. For example, Saari *et al.* (2022) found that perceived usefulness significantly influences behavioral intention to use for early adopters of social robots, while perceived enjoyment plays a key role in shaping the perceived usefulness of social robots for mass market users. For primary care physicians, the expanded technology acceptance models was used to explore early adoption of electronic prescribing (Sicotte *et al.*, 2013). TAM and innovation diffusion theory (IDT) have also been employed in the context of LLMs in classroom settings. Recent results have shown that perceived usefulness has a strong influence, while perceived ease of use has a less significant impact on AI generative adoption (Ghimire and Edwards, 2024).

Technology acceptance models have also been used to investigate users' perceptions of ease of use and usefulness including the following: users' attitudes and intension to use smartphone chatbots for shopping (Kasilingam, 2020), users' acceptance of COVID-19 contact-tracing applications (Nguyen *et al.*, 2022), video digital libraries (Ju and Albertson, 2018), E-learning acceptance (Ibrahim *et al.*, 2017), undergraduate students' mobile library apps in China (Hu and Zhang, 2016), acceptance of telemedicine services (Kamal *et al.*, 2020), social media usage (Rauniar *et al.*, 2014), ICT adoption by older citizens and young adults (Guner and Acarturk, 2018), smartphone use (Jan *et al.*, 2019; Joo and Sang, 2013) and wireless technology (Yen *et al.*, 2010). Researchers have also adopted TAM to situate libraries' Web database subscriptions (Kim, 2006), digital libraries (Thong *et al.*, 2002) and physicians' intention to adopt Internet-based health applications (Chismar and Wiley-Patton, 2003). These studies have focused on the relationships among perceived ease of use, perceived usefulness and attitudes toward use.

Based on the results of these studies, the following three hypotheses are proposed:

H1a. Perceived ease of use is positively associated with perceived usefulness of AI chatbots.

H1b. Perceived ease of use is positively associated with attitudes toward using AI chatbots.

H1c. Perceived usefulness is positively associated with attitudes toward using of AI chatbots.

2.2 Social influence

Social influence in our context can be described as the degree to which an individual believes that significant others endorse the adoption of a new technology (Venkatesh *et al.*, 2003). This concept was newly incorporated into the extended technology acceptance model (TAM3) by Venkatesh and Bala (2008). They utilized subjective norms as a determinant of behavioral intention based on both the theory of reasoned action (TRA) and the theory of planned behavior (TPB) to access social influence. In contrast to social influence, subjective norms refer to a an individual's perception of whether significant others believe the individual should or should not engage in a specific behavior. Several studies have indicated that these norms significantly influence the use of personal computers among knowledge workers (Thompson *et al.*, 1991), IT usage (Taylor and Todd, 1995) and users' perceived usefulness of web-based subscription databases (Kim, 2006). However, Mathieson (1991) did not find a significant impact of social norms on intention to use.

In a more recent study on people's decisions to adopt new renewable energy technology, He *et al.* (2022), found that a mainstream mechanism, such as social influence, played a significant role in promoting technology adoption, particularly when government officials in China led by example. Studies on users' adoption of chatbots and AI chatbots have also shown that social influence reduces the perception of uncertainty based on information from significant others (Oldeweme *et al*., 2021). Users also relied on renowned tech figures like Lisa Su and Bill Gates, particularly in the context of ChatGPT (Ma and Huo, 2023).

Scholars have also examined the mediating role of perceived usefulness in linking factors that influence individuals' perceptions of technology to attitudes toward its use across various contexts (Hussain *et al*., 2025; Rezvani *et al*., 2022). Given that social influence highlights how individuals' decisions are shaped by the perceptions and behaviors of others, perceived usefulness may serve as a critical bridge that enhances attitudes toward the use of AI chatbots. Hence, we propose the following hypotheses:

H2a. Social influence is positively associated with perceived usefulness of AI chatbots.

H2b. Perceived usefulness mediates the relationship between social influence and attitudes toward use.

2.3 Trust

Trust is another measure of trust in technology (McKnight *et al*., 2011) including in the adoption of AI chatbots. This type of trust is defined as an individual's confidence in the reliability, authenticity and security of AI chatbots and the information they provide. Hsiao and Chen (2022) found that anthropomorphism affected users' trust in the chatbot and that a users' trust had a "direct effect" on their intentions to continue using chatbots. Nordheim *et al.* (2019) found that expertise was the most important factor in users' trust in chatbots. When the risk of using chatbots was low for consumers, chatbots were "easier to trust." Other important factors were responsiveness and brand perception. Similar to Hsiao and Chen (2022), anthropomorphism was a factor in Pelau *et al.* (2021) study of AI chatbots, but it acted in unison with users' perceptions of quality interactions, which resulted in higher trust. In contrast, Cheng *et al.* (2022) found that specific aspects of anthropomorphism such as warmth and perceived competence had an effect on consumers' trust in chatbots. Thus, the following hypotheses are proposed:

H3a. Trust is positively associated with perceived usefulness of AI chatbots.

H3b. Perceived usefulness mediates the relationship between trust and attitudes toward use.

2.4 Conversational ability

The ability to converse is a defining characteristic of chatbots. Brandtzaeg and Følstad's (2017) early baseline study on why people use chatbots found that conversational ability was one of the most crucial factors that drove users' motivation to use the application. This motivation fulfilled users' social and relational purposes, such as using it as a strategy to "avoid loneliness or fulfill a desire for" two-way communication. Communicating with chatbots can also change how people converse. For example, individuals may talk to a chatbot longer than they would to a human, their words are shorter, their vocabulary is restricted and they tend to use foul language more than in human to human interaction (Hill *et al*., 2015). Travel commerce consumers also valued the bi-directional human-like conversational interactions produced by chatbots. Nordheim *et al.* (2019) found that anthropomorphism (i.e. the attribution of human characteristics to nonhuman entities) was integral to users' perceptions of "fun" and "pleasure" while using chatbots to make travel arrangements. The authors concluded that when people ascribe anthropomorphism to digital objects, deep cognitive ties are established. In other words, individuals may "prefer to treat technological items (e.g. chatbots) like real people" (Cai *et al*., 2022). This finding implies that chatbots can be designed to enhance conversational ability using avatars, giving the chatbot a personal name or adding conversational "cues" such as "Hello" (Cai *et al*., 2022). Adding a professional identity (Kim *et al.*, 2022) such as a medical doctor or other health care provider in health-related domains could also be incorporated. In this study, we define conversational ability as bi-directional human-like communication. Thus, the following hypotheses are proposed:

H4a. Conversational ability is positively associated with perceived ease of use of AI chatbots.

H4b. Perceived ease of use mediates the relationship between conversational ability and attitudes toward use.

2.5 Personalization

Studies have examined the effects of personalization on users' experiences and outcomes when engaging with chatbots. Liu *et al.* (2022) demonstrated that personalization increases users' perceived benefits of health-related chatbots and banking (Wu and Ho, 2022). Chen *et al.* (2021) also found that personalization had a positive relationship on users' experiences using a government-based AI service chatbot. In their study, the AI-based tool "automatically provide[ed] personalized service recommendations that align[ed] with users' interests and needs." In the current study, we adopt Chen *et al.*'s (2017) conception of personalization as defined as the "provision of personally relevant content, products, and services based on the users' unique characteristics and needs." The following hypotheses are proposed:

H5a. Personalization is positively associated with perceived ease of use of AI chatbots.

H5b. Perceived ease of use mediates the relationship between personalization and attitudes toward use.

2.6 The impact of attitude toward use on intention to use AI chatbots

The research on the original TAM introduced by Davis in 1989 and the extended TAMs (TAM 2 and TAM 3) examined the causal connections among system design features, perceived usefulness, perceived ease of use, attitude towards usage and actual usage behavior. Davis hypothesized that a user's overall attitude towards using a specific system is a determining factor in whether they ultimately use it or not. The user's attitude is influenced by two major beliefs: perceived usefulness and perceived ease of use. The findings of Davis' study revealed that the system design features indirectly impact users' attitudes towards usage, whereas perceived usefulness and perceived ease of use have a direct influence on their attitudes. Attitude refers to individuals' overall stance such as whether it leans positively or negatively towards a specific behavior, which shapes their intention to engage in that behavior. This concept is evident in various studies, such as health scientists' attitudes and intentions regarding data reuse (Joo *et al.*, 2017), physicians' attitudes and intentions related to knowledge sharing (Ryu and Kim, 2017), attitudes and intentions concerning e-banking use (Ahmad, 2018) and attitudes and intentions surrounding the use of shopping chatbots (Kasilingam, 2020). Consequently, we present the following hypothesize on the connection between attitudes towards AI chatbots and the intention to use them.

H6. Attitude toward use is positively associated with the intention to use AI chatbots.

Building on these theoretical frameworks and the corresponding hypotheses, the following research model was developed.

3. Methodology

3.1 Recruitment of study participants

We conducted a cross-sectional online survey involving the general public who have utilized an AI-chatbot such as ChatGPT, Bard or Bing. The recruitment process took place between

June 13 and July 10, 2023, using Qualtrics Panel Services, following the approval of the Institutional Review Board. The survey garnered responses from a total of 323 individuals. Leveraging the Qualtrics panel service for recruitment represents a crowdsourcing approach recognized for its reliability and validity in gathering research data. This method is particularly valuable for accessing a specific target population that might otherwise be difficult to reach, while upholding data quality (Behrend *et al.*, 2011; Gosling and Mason, 2015; Weinberg *et al.*, 2014). The current study adhered to all applicable national regulations and institutional policies and received approval from the authors' institutional review board for participant data collection.

The sampling frame utilized was convenience sampling, including individuals aged 18–65, residing in the USA and having engaged with AI-powered chatbots for information seeking within the 6 months preceding the initiation of data collection. The survey questionnaire comprises 28 items of questions, encompassing eight research constructs. Additionally, participants were asked demographic questions and provided with supplementary questions concerning their usage of and concerns regarding AI chatbots. Table 1 summarizes the demographics of the study participants. After excluding responses that did not complete the survey questions or provided identical answers for every question, the resulting sample size ($N = 323$) is considered sufficient for producing reliable results using structural equation modeling (SEM).

Table 1 shows the demographical characteristics of the sample who responded our online survey.

3.2 Measures

The survey questions were developed or adapted from the previous literature with the aim of rigorously investigating the research question and testing the hypotheses outlined in the preceding section of the study. Prior to the collection of official data, preliminary versions of the survey questions underwent pilot testing. Following the feedback received from this pilot test, the questions underwent revisions and improvements. Ultimately, the final set of survey questions on eight research constructs was disseminated online to collect responses from the participants in the study.

In terms of social desirability, we assumed that all participants would not differentially respond to items on each scale, as the survey was conducted anonymously, minimizing the

Table 1. Demographical characteristics

		Total Frequency	%
Gender	Man	100	31.2
	Woman	223	69.0
Birthyear	1928–1964 (Baby Boomer)	48	14.9
	1965–1980 (Gen X)	69	21.4
	1981–1996 (Millennials)	122	37.8
	1997–2012 (Gen Z)	84	26.0
Education	Graduate/Professional degree	102	31.6
	Post-secondary (some college or bachelors)	142	44.0
	No college	79	24.5
Race	Asian/South Asian (including Middle Eastern and Pacific Islanders)	13	4.0
	Black/African American	62	19.2
	Hispanic/Latinx	38	11.8
	Native/Indigenous	6	1.9
	White	204	63.2

Source(s): Authors' own work

pressure to provide socially desirable responses. Additionally, participants were explicitly instructed to answer based on their own experiences rather than perceived expectations. To assess common method bias, we conducted Harman's one-factor test (Podsakoff *et al.*, 2003). The results indicated that the first factor accounted for 40.92% of the total variance, which is below the 50% threshold. Therefore, common method bias is unlikely to significantly affect the results.

Conversational capability (CA) refers to the system's ability to simulate human-like turn-taking dialogues and interactions between users and the system (Haleem *et al.*, 2022; Liao *et al.*, 2023). Based on this conceptualization, we assessed study participants' perceptions of AI chatbots' conversational capability using four questions, including: "I value natural human conversation," "I value engaging conversation," and "I value two-way conversation."

Personalization (PERS) is defined as a system's ability to cater to users' specific and unique needs and preferences (Ju and Stewart, 2024; Harahap *et al.*, 2023). To assess participants' perceptions of AI chatbots' personalization, we posed three questions: AI chatbots "Responses to my specific information needs and preferences", "Provide information that is relevant to my information requests, or interests" and "Provide responses my query that is tailored to my information search."

Social influence (SI) refers to the extent to which an individual perceives that important people in their life support their decision to adopt new technology or engage in a specific behavior (Venkatesh and Bala, 2008; Kim, 2006; Ma and Huo, 2023). We measured participants' perceived social influence by presenting three questions. "People important to me think I should use AI chatbots", "It is expected that people like me use AI chat bots" and "People I look up to expect me to use AI chatbots."

In this study, *Trust (TR)* refers to technological trust, defined as people's belief that a system, such as AI, software or devices, functions as expected, protects user data and delivers accurate and reliable outcomes (McKnight *et al.*, 2011; Dilleen *et al.*, 2023). We assessed participants' trust in AI chatbots by presenting the following five questions: "I believe that the information provided by AI chatbots is trustworthy", "I believe that AI chatbots provide accurate information", "I trust AL chatbots used in language models", " I believe that my search queries executed on AI chatbots are secure" and "I believe that my personal information used in information searches using AI chatbots are kept private."

Perceived ease of use (PEOU) and *Perceived usefulness (PU)* are constructs derived from the theoretical models of TAMs and UTAUT, widely applied in technology adoption and use studies. Perceived ease of use is defined as the extent to which an individual believes that using a particular system requires minimal effort, while perceived usefulness refers to the extent to which an individual believes that using a particular system enhances their job performance and effectiveness (Davis, 1989).

To measure participants' perceived ease of use, we presented four questions: "Learning to use AI chatbots is easy for me," "Using AI chatbots is clear and understandable to me," "It is easy to become proficient at using AI chatbots to help find information," and "I understand the features of chatbots when I use them."

For perceived usefulness, we presented four questions: "Using AI chatbots enables me to accomplish tasks," "Using AI chatbots increases my productivity," "I find AI chatbots useful for my tasks and information needs," and "Using AI chatbots enhances my effectiveness in completing tasks."

According to the Theory of Planned Behavior (Ajzen, 1991), an individual's attitude toward a particular behavior positively influences their intention to engage in that behavior, which in turn leads to the actual behavior (Kim and Adler, 2015; Weng *et al.*, 2018; Kasilingam, 2020). For *Attitude toward using AI chatbots (ATT)* was assessed in the current study by asking participants' attitude toward using AI chatbots with three questions: "Using AI chatbots to find information is a good idea", "I like using chatbots for information searching" and "Using chatbots for seeking information is rewarding."

For *Intention to use AI chatbots (INT)*, we assessed participants intention to use AI chatbots by presenting 3 items: "I intend to use AI chatbots for seeking everyday life information", "I intend to use AI chatbots for seeking work/school related information" and "Assuming I have access to AI chatbots, I will use them."

Survey participants provided responses to all the questions on a scale ranging from 1 (strongly disagree) to 5 (strongly agree).

4. Results

Structural equation modeling (SEM) was employed to examine the direct and indirect effects of research constructs on early adopters' attitudes toward AI-powered chatbots and their subsequent intention to use these tools for everyday information seeking. SEM is a powerful method that allows researchers to explore complex, interactive causal relationships among latent variables and identify key constructs within a model. Using this approach, we evaluated our measurement model to ensure the validity and reliability of our instruments. We also assessed the research model to determine its fit with the collected data and alignment with our hypotheses, thereby validating the proposed structural model.

4.1 Descriptive statistics and correlations

Table 2 presents the correlations among the eight constructs and the descriptive statistics. All correlations among the variables were statistically significant ($p < 0.05$). The relationship between attitude toward use (ATT) and intention to use (INT) was the highest ($r = 0.72$), followed by the relationships between conversational ability and INT ($r = 0.67$), between social influence and INT ($r = 0.67$) and between trust and INT ($r = 0.67$). The results of skewness and kurtosis show that the data met the assumption of a multivariate normal distribution based on the skewness and kurtosis values (skewness <3; kurtosis <10) (Kline, 2015).

Data were collected from 323 individuals across the United States. With respect to gender, females comprised nearly 70% of participants with males comprising the remaining 31%. With respect to age, we classified participants into four (4) categories: Millennials and Gen Z comprised 63.8%; Gen X and Baby Boomers were 36.3% of participants. The majority of individuals had some college or a bachelor's degree (44%), less than 31.6% held graduate or

Table 2. Descriptive statistics and correlations

		1	2	3	4	5	6	7	8
1	CA	–							
2	PERS	0.26*	–						
3	SI	0.05*	0.47*	–					
4	TR	0.10*	0.58*	0.62*	–				
5	PEOU	0.41*	0.48*	0.41*	0.38*	–			
6	PU	0.58*	0.61*	0.58*	0.65*	0.62*	–		
7	ATT	0.58*	0.54*	0.58*	0.65*	0.38*	0.63*	–	
8	INT	0.67*	0.54*	0.67*	0.67*	0.42*	0.64*	0.72*	–
Mean		4.24	3.71	3.16	3.39	3.63	3.54	3.64	3.49
Standard Deviation		0.74	0.82	0.97	0.88	0.88	0.89	0.90	0.94
Skewness		−0.88	−0.76	−0.21	−0.45	−0.59	−0.50	−0.77	−0.73
Kurtosis		0.38	0.78	−0.34	0.08	0.19	−0.10	0.55	0.32

Note(s): $n = 323$. $*p < 0.05$. Personalization (PERS), Conversational ability (CA). Trust (TR), Social Influence (SI), Perceived ease of use (PEOU), Perceived usefulness (PU), Attitude toward Use (ATT) and Intention to use (INT)
Source(s): Authors' own work

professional degrees while 24.5% had no college education. Overall, the study comprised a diverse population with respect to racial and ethnic background. Black/African Americans were 19%, almost 12% identified as Hispanic/Latinx, Asians/South Asians 4% and White participants were 63.2%.

4.2 Reliability and construct validity

For reliability, Cronbach's alpha and composite reliability (CR) were examined. The Cronbach's alpha coefficients ranged from 0.80 to 0.87. In addition, the CR of the latent variables was between 0.80 and 0.88, which was higher than 0.70, the minimum critical value for good internal consistency (Fornell and Larcker, 1981). Our validity analysis involved both convergent and discriminant validity. The standardized factor loadings of all the elements measured were between 0.72 and 0.88. The average variance extracted (AVE) values were between 0.58 and 0.69, which was higher than 0.50, the minimum critical value for acceptable level of convergent validity (Fornell and Larcker, 1981). Table 3 demonstrates that all variables have good convergent validity.

As some factor loadings were relatively high, the possibility of multicollinearity was examined. Multicollinearity can be severe if the tolerance (the proportion of variance that is not explained by other variables) values are less than 0.10, or if the variance inflation factor (VIF) values are higher than 10 (Kline, 2015). Table 4 presents the collinearity diagnostics and indicates that multicollinearity did not occur in variables examined in this study.

Table 3. Factor loading, Cronbach's alpha, composite reliability and average variance extracted

Construct		Factor loading	Cronbach's alpha	Composite reliability	AVE
Conversational ability	CA1	0.76	0.82	0.82	0.60
	CA2	0.82			
	CA3	0.75			
Personalization	PERS1	0.79	0.81	0.81	0.59
	PERS2	0.78			
	PERS3	0.73			
Social influence	SI1	0.80	0.82	0.81	0.59
	SI2	0.72			
	SI3	0.79			
Trust	TR1	0.78	0.87	0.88	0.58
	TR2	0.75			
	TR3	0.78			
	TR4	0.78			
	TR5	0.73			
Perceived ease of use	PEOU1	0.76	0.86	0.87	0.62
	PEOU2	0.74			
	PEOU3	0.88			
	PEOU4	0.76			
Perceived usefulness	PU1	0.76	0.85	0.86	0.60
	PU2	0.77			
	PU3	0.79			
	PU4	0.77			
Attitude toward use	ATT1	0.84	0.87	0.87	0.69
	ATT2	0.85			
	ATT3	0.80			
Intention to use	INT1	0.74	0.80	0.80	0.58
	INT2	0.79			
	INT3	0.75			

Source(s): Authors' own work

Table 4. Collinearity diagnostics

Variables		Tolerance	VIF
Conversational ability	CA1	0.49	2.03
	CA2	0.45	2.25
	CA3	0.49	2.06
Personalization	PERS1	0.42	2.41
	PERS2	0.43	2.31
	PERS3	0.50	2.01
Social Influence	SI1	0.40	2.51
	SI2	0.52	1.94
	SI3	0.40	2.52
Trust	TR1	0.34	2.94
	TR2	0.37	2.68
	TR3	0.43	2.36
	TR4	0.42	2.36
	TR5	0.43	2.32
Perceived ease of use	PEOU1	0.40	2.48
	PEOU2	0.29	3.40
	PEOU3	0.42	2.37
	PEOU4	0.46	2.19
Perceived usefulness	PU1	0.42	2.39
	PU2	0.41	2.43
	PU3	0.41	2.45
	PU4	0.41	2.44
Attitude toward use	ATT1	0.37	2.70
	ATT2	0.34	2.91
	ATT3	0.40	2.43
Intention to use	INT1	0.43	2.31
	INT2	0.41	2.44
	INT3	0.41	2.43

Source(s): Authors' own work

4.3 Measurement and structural models

Based on the suggestion from Schumacker and Lomax (2010), this study used four goodness-of-fit indices to evaluate how the research model fits data, including chi-square (χ^2), Tucker Lewis Index (TLI), comparative fit index (CFI) and root mean square error of approximation (RMSEA) for both measurement model and structural model. For reasonable or better fits, TLI and CFI should be larger than 0.90 and RMSEA should be between 0.05 and 0.08 (Hair *et al*., 2005).

The measurement model was evaluated before examining the structural model. All fitness indices of the measurement model seemed desirable ($\chi 2 = 643.67$; df = 322; χ^2/df = 2.00; TLI = 0.93; CFI = 0.94; RMSEA = 0.06). All factor-loading values of the items in the confirmatory factor analysis were acceptable, ranging from 0.72 to 0.88 (Table 3). The results indicated adequate validity of all factors in the measurement model.

As the fitness index of the measurement model satisfied the fitness index criteria and the estimate possibility of the structural model was theoretically confirmed, the fitness of the initial research model was estimated using a maximum likelihood estimation method. The initial structural model provided a good fit to the data ($\chi 2 = 731.58$; df = 332; χ^2/df = 2.20; TLI = 0.91; CFI = 0.92; RMSEA = 0.06).

4.4 Hypotheses testing

To test the hypotheses, the statistical significance of the path coefficient between the variables was examined. The findings showed that all hypotheses were supported except Hypothesis 1c

(PU- ATT) (Table 5). As hypothesized, perceived ease of use was positively associated with perceived usefulness of AI chatbots (H1a) and attitude toward using AI chatbots (H1b). To rephrase, when users feel AI chatbots are easy to use, they are more likely to perceive AI chatbots are useful and have a positive attitude toward using AI chatbots.

Social influence (H2a) and trust (H3a) were positively associated with perceived usefulness of AI chatbots, while conversational ability and personalization were positively associated with perceived ease of use of AI chatbots (H4a and H5a). When users (a) use AI chatbot because of important people to them, and (b) trust information provided by AI chatbots, they are more likely to feel that AI chatbots are useful. When users value engaging conversations and receive personalized information tailored to their requests, they are more likely to think that AI chatbots are easy to use.

In addition, attitude toward use was positively associated with intention to using AI chatbots (H6). When users have positive attitude toward using AI chatbots, they have stronger intention to use AI chatbots in their life.

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By estimating the 95% bias-corrected confidence intervals (CI) (Hayes, 2021), the bootstrapping results demonstrated that perceived usefulness mediates the relationships between social influence and attitude toward use (H2b, $\beta = 0.31$, $p < 0.05$, CI [0.11, 0.31]) and between trust and attitude toward use (H3b, $\beta = 0.46$, $p < 0.05$, CI [0.30, 0.68]). In other words, social influence and trust can make users' attitude toward use stronger through their perception of usefulness about AI chatbots. Perceived ease of use also mediates the relationship between conversational ability and attitude toward use (H4b, $\beta = 0.46$, $p < 0.05$, CI [0.01, 0.04]) 10 and between personalization and attitude toward use (H5b, $\beta = 0.46$, $p < 0.05$, CI [0.01, 0.18]). That is to say, users' value on conversation can make attitude toward using AI chatbots more positive through their perception of easy usage about AI chatbots.

5. Discussions and conclusions

In this study, we explored the burgeoning adoption and use of AI chatbots in information-seeking, emphasizing factors such as conversational ability, personalization, social influence, trust and attitudes in the context of users' acceptance and use of these technologies. A key

Table 5. Hypothesis testing: direct and indirect effects of path estimates

	Paths			Direct effect	Indirect effect	Total effect
H1a	PEOU	→	PU	43*	–	0.43*
H1b	PEOU	→	ATT	0.11*	–	0.11*
H1c	PU	→	ATT	0.10	–	–
H2a	SI	→	PU	0.28*	–	0.28*
H2b	SI	→	ATT (through PU)	–	0.31*	0.31*
H3a	TR	→	PU	0.42*	–	0.42*
H3b	TR	→	ATT (through PU)	–	0.46*	0.46*
H4a	CA	→	PEOU	0.42*	–	0.42*
H4b	CA	→	ATT (through PEOU)	–	0.46*	0.46*
H5a	PERS	→	PEOU	0.42*	–	0.42*
H5b	PERS	→	ATT (through PEOU)	–	0.46*	0.46*
H6	ATT	→	INT	0.91*	–	0.91*

Note(s): *$p < 0.05$. Personalization (PERS), Conversational ability (CA), Trust (TR), Social Influence (SI), Perceived ease of use (PEOU), Perceived usefulness (PU), Attitude toward use (ATT) and Intention to use (INT)
Source(s): Authors' own work

distinction between AI-generated content (AIGC) chatbots and traditional chatbots is their generative capability. Traditional chatbots primarily rely on predefined rule-based or retrieval-based systems, offering responses limited to a fixed set of scripted interactions. In contrast, AI chatbots, powered by large-scale language models, dynamically generate human-like responses by understanding context, adapting to user inputs and producing novel content. This fundamental difference enables AI chatbots to engage in more complex, nuanced and context-aware conversations, making them more effective for diverse information-seeking tasks. As a result, the adoption dynamics of AI chatbots may differ significantly from traditional chatbots, as users encounter greater flexibility, personalization and adaptability in their interactions, necessitating further investigation into their impact on user engagement and trust.

Our research reveals a critical insight on information seeking in this new information landscape: AI chatbot consumers' intentions to accept and use this technology is primarily influenced by system affordances such as conversational ability as well as users' trust in the AI chatbots. Expectedly, social influence had a significant impact on users' perceptions of usefulness about AI chatbots. This finding aligns with broader trends in technology adoption, highlighting the paramount importance of user-friendly interfaces. The results of this study suggest that, particularly in the realm of AI chatbots, user interaction, which is inherently conversational, must be straightforward and intuitive to foster widespread adoption. Although this study does not explicitly examine the relationship between social influence and intention to use, social influence may indirectly impact the intention to use AI chatbots through attitude toward use. Given the established positive and direct effect of social influence on attitude toward use, it is plausible that attitude serves as a mediating factor in this relationship. This potential mediation presents an avenue for future research to explore in greater depth. Our study did not observe a statistically significant relationship between social influence and intention to use AI chatbots (INT). This finding indicates that AI chatbot adoption may be driven more by individual factors compared to traditional social technologies. A recent study by Skjuve *et al*. (2024) provides further insights, indicating primary individual motivations in chatbot adoption including productivity (55%), referring to the chatbot's utility in enhancing personal efficiency or task performance; novelty (50%), meaning curiosity or intrinsic interest in AI and fun and amusement (41%), reflecting entertainment value from interaction with this emerging technology. Although the same study found some individuals were influenced by a "social push" associated with the novelty factor, this influence appeared weaker compared to individual motivations. Thus, future research should examine specific user groups (e.g. younger versus older users) separately to determine how social influence might differently affect AI chatbot adoption intentions.

According to the original TAM and its extensions (TAM2 and TAM3), ease of use of a technology/system has a significant direct effect on usefulness. This implies that an increase in the ease of use enhances the perception of the technology's usefulness in terms of how a technology/system functions and performs. Previous literature echoed this relationship in their empirical studies: patients' acceptance of personal health records (PHR) systems (Alsyouf *et al.*, 2023), incorporation of virtual reality into students' curricular and training program and student's perception and adoption of VR (Fussell and Truong, 2022), users' acceptance of metaverse technology (Toraman, 2022), online banking adoption in Spanish cities (Albort-Morant *et al.*, 2022), acceptance of video digital libraries (Ju and Albertson, 2018), students to accept e-portfolios (Abdullah *et al.*, 2016). Interestingly, usefulness did not have a statistically significant influence on attitude, which contradicts with the major findings in the mainstream TAM literature. Given that LLMs are a disruptive technology that closely simulates human intelligence, it could present a situation wherein users' attitudes toward LLMs are influenced more by their novelty and sentiment rather than solely their utility. Baek and Kim (2023) for example found that emotional reactions such as feelings of "creepiness" may have had a stronger influence on users' attitudes than traditional perceptions of usefulness. In their study, *creepiness* was defined as a user's feeling of discomfort and uncertainty about how to interact with the technology. Similarly, Shank *et al.* (2019) found that users' attitudes can be shaped by experiences in which AI task performance exceeds their expectations, with "extraordinary outcomes" further complicating traditional adoption patterns. Furthermore, the mediating variable, attitude, was observed to strongly influence intended use. Attitude toward use indicates a person's positive or negative assessment of a given behavior (Ajzen, 1991). This attitude toward use was derived from the analysis, where intention played a prominent role, consistent with findings in the existing literature. The attitude toward AI chatbots is a crucial factor in the research model for determining people's intentions to use.

It was found that perceived usefulness was significantly influenced by the two cognitive determinants, social influence and trust respectively. The concept of social influence in technology adoption research has multiple meanings and manifests in many aspects. Social influence in human behavior and technology research has been widely recognized as an essential factor since it was first coined, referring to changes in an individual's thoughts, behavior or feelings resulting from interactions with another individual or a group (Chan *et al.*, 2010; Graf-Vlachy *et al.*, 2018; Venkatesh *et al.*, 2003). This concept has been incorporated into technology adoption-related models, such as Ajzen's Theory of Planned Behavior, defined as subjective norm, meaning a person's perception about whether the individuals significant to them generally approve or disapprove of their engagement in a specific behavior (Ajzen, 1991), or TAM 2 by Venkatesh and Davis (2000). Social influence, especially, has been linked to perceived usefulness in technology adoption and use within influential relationships, as shown in extant studies (Kim, 2006; Sugumar and Chandra, 2021; Wang and Chou, 2014). The positive impact of social influence by other users in the current study suggest that user perceptions of the usefulness of AI chatbots are likely to be reinforced when they are recommended by someone they know.

While this study lacks direct analogs with our constructs around conversational ability, personalization and trust we do see support in the previous literature while simultaneously extending these constructs within the context of AI chatbots. The literature suggests that conversational ability is a highly valued affordance in the context of chatbot infrastructure. The presence of bi-directional conversation essentially enhances the experience of chatbot usage and also appears to produce positive sentiment such that the use of the chatbot is constructed as "fun" (Nordheim *et al.*, 2019). In this study, conversational ability has a significant relationship on users' perceived ease of use. What is likely occurring here is that the ability to *talk* in a *normal way*, allowing users to ask questions and more importantly, receive feedback helps their perception that the application is easy to use because in part they are comfortable in the application. Likewise, with personalization; one's ability to tailor chatbots to their specifications helps users feel the application is more beneficial and results in a "positive relationship" with user experiences (Hayes, 2021). The affordance of personalization, being able to manipulate aspects of chatbot interfaces, affects perceived ease of use because the space is customized to the users' preferences in some way. It is possible that this act results in the removal of, or minimizes barriers and/or irritants that would have influenced perception that the application was difficult to use. With respect to trust, we found a statistically significant relationship between the construct and perceived usefulness. One of the factors that influence users' trust is related to their perception of low risk in chatbot applications. For example, if users are not required to share "personal or sensitive information" (Nordheim *et al.*, 2019), they will likely feel safer using the chatbot, wherein they can truly experience what the application can do. Trust removes barriers that may otherwise result in chatbot avoidance.

The significance of our study extends beyond the immediate investigation, as we hope our results serve as a foundational study of information-seeking using AI-chatbots. By shedding light on the nuances of user engagement, we seek to contribute a valuable baseline resource that may guide and stimulate future empirical studies on emerging information behaviors on large language model applications, establishing a deeper understanding of ever evolving human information behaviors.

6. Implications

The current study delves into the novel interaction factors influencing users' adoption of a new information-seeking environment facilitated by AI chatbots, including those available with ChatGPT, Google Bard (now Gemini) and Ernie. Our contribution lies in extending previous theoretical models related to users' intentions to use and adopt new technology, incorporating key elements such as social influence, trust, personalization and conversational ability of the tools. The study's findings highlight the significant impact of these factors on users' decision-making processes, thereby empowering and enhancing their information-seeking experiences. Specifically, the findings highlight additional areas for exploration, particularly the influence of social influence, trust and conversational ability on intention to use, as well as the mediating role of attitude toward use in this relationship. Additionally, the findings suggest considerations for improving various interface designs, despite not delving deeply into design features. Regarding the practical implications of this study, there are potential benefits for software companies and designers. Trust remains a significant concern among early adopters, as our findings indicated as a significant influence on usefulness; therefore, designers and developers should prioritize transparency and meaningful user engagement throughout the product development process. Recognizing that the impact of AI technologies is often unevenly distributed due to factors such as algorithmic bias and unequal access (Gillespie, 2024; Ozkul, 2024), it is essential for designers to actively address these issues. Drawing on Bircan and Özbilgin's (2025) proposal for "co-ownership" where stakeholders, especially those from underrepresented populations, hold significant ownership and influence over AI development, we advocate for integrating diverse user perspectives directly into the AI chatbot design process. Such inclusive practices could enhance trust, mitigate economic inequalities associated with AI and foster equitable adoption across user groups. Emerging features such as conversational ability and personalized responses of LLMs have shown a significant influence on users' perceptions of LLM usefulness in our study. These findings underscore the importance for developers to enhance training data quality and optimize interaction models to support more effective and adaptive communication between users and AI-powered systems.

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7. Limitations and future research

In June–July 2023, the stage of AI chatbot technology, particularly in terms of our data collection from users, was still in the developmental phase. Our research focused on early adopters, individuals whose engagement with this emerging technology could be significantly enriched through prolonged usage. A longitudinal study would offer a unique perspective by introducing a different set of variables for examination. The current study was conducted with a convenience sample of 323 adults residing in the USA, aiming for a diverse representation. The results derived from our study can potentially be generalized across the country, given the varied demographic makeup of our participant pool. However, it is crucial to acknowledge the fact that cultural differences may influence certain variables, such as social influence or trust formation within a society. While our findings may have broad applicability within the USA, caution is advised when extending them to different countries due to variations in societal norms. Different cultural settings could introduce unique dynamics that might impact the generalizability of our results in an international context. Although common method variance is not a serious concern in this study, as indicated by Harman's single-factor test, future research would benefit from collecting data from multiple sources to further enhance validity and reduce potential bias.

There are several conceptualizations of trust including functional trust (e.g. system reliability and security) and social trust (e.g. perceptions of anthropomorphism, empathy) therefore, future studies may explore these differing iterations of trust and their relationship with perceived usefulness. Another new stream could explore more diverse factors influencing attitude toward using AI chatbots and intention to use by adding other individual and external variables based on TAM. Researchers might also consider integrating a qualitative component, such as open-response questions to any survey questionnaire to better contextualize users' perceptions. Additionally, future research could explore variables by leveraging other technology adoption models, such as the Unified Theory of Acceptance and Use of Technology (UTAUT) or Diffusion of Innovation (DOI) theory. Beyond self-reporting on perceived usefulness and perceived easy to use, obtaining data from multiple sources (e.g. interviews and observations) would be useful to ascertain the different perception levels of users on AI chatbots. Including more demographic characteristics such as participants' age, technology experience and jobs (e.g. scientists versus undergraduate students) will also help researchers and practitioners better understand their perceptions and preferences of using AI chatbots by comparing their difference and similarities in social influence and trust in the practice. These demographic factors can be analyzed as moderating variables to examine their interaction effects across different demographic groups in the relationships explored in this study. As attitudes toward using AI chatbots may evolve over time, longitudinal research can be conducted to track users' experiences, attitudes and intentions to use in alignment with advancements in AI chatbot technology. Researchers could also explore a similar research model in different cultural contexts or settings to compare with the findings in this study. Researchers could also explore a similar research model in different countries, cultural contexts or settings to compare with the findings in this study. To advance methodological rigor, future research could employ multilevel analysis, moderated mediation and subgroup analysis to examine alternative pathways between variables and compare differences across age, gender and levels of technological experience.

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Appendix
Constructs and measures

Online survey participation

Conversational ability (CA)

I value natural human conversation.

I value engaging conversation.

I value two-way conversation.

Personalization (PER)

AI chatbots provide responses to my specific information needs and preferences.

AI chatbots provide information that is relevant to my information requests, or interests.

AI chatbots provide responses my query that is tailored to my information search.

Social influence (SI)

People important to me think I should use AI chatbots.

It is expected that people like me use AI chatbots.

People I look up to expect me to use AI chatbots.

Trust (TR)

I believe that the information provided by AI chatbots is trustworthy.

I believe that AI chatbots provide accurate information.

I trust AL chatbots used in language models.

I believe that my search queries executed on AI chatbots are secure.

I believe that my personal information used in information searches using AI chatbots are kept private.

Perceived ease of use (PEOU)

Learning to use AI chatbots is easy to me.

Using AI chatbots are clear and understandable to me.

It is easy to become good at using AI chatbots to help find information.

I understand the features of chatbots when I use them.

Perceived usefulness (PU)

Using AI chatbots enable me to accomplish tasks.

Using AI chatbots increases my productivity.

I find AI chatbots useful for my tasks and information needs.

Using AI chatbots enhances my effectiveness for completing tasks.

Attitudes toward use (ATT)

Using AI chatbots to find information is a good idea.

I like using chatbots for information searching.

Using chatbots for seeking information is rewarding.

Intention to use (INT)

I intend to use AI chatbots for seeking everyday life information.

I intend to use AI chatbots for seeking work/school related information.

Assuming I have access to AI chatbots, I will use them

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