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ChatGPT across generations: understanding continued use intention of generative AI technology

Boryung Ju, J. Brenton Stewart, and Sunyoung Park

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Abstract

Introduction. OpenAI's ChatGPT has revolutionised how people search, organise, and create information in work and daily life. This paper explores how different age groups adopt, use, and sustain their use of ChatGPT and other AI generative technologies.

Method. We conducted a cross-sectional online survey of 323 U.S. users of generative AI chatbots to examine individual and collective adoption experiences. Using generational cohort theory, we explored intentions for continued use and the influence of chatbots' conversational ability, personalisation, social influence, trust, and satisfaction across generations.

Analysis. Analysis of variance (ANOVA) and multiple regression were used to analyse the collected data.

Results. Trust, social influence, and personalisation significantly affected users' intention to continue using generative AI chatbots. Significant differences across generations were observed in social influence and conversational ability. Baby Boomers exhibited the lowest levels of social influence but the highest levels of engagement with chatbots' conversational ability.

Conclusions. Baby Boomers (born 1946–1964) are an obscure but enthusiastic cohort among the users of generative AI technologies. Libraries, archives, and museums, among other institutions, should target outreach campaigns at older users, emphasising the potential of AI chatbots to assist users and improve everyday tasks.

Introduction

Introduced nearly two years ago, Open AI's ChatGPT has ushered in a radical paradigm shift in the ways people search, organise, and create information in both work and everyday practice. The value of ChatGPT and other large language models, such as A Lite Bidirectional Encoder Representation from Transformers (ALBERT), Bidirectional Encoder Representation from Transformers (BERT), and Enhanced Representation through kNowledge IntEgration (ERNIE), is in their capacity to understand language requests, process them, and generate human-like analyses from large data sets. This makes them adept at a plethora of user tasks. They can answer diverse questions and answers, write in different genres (such as stories, poems, emails, and essays), code in programming languages, create infographics, translate languages, and solve mathematical problems. A recent report by Pew Research (McClain, 2023), provided an intriguing snapshot of early users based on several demographic characteristics. The largest age demographic, for example, was eighteen- to twenty-nine-year-olds, who made up almost 45% of overall users, followed by thirty- to forty-nine-year-olds comprising 27%. While a majority of younger users is expected, it is noteworthy that nearly 25% of users were aged fifty or older.

While researchers have begun to study different factors in the adoption and use of ChatGPT and other generative AI technologies, few studies have been designed from a cross-generational perspective that could capture the nuanced information behaviour of different age cohorts. Factors such as trust (Choudhury & Shamszare, 2023), users' performance expectations (Camilleri, 2024), motivations, and continued use intentions (Wolf & Maier, 2024) have been explored, yet age-based variations among users remain unexamined. However, unexpected patterns of use, in both adoption and continued use, appear to be emerging in the scant literature on age-related uptake of large language models. Draxler et al. (2023) found that older cohorts were less likely to use large language models than younger people; however, adult cohorts (fifty-five- to sixty-four-year-olds) were more frequent users than younger cohorts (eighteen- to twenty-four-year-olds). Similarly, Baek et al. (2024) reported that college students in their thirties to forties were more likely to use ChatGPT frequently than their younger peers. At this early stage in the proliferation of generative AI technology, much is still unknown about how users' age influences their information behaviour related to the uptake and continued use of large language models across a spectrum of contexts. Therefore, it is imperative that information science researchers work to better understand how diverse populations across generations perceive, adopt, and implement this disruptive technology so that broad constituencies are included in the emerging AI revolution.

Consequently, this study examines how different age cohorts adopt, use, and continue to use ChatGPT and other generative AI technologies, capturing both individual and collective experiences and perspectives associated with their use. This paper adds to the growing body of knowledge on generative AI technologies and continued use intentions from an information science perspective. We leverage generational cohort theory which affords the study a multifocal view, emphasising future use intentions and the influence of generational cohorts among a distinctive set of factors encompassing conversational ability, personalisation, social influence, trust, and continued use intention. On this basis, we pose the following research questions:

> RQ1: Are there any differences among generations in their continued use intention of ChatGPT in terms of social influence, trust, conversational ability, and personalisation?
>
> RQ2: To what extent do generational factors influence information users' attitudes towards their continued use intention of ChatGPT?

Background

In this paper, we adopt generational cohort theory to frame our theoretical approach. Derived from marketing research, generational cohort theory centres on groups of individuals who have experienced similar societal events, particularly during their formative years. Consequently, the cohort shares similar sociocultural behaviour (Schewe & Meredith, 2004). Generation X (born 1965–1980), for example, is distinct from Baby Boomers (1946–1964) because the former witnessed the proliferation of Internet adoption during their highly formative coming-of-age years (approximately seventeen to twenty-three years old), thereby 'producing distinctive cohort effects' (Schewe & Meredith, 2004). Likewise, Baby Boomers and Generation X are further differentiated from Millennials or Generation Y (born 1981–1996), who are considered digital natives, having grown up with digital culture their entire lives (Prensky, 2001). Generational cohort theory has been leveraged by researchers to interpret a cross section of human behaviour, including remote work (Cera et al., 2024), consumerism (Eger et al., 2021), tourism behaviour (McKercher, 2023), and, increasingly, human information behaviour (Beldona, 2005; Karadal & Abubakar, 2021). The following section discusses variations in technology uptake and its use by age group.

Generational differences in technology adoption and use

Global demographic projections estimate that there will be 1.4 billion people over the age of sixty by 2030, surpassing the working-age population and reflecting rapid ageing (Whitman & Jivnani, 2023). Previous studies have explored how older adults adopt and use emerging technologies (Gitlow, 2014). Age significantly impacts Internet adoption and use, among other sociodemographic factors. For example, unlike younger generations, older adults (aged sixty and over) prioritise perceived value when adopting PCs and emotional benefits when using mobile devices (Friemel et al., 2016; Lee & Coughlin, 2015). Volkom et al. (2014) also compared generational use of various digital tools, including the Internet, cell phones, search engines, and social media. Age was a central differentiator in use, with adults aged sixty-five and over finding technologies less user-friendly and feeling less comfortable. Among younger age groups, preschool children and young adults are the most susceptible to smartphone-related addictive behaviour (Csibi et al., 2021). Millennials, Internet-raised but not digital-born, leverage social media at work for diverse tasks, including technostress, burnout, and personal branding (Oksa et al., 2021). In contrast, digital-native Generation Z (1997–2012) prefers frequent use of online technology for learning, favouring technology-integrated education (Szymkowiak et al., 2021).

Although ChatGPT was launched in late 2022 and remains new to most people, by July 2023 younger U.S. adults (under thirty, representing 25% of the adult population) were more aware of it and more likely to use it for education or entertainment than older adults (Park & Gelles-Watnick, 2023). Few studies have examined generational differences in intentions to continue using ChatGPT. Thus, it is necessary to investigate how generations perceive and are motivated to continue using this technology.

Factors influencing users' intention towards continued use of ChatGPT

This study examines the intentions of early adopters of ChatGPT to continue using the technology, influenced by key factors such as social influence, trust, conversational ability, and personalisation.

Social influence refers to the process by which an individual's behaviour, opinions, or beliefs are altered through their social connections, often aligning more closely with the people in their social network. It can also be conceptualised as an individual's perception of whether important people in their life believe they should or should not engage in certain behaviour (Graf-Vlachy et al., 2018; Vannoy & Palvia, 2010). This perception is reflected in social conditions or contexts, such as a 'paucity of social landscape' (Workman, 2014) or social identity (Shen et al., 2013) and may also arise through vicarious learning from observing the experiences of others (Bandura & Cervone, 1986; Fulk et al., 1990). A significant body of research has identified social influence as one of the factors influencing users' intentions to adopt, use, or continue to use a specific technology (Chatterjee et al., 2015).

For individuals, *trust* in various technologies has been conceptualised and investigated for its impact on behavioural intention to adopt such technologies (Hooda et al., 2022; Jo, 2023). In the case of AI chatbots like ChatGPT, trust is defined as the degree of confidence users have in the reliability and accuracy of the information provided. This trust significantly influences the adoption of these technologies. Choudhury and Shamszare (2023) found that trust has a significant direct effect on intention to use and actual usage of ChatGPT for information gathering, entertainment, and problem-solving, but potentially risky for health-related queries. Hsiao and Chen (2022) noted that anthropomorphism, or attributing human characteristics to nonhuman entities, influenced users' trust in chatbots, which in turn directly affected their intentions to continue using them. Nordheim et al. (2019) identified expertise as the most critical factor in building users' trust in chatbots. In addition, the perceived low risk of using chatbots, along with other significant factors such as responsiveness and brand perception, made them easier to trust. Similarly, Pelau et al. (2021) found that anthropomorphic design, combined with users' perceptions of quality interactions, led to increased trust in AI chatbots.

Conversational ability refers to the chatbot's ability to converse and is one of the key features chatbots offer to users, with 'natural language understanding by effectively capturing context and long-range dependencies' (Bansal et al., 2024). It can also be defined as the capability for bidirectional, human-like communication, as exemplified by ChatGPT. In their research on chatbot use, Brandtzaeg and Følstad (2017) identified conversational ability as a significant factor motivating use, often serving social and relational purposes such as alleviating loneliness or fulfilling the need for two-way communication. Chatbot interactions can also alter conversational behaviour: individuals may engage with chatbots longer than with humans, use shorter words, limit their vocabulary, and employ foul language more frequently than in human-to-human interactions (Liu et al., 2022). Early adopters of ChatGPT appreciate its natural, human-like conversation and find value in engaging in conversations that motivate them to adopt the technology, even though this was not a significant factor for continued use (Ju & Stewart, 2024). Anthropomorphism is observed among users of travel-related services (Nordheim et al., 2019), and the humanisation of technological items is used to simulate real interaction for pleasure (Pelau et al., 2021).

In the current study, *personalisation* refers to generative AI, such as ChatGPT, delivering content and services that are tailored to each user's unique questions and needs, where the system responses are highly relevant to the information they seek (Bansal et al., 2024). Studies have investigated how personalisation impacts users' experiences and outcomes when interacting with chatbots. In Baek and Kim's study (2023), which explored users' motivations to continue using generative AI, 'creepiness', feelings of discomfort when using new AI tools, was conceptualised as an opposite of trust. The findings indicate that personalisation has a positive impact on trust and correlates negatively with creepiness. Liu et al. (2022) showed that personalisation also enhances users' perceived benefits of health-related chatbots, and Wu and Ho (2022) found similar effects in the banking sector. In this case, the AI tool automatically provided personalised service recommendations that matched users' interests and needs.

Continuance intention is distinct from initial intention to use, as explored in prior studies. It refers to an individual's willingness to continue using a specific technology, reflecting their commitment beyond the initial adoption (Gu et al., 2019; Song et al., 2021). In this study, the construct of *continued use intention* was operationalised through questions assessing respondents' intentions to continue using AI chatbots and their inclinations towards discontinuing use or switching to non-AI chatbot alternatives. Continued use intention is crucial because it signifies the technology's sustainability (Salloum et al., 2023), closely correlates with user satisfaction (Abu Salim et al, 2021), and serves as a reliable predictor of ongoing use behaviour. The following section details the study's measures and data analysis.

Method

Data collection and study participants

Data for the study were collected from Qualtrics Panel Services between June and July 2023. Qualtrics Panel Services (Qualtrics, n.d.) provides researchers with access to diverse and specific audiences, including general population samples and hard-to-reach groups, effectively and within a reasonable timeframe. The crowdsourcing approach for data collection enabled us to rapidly and inexpensively target specific groups of individuals while maintaining data quality (Weinberg et al., 2014). A cross-sectional online survey was administered to individuals with experience using AI chatbots, such as ChatGPT. A total of 323 individuals, aged eighteen to sixty-four and residing in the United States, completed the survey. The participants had used AI-powered chatbots for information-seeking and other daily life tasks within the six months prior to data collection.

The online survey questionnaire included demographic questions about the participants and five multidimensional research constructs: the conversational ability of an AI-powered chatbot, the personalisation of the chatbot, social influence, trust, and participants' continued use intention. Table 1 presents the demographic characteristics of the participants. After excluding incomplete responses or those with identical answers for all questions, the final sample size (N = 323) was deemed sufficient for conducting reliable ANOVA and regression analyses.

		Total	
		Frequency	%
Gender	Male	100	31.2
	Female	223	69.0
Birthyear	1946–1964 (Baby Boomer)	48	14.9
	1965–1980 (Generation X)	69	21.4
	1981–1996 (Millennials)	122	37.8
	1997–2012 (Generation Z)	84	26.0
Education	Graduate/Professional degree	102	31.6
	Post-secondary (some college or bachelors)	142	44.0
	No college education	79	24.5
Ethnicity	Asian/South Asian (including Middle Eastern & 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

Table 1. Participant demographics

Measures

The survey questions relating to the five research constructs were developed by conceptualising and operationalising findings from previous studies or by adapting them from existing literature. To rigorously investigate the research question and test the corresponding factors in the study, preliminary versions of the survey questions were pilot tested before official data collection. Based on the feedback, the questions were revised. The final set of survey questions, covering five factors, was then distributed online to gather responses from the study participants. Participants rated their responses to survey questions using a five-point Likert scale.

The study measured theoretically derived factors using a scale ranging from one (strongly disagree) to five (strongly agree). Details of the survey items are provided in Appendix IA, and internal consistency measurements, including Cronbach's alpha for each factor are presented in Appendix IB. Cronbach's alpha is a widely employed statistic for evaluating the internal consistency of a scale, reflecting the degree to which its items are interrelated (Cronbach, 1951). This coefficient provides an estimate of reliability, where elevated values signify robust inter-item correlations. A commonly accepted threshold of 0.70 is considered satisfactory for research applications (Nunnally & Bernstein, 1994). This measure helps ensure that the scale produces stable and coherent results across items (Tavakol & Dennick, 2011). The survey questionnaire assessed five key factors. Social influence (SI) was defined as the extent to which individuals perceive that people in their lives (friends, family, colleagues) believe they should use or interact with a generative AI tool, drawing on the work of Venkatesh and Bala (2008) and Vannoy and Palvia (2010). Trust (TR), in this context, referred to confidence in the technology's reliability and accuracy, as well as trust in AI chatbots, based on the work of Dilleen et al. (2023).

Personalisation (PERS) captured the ability of an AI chatbot to tailor its responses to specific user requests, as described by Harahap et al. (2023). Following insights from Ju and Stewart (2024) and Liao et al. (2023), conversational ability (CA) assessed the chatbot's ability to simulate authentic, human-like conversations, elaborating on ideas and recalling previous statements within a dialogue. Lastly, building on the definitions provided by Gu et al. (2019), continuance intention (CI) represented a user's willingness to continue using a particular technology over time.

Data analysis

We used descriptive statistics, correlations, ANOVA, and multiple regression analysis to address our two research questions. To examine generational differences in continued use intentions of ChatGPT regarding social influence, trust, conversational ability, and personalisation (RQ1), we conducted an ANOVA followed by Tukey's honestly significant difference test. Tukey's test is a post hoc method used after a significant ANOVA to determine which specific group means differ. It applies the studentised range distribution to control the overall Type I error rate across multiple pairwise comparisons (Tukey, 1953). This method is commonly employed to ensure a rigorous analysis of multiple comparisons (Abdi & Williams, 2010; Maxwell & Delaney, 2004). We conducted multiple regression analysis using IBM version SPSS® 28 to explore how generational factors influence users' attitudes towards their continued use intentions of ChatGPT (RQ2). The subsequent section presents the study's results.

Results

Descriptive statistics and correlations

Table 2 presents the correlations among the five constructs and the descriptive statistics. All correlations among the variables were statistically significant ($p < 0.05$). The relationship between social influence and continuance intention was the highest ($r = 0.635$), followed by the relationships between social influence and trust ($r = 0.621$), between trust and continuance intention ($r = 0.616$), and between personalisation and continuance intention ($r = 0.610$). The results of the skewness and kurtosis tests show that the data met the assumption of a multivariate normal distribution (skewness < 3; kurtosis < 10) (Kline, 2015).

		1	2	3	4	5
1	CA	(0.821)				
2	PERS	0.257*	(0.812)			
3	SI	0.045*	0.467*	(0.815)		
4	TR	0.096*	0.577*	0.621*	(0.872)	
5	CI	0.169*	0.610*	0.635*	0.616*	(0.859)
Mean		4.239	3.715	3.162	3.389	3.607
SD		0.735	0.819	0.973	0.879	0.904
Skewness		−0.878	−0.760	−0.213	−0.449	−0.790
Kurtosis		0.377	0.781	−0.336	0.077	0.706

Note. n = 323. *p < 0.05. Conversational ability (CA), personalisation (PERS), social influence (SI), trust (TR), and continuance intention (CI); standard deviation (SD). Parentheses are reliability values.

Table 2. Descriptive statistics and correlations

ANOVA and multiple regression

ANOVA was used to examine significant mean differences in conversational ability, personalisation, social influence, trust, and continuance intention across generations: Baby Boomers, Generation X, Millennials, and Generation Z (Table 3). Baby Boomers showed the highest mean (4.535) for conversational ability, while Generation Z showed the lowest (4.091). For social influence, Millennials had the highest mean (3.448), whereas Baby Boomers had the lowest (2.868).

	Age	Mean	SD
CA	1946–1964 (Baby Boomers)	4.535	0.553
	1965–1980 (Generation X)	4.314	0.674
	1981–1996 (Millennials)	4.183	0.751
	1997–2012 (Generation Z)	4.091	0.806
PERS	1946–1964 (Baby Boomers)	3.535	0.847
	1965–1980 (Generation X)	3.638	0.804
	1981–1996 (Millennials)	3.836	0.855
	1997–2012 (Generation Z)	3.706	0.749
SI	1946–1964 (Baby Boomers)	2.868	0.858
	1965–1980 (Generation X)	2.971	0.996
	1981–1996 (Millennials)	3.448	0.957
	1997–2012 (Generation Z)	3.071	0.949
TR	1946–1964 (Baby Boomers)	3.200	0.947
	1965–1980 (Generation X)	3.362	0.838
	1981–1996 (Millennials)	3.528	0.890
	1997–2012 (Generation Z)	3.319	0.842
CI	1946–1964 (Baby Boomers)	3.403	0.930
	1965–1980 (Generation X)	3.478	0.981
	1981–1996 (Millennials)	3.768	0.886
	1997–2012 (Generation Z)	3.595	0.818

Table 3. Mean and standard deviation for conversational ability, personalisation, social influence, trust, and continuance intention

In Table 4, the results showed that there were generational differences in conversational ability and social influence, while there were no significant differences in personalisation, trust, and continuance intention.

		Sum of squares	Degrees of freedom	Mean square	F statistic	Significance
CA	Between groups	6.801	3	2.267	4.321*	0.005
	Within groups	167.351	319	0.525		
	Total	174.151	322			
PERS	Between groups	3.767	3	1.256	1.883	0.132
	Within Groups	212.695	319	0.667		
	Total	216.462	322			
SI	Between groups	17.338	3	5.779	6.410*	0.001
	Within Groups	287.627	319	0.902		
	Total	304.965	322			
TR	Between groups	4.527	3	1.509	1.968	0.119
	Within groups	244.677	319	0.767		
	Total	249.204	322			
CI	Between groups	6.310	3	2.103	2.613	0.051
	Within groups	256.755	319	0.805		
	Total	263.065	322			

Note.$*p < 0.05$, $R^2 = 0.554$

Table 4. ANOVA results

Additionally, we conducted post hoc tests using Tukey's honestly significant difference test to compare all pairs of generation groups (Appendix IC). In conversational ability, the largest and most significant mean difference was between Baby Boomers (4.535) and Generation Z (4.091), with a mean difference of 0.444. The next significant difference was 0.352 between Baby Boomers (4.535) and Millennials (4.183). In terms of social influence, the largest significant mean difference was found between Millennials (3.448) and Baby Boomers (2.868), with a difference of 0.580. The second-largest difference, 0.477, was between Millennials (3.448) and Generation X (2.971). The smallest difference, 0.377, occurred between Millennials (3.448) and Generation Z (3.071). No significant differences were found among generational groups for personalisation, trust, and continuance intention ($p > 0.05$).

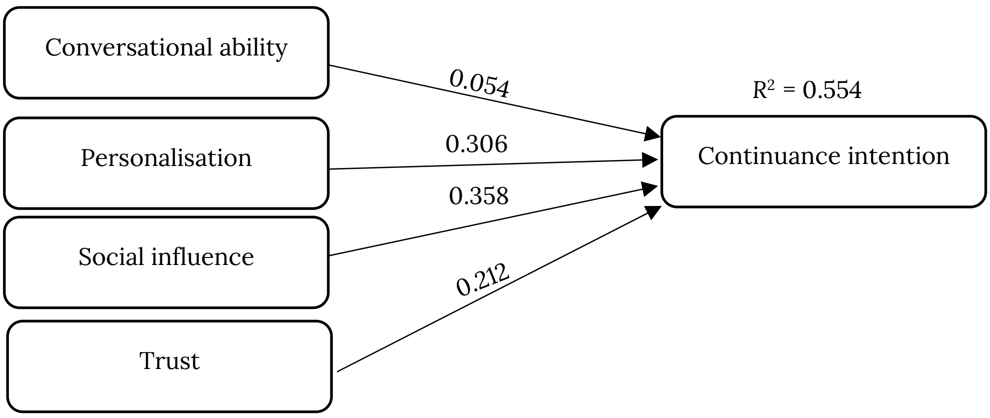

Figure 1. Multiple regression results ($*p < 0.05$)

In regression results, personalisation ($\beta = 0.306$, $t = 6.362$, $p < 0.05$), social influence ($\beta = 0.358$, $t = 7.372$, $p < 0.05$), and trust ($\beta = 0.212$, $t = 4.036$, $p < 0.05$) significantly affected continuance intention (Figure 1). Conversational ability did not have a significant effect on continuance intention. Personalisation, social influence, and trust account for 55.4% of the total variance in continuance intention ($R^2 = 0.554$), which means that these three factors influence continuance intention of AI-powered chatbots. In the following section we interpret the significance of the study's findings.

Discussion

Since its introduction to the public and integration into everyday life, generative AI has garnered attention and sparked widespread discussion. Despite the enthusiasm of early adopters among the public, little was known about their intentions to continue using this technology. In this study, we designed and tested a research model of generative AI technology acceptance and use through the lens of generational cohort theory. Specifically, we explored the impacts of system features, such as personalisation tailored to specific user needs and requests and the human-like conversational ability of its communication style; users' trust in the technology; and the social influence exerted by their acquaintances on behavioural intention of continued use across different generational groups.

In July 2023, we collected cross-sectional data in the United States from early adopters of generative AI to explore individuals' intentions to continue using this technology. Our investigation focused on two perspectives: social aspects, such as trust and social influence, and the interface features of generative AI tools, including personalisation and conversational ability. The findings indicate that trust and social influence significantly affect users' intention to continue using this technology. This result has been supported by similar research. Ju and Stewart (2024), for example, identified social influence and trust as two of four factors that motivate continued use of generative AI tools. Similarly, Choudury and Shamszare (2023) found trust to be significant factor in 'both intentions to use [...] and actual use'. Another study by Camilleri found that social influence affects users' 'interactions with ChatGPT' (2024), that is, influence from individuals in users' social networks spurred their use of the new technology. This study also found that personalisation factors have a notable impact on users' intentions to continue use. This, too, was substantiated by Camilleri's construct of *interactivity*, which is analogous to personalisation in this study. Camilleri (2024) found that 'individuals' perceptions about the interactivity of ChatGPT are a precursor of their intentions to use it'.

Significant differences were observed in social influence related to this technology. Specifically, the Baby Boomer cohort exhibited lower social influence in their decision to continue using the technology, whereas Millennials demonstrated the highest level of social influence. This result was unsurprising: while less than a quarter of adult Americans have used ChatGPT, one of the most widely adopted large language models, 70% of its users in the United States are forty-nine years old or younger (Park & Gelles-Watnick, 2023). Social influences would therefore be highest among these younger users. However, this result reveals the advantage of leveraging generational cohort theory in this study's design because it prompts researchers to consider the nuanced differences that exist among users.

Users' perceptions of ChatGPT and other generative AI technologies' ability to mimic human-like bidirectional communication, showed significant differences between age cohorts: Baby Boomers exhibited the highest levels of engagement, while Generation Z showed the lowest. While we do not have a direct comparison with this result, however, previous work by Ju and Stewart (2024) showed conversational ability as an influential factor in both current and future use; however, their study did not analyse results by generation or cohort. It is possible that Baby Boomers held higher perceptions of conversational ability because the bidirectional, human-like communication helped reduce barriers to use, making the technology approachable. Other clues as to why older cohorts had high engagement with conversational ability may lie in the growing body of research on older users and chatbots, particularly studies showing the ways in which the interaction helps assuage feelings of loneliness and isolation (Brewer, 2022; Ewers, 2021). By contrast, younger users, Generation Z and Millennials, as digital natives, may engage more with other features, such as the ability to personalise and the push-pull effect of a persons' social network of influence.

Our findings indicate, not surprisingly, that acceptance, use, and continued use behaviour of a new technology are largely the result of users' ability to personalise it, the social influence of others, and individuals' trust of generative AI technologies. Our findings have several practical implications for cultural heritage institutions. Trust is a major concern among users, and workshops, especially for new users, hosted by cultural heritage institutions should emphasise trust factors such as information sources, and privacy and data security. Additionally, information sessions and workshops targeting older users could be beneficial. Information professionals could emphasise features important to this cohort, such as conversational capabilities and personalisation.

The theoretical significance of this study lies in its insights into how social and technological factors co-evolve towards more user-centred system design. In other words, the findings highlight the relationship between these factors, suggesting that, as social need and behaviour evolve alongside technological advancements, these factors influence each other in ways that shape systems more attuned to users' needs and experiences. For instance, design elements such as personalisation and conversational capabilities can extend existing theories of user acceptance models. Furthermore, identifying and analysing generational gaps in technology acceptance can inform educational strategies and policy decisions, contributing to the development of AI literacy frameworks. These insights provide both practical and theoretical guidance for improving interaction design between users and AI systems, fostering more intuitive and seamless user experiences.

Conclusion

This study explored the research literature on age-related information behaviour among users of generative AI technologies. It explored how generational cohorts perceive, adopt, and implement this disruptive technology into their daily information practices. Trust, social influence, and personalisation significantly affect users' intentions to continue using generative AI chatbots. While significant differences were observed in social influence and conversational ability, Baby Boomers exhibited the lowest levels of social influence yet the highest levels of engagement with conversational ability. This research shows that older users are an obscure but enthusiastic cohort among users of generative AI technologies and work should be centred on outreach campaigns that promote generative AI adoption.

However, no study is without limitations. In this study, the uneven number of participants in each cohort could have skewed the results, despite their overall reliability. To address this, future research should use a different sampling method, such as purposive sampling with specific criteria, to achieve more balanced sample sizes. Moreover, the study participants were early adopters of the technology and tended to be more skilled, experienced, and highly motivated to engage with it. We did not collect data regarding which AI chatbot was used (for example, ChatGPT, Gemini, or Grok) or on the complexity of users' queries, which could have influenced our results. Collecting this information in subsequent studies would strengthen the results. Consequently, the findings may not be fully representative of the general public, whose backgrounds and motivations could differ significantly. As AI-related technology continues to evolve, research design and approaches to collective perception and behaviour can be refined to become more effective and timelier.

Future studies could include a mixed-method approach that integrates qualitative analysis on trust, social influence, and personalisation. Considering that the present study's participants were drawn solely from the United States, future investigations would benefit from including participants from diverse geographical regions. Additionally, during this early period of AI large language model research, very little research has been conducted, particularly in information science, that centres on the experiences of users of colour. We therefore plan to test a distinctive set of factors influencing future use intentions of generative AI applications among Black, Indigenous, and other people of colour.

About the authors

Boryung Ju is a Professor in the School of Information Studies at Louisiana State University, Louisiana, USA. She received her Ph.D. from the School of Information at Florida State University. Her research interests include human–AI interaction and social informatics. She can be contacted at bju1@lsu.edu

J. Brenton Stewart is an Associate Professor in the College of Information at The University of Arizona, USA. He earned his Ph.D. in information studies from the iSchool at the University of Wisconsin-Madison and a M.S. from Clark Atlanta University. His research focuses on cultural heritage informatics, with particular emphasis on university information environments, social media, emerging technology studies, and college students' information use and seeking behaviour. He can be contacted at brentonstewart@arizona.edu

Sunyoung Park is a Professor in the School of Leadership and Human Resource Development, Louisiana State University, Baton Rouge, USA. She received her Ph.D. from University of Minnesota, and her research interests include organisational culture and employee behaviour, learning and performance in the workplace, and research trends in the field. She can be contacted at spark65@lsu.edu

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Appendix IA

Constructs (Factors)	Sources	Items asked
Continue to use (CI)	Gu et al. (2019)	I intend to continue using AI chatbots, rather than discontinue my use; I intend to continue using AI chatbots, rather than use any non-AI based chatbots; I fully intend to continue using AI chatbots in the future.
Conversational ability (CA)	Liao et al. (2023); Ju & Stewart (2024)	I value natural human conversation; I value engaging conversation; I value two-way conversation.
Personalisation (PERS)	Harahap et al. (2023)	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)	Venkatesh & Bala (2008); Vannoy & Palvia (2010)	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)	Dilleen et al. (2023)	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.

Table IA. Key constructs and survey items for evaluating AI features perceived by participants

Appendix IB

Construct	Cronbach's alpha
Continue to use	0.859
Conversational ability	0.821
Personalisation	0.812
Social influence	0.815
Trust	0.872

Table IB. Measurement of Cronbach's alpha for internal consistency

Appendix IC

Variable	(I) Age	(J) Age	Mean difference (I–J)	Std. error	Sig.
CA	B	X	0.221	0.136	0.368
		M	**0.352***	0.123	0.024
		Z	**0.444***	0.131	0.004
	X	B	-0.221	0.136	0.368
		M	0.131	0.109	0.627
		Z	0.223	0.118	0.233
	M	B	**-0.352***	0.123	0.024
		X	-0.131	0.109	0.627
		Z	0.092	0.103	0.808
	Z	B	**-0.444***	0.131	0.004
		X	-0.223	0.118	0.233
		M	-0.092	0.103	0.808
PERS	B	X	-0.103	0.153	0.908
		M	-0.301	0.139	0.135
		Z	-0.172	0.148	0.651
	X	B	0.103	0.153	0.908
		M	-0.198	0.123	0.373
		Z	-0.069	0.133	0.955
	M	B	0.301	0.139	0.135
		X	0.198	0.123	0.373
		Z	0.130	0.116	0.677
	Z	B	0.172	0.148	0.651
		X	0.069	0.133	0.955
		M	-0.130	0.116	0.677
SI	B	X	-0.103	0.178	0.939
		M	**-0.580***	0.162	0.002
		Z	-0.203	0.172	0.638
	X	B	0.103	0.178	0.939
		M	**-0.477***	0.143	0.005
		Z	-0.100	0.154	0.915
	M	B	**0.580***	0.162	0.002
		X	**0.477***	0.143	0.005
		Z	**0.377***	0.135	0.028
	Z	B	0.203	0.172	0.638
		X	0.100	0.154	0.915
		M	**-0.377***	0.135	0.028
TR	B	X	-0.162	0.165	0.757
		M	-0.328	0.149	0.126
		Z	-0.119	0.158	0.876
	X	B	0.162	0.165	0.757
		M	-0.166	0.132	0.592
		Z	0.043	0.142	0.990
	M	B	0.328	0.149	0.126
		X	0.166	0.132	0.592
		Z	0.209	0.124	0.335
	Z	B	0.119	0.158	0.876
		X	-0.043	0.142	0.990

Variable	(I) Age	(J) Age	Mean difference (I–J)	Std. error	Sig.
		M	-0.209	0.124	0.335
CI	B	X	-0.076	0.169	0.970
		M	-0.365	0.153	0.081
		Z	-0.193	0.162	0.636
	X	B	0.076	0.169	0.970
		M	-0.290	0.135	0.142
		Z	-0.117	0.146	0.853
	M	B	0.365	0.153	0.081
		X	0.290	0.135	0.142
		Z	0.173	0.127	0.528
	Z	B	0.193	0.162	0.636
		X	0.117	0.146	0.853
		M	-0.173	0.127	0.528

Note. **p* < 0.05. Conversational ability (CA), personalisation (PERS), social influence (SI), trust (TR), and continuance intention (CI); B (Baby Boomers), X (Generation X), M (Millennials) and Z (Generation Z).

Table IC. Tukey's post hoc comparisons