Empowering Users with ChatGPT and Similar Large Language Models (LLMs): Everyday Information Needs, Uses, and Gratification

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ABSTRACT
Disruptive technologies such as ChatGPT and similar Large Language Models (LLMs) have transformed mundane everyday tasks of information users since their debut in late 2022. In this study, we leverage uses and gratifications theory to test a distinct set of motivations that drive users' satisfaction and continued use intentions of ChatGPT and similar large language models. Data were collected using a national online survey of 323 adults residing in the United States. We conducted data analysis using Partial Least Squares (PLS-SEM) to investigate both direct and indirect impact of factors on users' gratification, thereby influencing the continued utilization of these tools for everyday information seeking. Results show four motivational factors - social influence, trust, personalization, and perceived usefulness - that positively influence users' satisfaction or sense of gratification, impacting their intentions to continue using these tools. This is one of the few early studies of ChatGPT and other LLMs from an information science perspective.

KEYWORDS
Information seeking; ChatGPT; Large Language Model (LLM); Use and Gratification; Continued use intention

INTRODUCTION
Disruptive technologies usher in new ways of doing things. Specifically, they upend "systems or habits" because they can do the task or the thing faster and arguably better (Smith, 2022). The 21st century has been marked by the rise of several disruptive technologies, from blockchains to cloud services, smart assistants, Airbnb and 3D printing. However, none have disrupted the conventional way of doing things like the appearance of ChatGPT-3.5, in late 2022 and other large language models (LLM) such as BingChat, Bard, Ernie, Plutchik, and WebGPT. Compared to other recent technological phenomena, ChatGPT's growth has been stratospheric and has no revivals with respect to user adoption; over 100 million monthly active users just two months after its emergence in November 2022; by comparison, TikTok, Instagram and Spotify needed 9 months, 2.5 years, and 4.5 years respectively to reach the similar numbers of users (Bhaimiya, 2023). ChatGPT and other LLMs (hereafter, referred to as ChatGPT) can generate human-like text from simple questions posed by users. For example, ChatGPT can answer questions, create code for programs, write songs, poems, essays, email and solve mathematical problems to name a scattering of its capabilities.

With respect to information labor LLMs have the potential to radically transform work processes. Lund et. al. (2024) suggest ChatGPT specifically can serve as a 'valuable support system in medical libraries' by assuming a plethora of tasks including 'reference inquiries, facilitating website navigation, and aiding in research, cataloguing, classification, and collection development.' Public and academic libraries can also leverage ChatGPT for patron outreach and engagement, reader's advisory, and after hours support services (Mail & Deshmukh, 2024). While there is little doubt of the ChatGPT to radically transform everyday information seeking and work information practices we need to better understand how users engage with ChatGPT and also the characteristics that drive their adoptions at this early stage in its development.

The primary objective of this study is to test and measure a distinct set of motivations to predict their influence on users' satisfaction and continued use intentions among users of ChatGPT and similar large language models. Additionally, we aim to explore users' tasks orientations and their concerns about this new disruptive technology. Our study makes two significant contributions. First it extends uses and gratifications theory to include new dimensions of personalization and conversational ability not only in the context of large language models but also expands the research literature from an information science perspective. Secondly, we seek to uncover the extent that this set of factors drives users' satisfaction and continued used intentions of ChatGPT.

BACKGROUND
Researchers have begun to investigate users' experiences with AI chatbots from diverse disciplinary perspectives. One characteristic that unites the literature cited in this paper is their leverage of use and gratification theory as a lens to interrupt users' interactions with ChatGPT. Uses and gratification theory is an approach that is often used to investigate media and is especially robust in exploring new and emerging media and technologies. The theory centers the interplay between humans (users) and media, particularly the factors that motivate media/technological

use and what gratifications are garnered from using the particular media (McQuail, 2010). While researchers often adopt new dimensions to test, the core categories or gratifications are information seeking and information sharing, entertainment, ease and efficiency, and lastly personal identity, integration and social interaction (Rubin, 1981; Skjuve, et al., 2024). Information science researchers have leveraged use and gratifications theory to explore diverse phenomena including Facebook (Gazit, 2021), information seeking behavior (Chatman, 1991), children's use of computer tablets (Schlebbe, 2022), and health information seeking (Marton & Choo, 2012).

One of the earliest baseline studies on motivations of ChatGPT adoption found that productivity, novelty, creative work, learning and development, entertainment, and social interaction-support were the primary gratifications among users (Skjuve, et al., 2024). Baek and Kim (2023) introduced the new factor of 'creepiness' into users' motivations to use and trust ChatGPT. Paradoxically, results indicated that the more efficient the users' task was performed the higher users' perception that ChatGPT was creepy. In essence the tool worked "too well" exceeding the users' expectations. However, a users' ability to personalize ChatGPT resulted in less 'creepiness' while also increasing trust. Artificial intelligence chatbots for the service industry are other iterations of LLMs researchers have examined. Their focus in these two studies were on users' satisfaction and uses continuance. Information, entertainment, media, technology and social presence were factors that predicted users' satisfaction in Cheng and Jiang's study (2020). Additionally, users' perceived risks (privacy) were associated with reduced user satisfaction. By contrast, Ashfaq Yun, Yu, & Loureiro (2020) identified factors related to quality-informational and service influence customer satisfaction. Continued use intentions were motivated by enjoyment, usefulness, and ease of use. Overall, this study found that users' satisfaction with chatbots is the strongest predictor of continued use intentions. Wang, Luo and Jiang (2022) introduced a new model for use intentions among diverse social media platforms. Hedonic or enjoyment was the strongest and most important factor, followed by perceived usefulness, subjective norms and relationship benefits.

A recent model introduced and tested 'perceived intelligence' as a new dimension of user gratification in continued use intentions (Gao, 2023). Results indicated that 'intelligence', a new type of technology gratification, was the most influential factor in predicting continued use of Liulishuo, an educational LLM. Other significant factors were convenience, enjoyment, status, achievement and education. An early quantitative metanalyses by Xie, Wang and Cheng (2022) on AI chatbots literature identified four factors in users' satisfaction. The most significant was utilitarian, followed by hedonic, technology, and social aspects. These results suggest that design features of LLM should coalesce around these factors in bolster user satisfaction. Ju and colleagues (2024) presented a new model of information seeking among early adopters of artificial intelligence chatbots. Focused on the dimensions of social influence, trust, personalization and conversational ability the study found that system affordances and users' trust were factors that drove users' decision to adopt AI chatbots for everyday information seeking.

The literature above helps researchers understand and situate future research on emerging LLMs. However, there is relatively little research on ChatGPT, from an information science perspective that makes everyday life information behaviors the focus of the analysis. Therefore, in this study we seek to uncover the extent to which a new array of factors drives users' satisfaction and continued use intentions of Chat GPT. Specifically, we ask:

RQ1: What are users' tasks and concerns when using ChatGPT?

RQ2: What are the factors driving information users' satisfaction and continued use of ChatGPT?

RESEARCH METHODS

We recruited 323 adults through Qualtrics Panel Services, all of whom had experience using AI chatbots for their information needs within the last 6 months preceding our data collection period. The online survey was administered from June to July 2023. The crowdsourcing approach to recruiting study participants is widely accepted in social sciences and health-related subject domains. It enables researchers to access more diverse populations, reducing costs and ensuring a fast completion of data collection while maintaining high-quality results (Keating et al., 2013; Gosling & Mason, 2015). Our collected data was analyzed employing PLS-SEM (Partial Least Squares - Structural Equation Modeling) to identify both direct and indirect influences of factors on users' gratification, ultimately contributing to the continued use of these tools for everyday information seeking.

STUDY PARTICIPANTS

All study participants are individuals aged 18-65, residing in the USA, and voluntarily took part in our online survey conducted on Qualtrics software. These participants are considered early adopters, constituting 18% of US adult users who are aware of and utilize AI-chatbots, as reported in a Pew Research survey conducted between July 17-23, 2023 (Pew Research Center, 2023).

Out of the 232 total participants, 223 (69%) identified as female, and 100 (31.2%) identified as male. Regarding age groups, 48 (14.9%) were Baby Boomers (1928-1964), 69 (21.4%) belonged to Gen X (1965-1980), 122 (37.8%) were Millennials (1981-1996), and 84 (26%) were part of Gen Z (1997-2012). Not surprisingly, their educational background is relatively high, with 102 (31.6%) holding a graduate degree, 142 (44%) having some college or a bachelor's degree, and 79 (24.5%) having no college education. Despite our sample being a convenience sample based on availability, this somewhat reflects the landscape of ChatGPT users as reported in the Pew Research survey in 2023, where 32% of adults with a college degree or higher have used it (Pew Research, 2024). Race?

Measures and research constructs

Our online survey questionnaire on the Qualtrics platform included questions about participants' usage of AI chatbots, their concerns regarding the technology, a 5-point Likert scale measuring six variables related to their motivations and continued use of the technology, and inquiries about their demographic backgrounds.

We adapted empirically validated measurement items from the existing literature. Table 1 provides a list of seven research constructs and previous research related to each of them. Social influence (SI) refers to 'the extent to which an individual perceives that important others believe he or she should use or interact with a Generative AI tool (Vannoy & Palvia, 2010, p. 152). It originated from the concept of subjective norm, which is the perception of whether the majority of individuals endorse or disapprove of the behavior, in the Theory of Planned Behavior (TPB; Ajzen, 1991). It then evolved through the Extended Technology Acceptance Model (TAM2; Venkatesh & Davis, 2000) and was further incorporated into the Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh, 2003). In the current study, SI was assessed through questions such as 'those significant to me believe I should employ AI chatbots,' 'individuals I admire anticipate my utilization of AI chatbots,' and 'an expectation that individuals similar to me should utilize AI chatbots.'

Research construct	Related research
Social Influence (SI)	Vannoy & Palvia, 2010; Venkatesh et al., 2003
Perceived Usefulness (PU)	Davis, 1989; Kasilingam, 2020; Nguyen et al., 2022
Trust (TR)	McKnight et al., 2011; Verma, 2022
Conversational Ability (CA)	Cai et al., 2022; Haleem et al., 2022; Liao et al., 2023
Personalization (PERS)	Harahap et al., 2023; Limo et al., 2023; Arslan, 2023
Satisfaction (SAT)	Fu et al., 2024; Koo et al., 2011; Bhattacherjee, 2001
Continued Use Intention (CUSE)	Bhattacherjee, 2001; Gu et al., 2019; Song et al., 2021

Table 1. Construct References

Perceived Usefulness (PU) can be defined as the extent to which an individual believes that utilizing a specific system would improve their job performance (Davis, 1989). It has been a significant factor influencing users' adoption (Chen & Huang, 2016; Kamal et al., 2020; Rauniar, 2014), attitudes (Ju & Albertson, 2018; Kim & Adler, 2015), and intentions to use (Kasilingam, 2020; Nguyen et al., 2022) a technology/system in existing literature. PU was measured in the current study through questions such as 'employing AI chatbots allows an individual to complete tasks', 'considering AI chatbots valuable for fulfilling his/her tasks and information requirements', and 'utilizing AI chatbots improves his/her efficiency in task completion.' Trust (TR) operates as a social mechanism that individuals employ to navigate the perceived instability and unpredictability of a complex world (Luhmann, 1979). It can be characterized as a condition that arises when an individual, regardless of the intentions or desires of the trusted entity, must make themselves vulnerable by relying on another person or object (McKnight et al., 2011). In Verma et al.'s (2022) study on the quality of COVID health information available on social media, they measured various aspects of trust, including trust in media and direct personal contacts. We assessed 'trust in AI chatbot's by posing questions about participants' confidence in the reliability of information presented by AI chatbots and their belief in the accuracy of the content delivered. Additionally, we asked about their trust in the use of AI chatbots in language models, and whether they perceive their search queries and personal information to be secure and private during information searches.

Conversational ability (CA) is a distinctive and potent feature that AI chatbots offer users for dialogue. It is designed to emulate authentic conversations, and its responses exhibit a very human-like quality, enabling the bot to elaborate on ideas and recall prior statements in the dialogue (Cai et al., 2022; Haleem et al., 2022) and improve human engagement cause by task-oriented conversational agent (Liao et al., 2023). We operationalized conversational ability by including questions that assessed the extent to which individuals appreciate natural human conversation, find value in engaging dialogues, and emphasize the importance of two-way communication. Personalization (PERS) of AI chatbots is a capacity to deliver experience based on the personalized distinctive needs, preferences, and characteristics of each individual (Harahap et al., 2023). This capability has been investigated for implementing personalized tutoring (Limo et al., 2023) and personalized recommendations for obesity treatment (Arslan, 2023). Personalization in this study was operationalized by querying respondents about whether the responses they received met their specific information needs and preferences, were relevant, and tailored to their search.

Satisfaction (SAT) has been one of the crucial factors in information system use and evaluation. In a study to investigate user intent and satisfactions with large LLMs (Bodonhelyi et al., 2024), user satisfaction was assessed based on answers derived from intent-based prompt reformulations for two versions of ChatGPT, namely GPT-3.5 Turbo and GPT-4 Turbo. In another recent study (Fu et al., 2024), user information satisfaction with ChatGPT was assessed with seven factors, accuracy, completeness, convenience, format, precision, reliability, and timeliness. End-user satisfaction was gauged through their expectations of knowledge, confirmation of knowledge, and perceived usefulness of a knowledge-intensive cancer website (Koo et al., 2011). Furthermore, user satisfaction, crucial for selecting and sustaining the use of an information system, was assessed through users' affection and content evaluation (Bhattacherjee, 2001). We measured satisfaction by inquiring about respondents' feelings or contentment levels regarding ChatGPT or similar large language models (LLMs). The continued use intention (CUSE) construct in this study was operationalized through questions that assessed respondents' intentions to persist in using AI-chatbots, intention to discontinuing usage or opting for non-AI chatbot tools. Continuance use intention is distinguished from the initial intention to use in many previous studies. Continuous use intention refers to the willingness of individuals to persist in using a particular technology over time. It reflects the user's intention to continue using the product or the technology in the future, indicating a level of commitment beyond the initial adoption or usage ((Bhattacherjee, 2001; Chang et al., 2015; Gu et al., 2019; Song et al., 2021).

In addition to the Likert scale questions assessing the seven research constructs mentioned above, our survey questionnaire also included two additional questions that specifically focused on respondents' concerns about using AI Chatbots as information-seeking tools and their usage patterns with these tools.

DATA ANALYSIS AND RESULTS

Partial Least Squares - Structural Equation Modeling (PLS-SEM) was employed to investigate the direct and indirect impacts of research constructs (factors) on users' gratification, thereby influencing the continued utilization of these tools for everyday information seeking. PLS is an effective method that enables researchers to explore complex and interactive causal relationships among latent variables and identify key constructs in a model (Chin, 1998). For this analysis, we utilized SmartPLS 4.1 (Ringle et al., 2024). Employing this method, we examined our measurement model to gauge the validity and reliability of our measurement instruments. We assessed our research model to ascertain its fit with the collected data and its alignment with our hypotheses, thereby validating the proposed research model (structured model) in this study.

Assessment of measurement model

We assessed the validity and reliability of our measurement model to ensure our measures are accurately capturing the intended constructs for this study. Average variance extracted (AVE) was assessed for convergent validity, where are all constructs exceeded the acceptable threshold of 0.5 (Hair, et al, 2010; Usakli &Kucukergin, 2018). This ensures that measurement items of the same construct are sufficiently corelated to each other. Discriminant validity was calculated to ensure distinctiveness of constructs, which means each of them are not supposed to measure the same underlying construct. The values of discriminant validity are all exceed than the acceptable threshold of 0.7 (Hair et al., 2010), therefore discriminant validity was ensured (Table 2). For reliability, Cronbach's alpha and composite reliability were computed (Table 3). Both of reliability values are in the range of 0.8 that satisfy the thresholds of 0.7 (Fornell & Larcker, 1981), suggesting that the items in the measurement items are consistently measuring the intended construct.

	Continue to use	Conversational Ability	Perceived Usefulness	Personaliz ation	Satisfact ion	Social Influenc e	Trust
Continue to use	0.884	-					
Conversational Ability	0.172	0.859	-				
Perceived Usefulness	0.694	0.2	0.835	-			
Personalization	0.611	0.255	0.612	0.853	-		
Satisfaction	0.764	0.129	0.648	0.623	0.938	-	
Social Influence	0.634	0.047	0.579	0.47	0.583	0.854	-
Trust	0.618	0.1	0.649	0.584	0.672	0.621	0.816

Table 2. Discriminant Validity – Fornell-Larcker Criterion

	Cronbach's alpha	Composite reliability	Composite reliability	Average variance extracted (AVE)
Continue to use	0.859	0.862	0.914	0.781
Conversational Ability	0.822	0.826	0.894	0.737
Perceived Usefulness	0.855	0.859	0.902	0.696
Personalization	0.812	0.814	0.889	0.727
Satisfaction	0.863	0.864	0.936	0.88
Social Influence	0.815	0.818	0.89	0.73
Trust	0.874	0.875	0.908	0.665

Table 3. Reliability Assessment of Constructs

Assessment of research model

Building upon the validated research construct measurements from the previous phase, we employed PLS modeling to address our research questions. Data analysis revealed that social influence, trust, perceived usefulness, and personalization have statistically significant effects on satisfaction, thereby directly and indirectly influencing the continued use intention of ChatGPT and similar LLMs. However, conversational ability did not exhibit any statistically significant effects on satisfaction. Figure 1 illustrates the evaluation of the structural model, while Table 4 demonstrates the tested hypotheses and the hypothesized relationships among variables respectively.

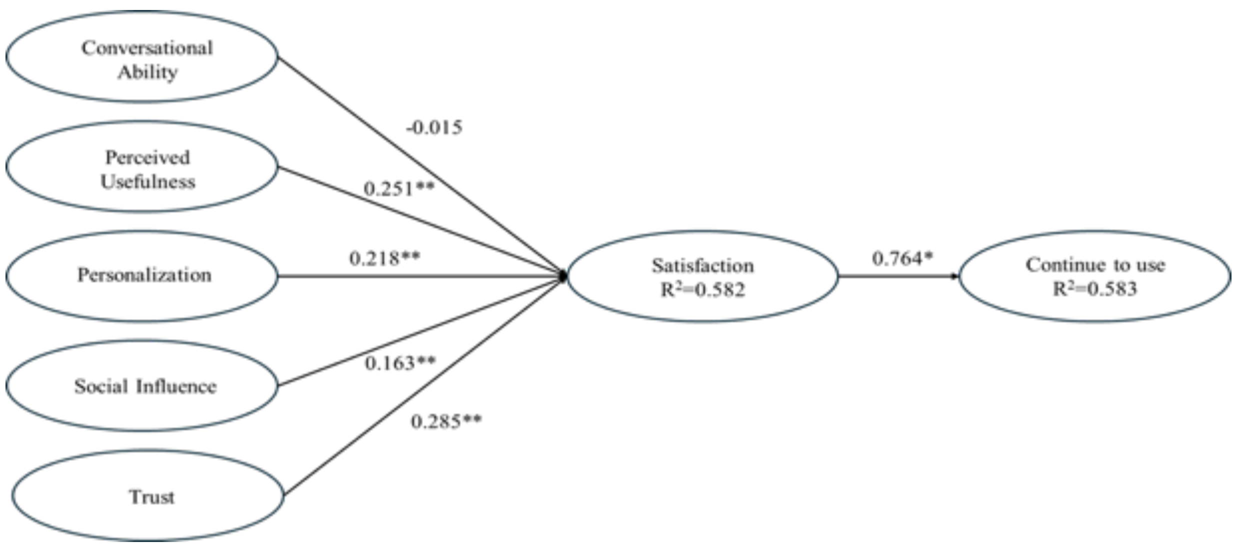

Fig.1. The Structural Research Model with Path Coefficients (*p < 0.001, **p < 0.01)

In Table 4, it is evident that perceived usefulness significantly impacts continued use (β = 0.167, $p < 0.001$), with its effect mediated by satisfaction (β = 0.218, $p < 0.001$). Similarly, personalization influences continued use (β = 0.251, $p < 0.001$), mediated by satisfaction (β = 0.192, $p < 0.001$). Rejection of both $H_0$2a and $H_0$2b as well as $H_0$3a and $H_0$3b implies support for hypotheses H2a, H2b and H3a and H3b. Social influence positively affects continued use (β = 0.167, $p < 0.001$), with mediation through satisfaction (β = 0.163, $p < 0.01$) and (β = 0.124, $p < 0.001$). Likewise, trust significantly impacts continued use (β = 0.285, $p < 0.001$), mediated by satisfaction (β = 0.217, $p < 0.001$). The rejection of $H_0$5a and $H_0$5b as well as $H_0$6a and $H_0$6b supports hypotheses H5a and H5b and H6ab. Additionally, satisfaction strongly influences continued use (β = 0.764, $p < 0.001$). However, conversational ability does not affect satisfaction or continued use. H1a and H1b are not supported, as $H_0$1a and $H_0$1b are not rejected.

Hypotheses	Path	Beta	P- value	Results
H1a	Conversational Ability -> Continue to use	-0.012	>0.05	Not Supported
H1b	Conversational Ability -> Satisfaction	-0.015	>0.05	Not Supported
H2a	Perceived Usefulness -> Continue to use	0.167	<0.001	Supported
H2b	Perceived Usefulness -> Satisfaction	0.218	<0.001	Supported
H3a	Personalization -> Continue to use	0.192	<0.001	Supported
H3b	Personalization -> Satisfaction	0.251	<0.001	Supported
H4	Satisfaction -> Continue to use	0.764	<0.001	Supported
H5a	Social Influence -> Continue to use	0.124	<0.001	Supported
H5b	Social Influence -> Satisfaction	0.163	<0.01	Supported
H6a	Trustworthiness -> Continue to use	0.217	<0.001	Supported
H6b	Trustworthiness -> Satisfaction	0.285	<0.001	Supported

Table 4. Results of Hypotheses Testing

The path coefficients of significant factors indicate that satisfaction exerts the strongest influence on continued use ($R^2 = 0.583$), explaining 58.3% of the variance. Following satisfaction, trust, personalization, and perceived usefulness collectively, their combined contribute ($R^2 = 0.582$), accounting for 58.2% of the variability in satisfaction explained by these three variables. Model fit is assessed using the standardized root mean square residual (SRMR), a commonly employed method. A value below 0.08 is considered acceptable (Hu & Bentler, 1999), therefore our SRMR of 0.071 indicates appropriate model fit.

Everyday usages and concerns perceived by users

In the everyday use of the tools, a range of applications was reported. We gathered responses to an open-ended question about how users employ these tools, aiming to categorize these responses within the framework of use and gratification theory (Skjuve et al., 2024). Table 5 provides a snapshot of the diverse ways in which the tools are utilized.

Usage Categories	Examples from study participants' responses
Information seeking/sharing	"To find something." "To write business reports." "To ask daily life questions." "I use AI chatbots to get answers to questions I need answered."
Entertainment	"Used AI image generators for fun." "To learn about history and make funny stories." "I use it specifically for fun." "Just to kill time when I'm bored." "Game ideas."
Ease & Efficiency	"To write lines of code." "To write essays." "I mainly use it to help write scripts for videos…" "Solve a math problem." "You ask to write something for you and it helps you finish faster."
Social interaction	"To talk." "To vent." "When I'm lonely." "You talk like their friends and ask them questions."

Table 5. Example Tasks Use of ChatGPT and LLMs

We inquired about the respondents' concerns regarding the use of AI chatbot tools, providing a list of potential concerns from which they could select multiple items. As depicted in Figure 2, privacy (23.31%), data security (20.67%), and mis/disinformation (14.70%) emerged as the most prominent concerns perceived by respondents.

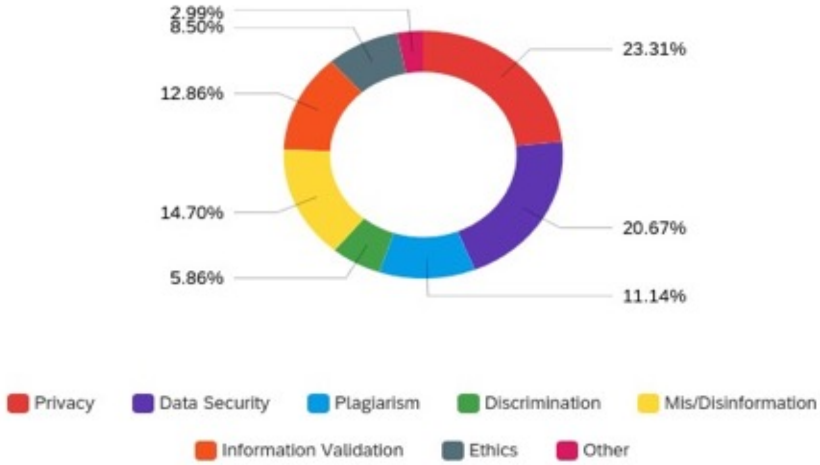

Figure 2. Perceived Concerns Regarding AI Chatbot Tool Usage

DISCUSSION

In this study, we aimed to investigate the motivational factors driving users to continue using generative AI chatbots like ChatGPT and similar large language models (LLMs) in their everyday information seeking, within the framework of the use and gratification theory. Specifically, we identified four motivational factors - social influence, trust, personalization, and conversational ability- that influence users' satisfaction or sense of gratification, leading to an intention to continue using these tools.

Initially we sought a baseline understanding of users' tasks and concerns when using ChatGPT. We identified four categories of participation, drawing on the core tenets of uses and gratification theory: information seeking, ease and efficiency, entertainment, and social interaction. With respect to information seeking, responses included tasks such as finding information, and asking questions. Domains spanned everyday life information, school, and work. Ease and efficiency coalesce around action-oriented tasks that produced something, such as writing lines of codes, scripts, reports, and solving mathematical problems were typical responses under this domain. Participants also mentioned the speediness of once laborious tasks that could now with the aid of ChatGPT "helps you finish faster." Skjuve, Brandtzaeg, and Følstad (2024) and Brandtzaeg and Følstad (2017) identified efficient information seeking as a driver of both ChatGPT and AI chatbots in general. It was of little surprise that study participants used ChatGPT for entertainment purposes. Skjuve, Brandtzaeg, and Folstad (2024) found that fun and amusement motivated 20% of ChatGPT use. Participants used the term "fun" outright to describe their use. Others suggested a more nuanced or muted entertainment such as a refuge from "boredom." The final category was social interaction, which was a need for connectivity. Here users treated the LLMs like a human, "conversing like a friend", "venting" or talking out of loneliness. Skjuve, Brandtzaeg, and Følstad (2024) found that 9 percent of participants in their study used LLMs in this way. Other studies have also noted this distinct affordance of AI chatbots to aid in social support (Alessa & Al-Khalifa, 2023; Elyoseph, Z., & Levkovich, 2023).

With respect to concerns the two biggest issues were data security and privacy at 23% and 21 % respectively. This was not unexpected as much of the public's concern and trepidation regarding AI seems to coalesce around these two issues (Wu, Duan & Ni, 2023; Choudhury & Shamszare, 2023).

Our proposed structural research model in this study was statistically validated. Not surprisingly, our findings highlight user satisfaction or gratification as the strongest motivational factor influencing the intention to continue use, which aligns with previous studies. This consistency is particularly evident in research on users' expectations, satisfaction, and continued use of new technologies/systems (Gupta et al., 2020; Joo et al., 2017; Stone & Baker-Eveleth, 2013). The Expectation-Confirmation Theory (ECT; Oliver, 1977) explains how users' satisfaction levels during initial Information Systems (IS) use, confirmation, perceived IS usefulness, and user confirmation interact. This theoretical framework validates that satisfaction primarily predicts users' intentions to continue, with confirmation significantly affecting satisfaction levels (Bhattacherjee, 2001; Mamun et al., 2020).

Our unique exploration delves into users' motivational factors for gratification and continued use intention regarding this new technology, focusing on its conversational ability. This means users can engage in natural, human-like two-way conversations with ChatGPT as they seek information. Additionally, the technology offers personalization, tailoring responses to users' information needs. Lastly, perceived usefulness is highlighted, indicating that the technology enhances effectiveness in task completion and increases productivity. Although conversational ability is typically considered a unique and defining motivational factor for chatbots (pre-AI powered chatbots) (Brandtzaeg & Følstad, 2017; Hill et al., 2015), our results did not confirm this to be the case with ChatGPT. It could be reasonably inferred that some users may already have experience with chatbots for travel arrangements (Cai et al., 2022), customer service (Law et al., 2021; Pavone et al., 2019), or health applications (Denecke & Warren, 2020). However, personalization, along with perceived usefulness, stands out as the driving force for user satisfaction and continued usage intentions. This aligns with Baek and Kim's study (2023) on the perception of creepiness and trust issues when using ChatGPT, where users feel greater comfort and control over the AI system thanks to its personalization feature. This, in turn, contributes to increased user satisfaction and gratification. The perceived usefulness of ChatGPT refers to its ability to assist users in completing their intended tasks effectively. This aspect is essential in the development and adoption of all newly developed systems or services, as highlighted in previous literature on information system design and evaluation. Without the utilitarian benefits of a given technology or system, attracting users to adopt and use it would be challenging. Prior studies on E-learning acceptance by undergraduate university students (Ibrahim et al., 2017), chatbot technology integrated into smartphone applications that assist users with shopping-related tasks (Kasilingam, 2020), telemedicine service utilization (Kamal et al., 2020), and acceptance of COVID-19 contact-tracing applications (Nguyen et al. 2020) illustrate how users carefully consider the perceived usefulness of newly introduced technology.

Our findings revealed that social influence emerges as one of the statistically significant motivating factors affecting user satisfaction and the intention to continue using ChatGPT. Within this study, social influence is operationalized as the impact of significant or meaningful figures on the decision to use this technology. However, the social aspects of adopting and using the technology can extend beyond mere influence, encompassing social interactions, fulfilling social needs, finding conversational partners, and addressing feelings of loneliness (Paul et al., 2023; Skjuve et al., 2024). With respect to trust, the study found that trust impacts continued use mediated by satisfaction. This suggests that participants trust ChatGPT *enough* to keep using them and reach a baseline level of satisfaction. It is possible that this population of early adopters are more trusting as noted in the literature (Brandtzaeg & Følstad, 2017) and therefore they are willing to assume more risk or uncertainty as an early adopter of a new technology.

CONCLUSION

Since their introduction in late 2022, ChatGPT and other LLMs have infiltrated the everyday lives of information users. This study sought to explore the drivers behind users' adoption of these tools, their ensuing satisfaction, and to develop a structural model aimed at elucidating the relationships among motivational factors, user satisfaction, and the intention to continue usage. Our findings demonstrate that users leverage ChatGPT for information seeking, their ease and efficiency in completing tasks, entertainment, and social interaction. Additionally, social influence, trust, personalization, and perceived usefulness are factors that drive users' satisfaction or sense of gratification, leading to an intention to continue using these disruptive technologies.

The current study's contribution lies in its early exploration of actual information users' interactions with ChatGPT. This involves integrating its unique system features, such as conversational ability and personalization, into our research model and validating it. Furthermore, our work extends the existing literature on ChatGPT, thereby advancing the understanding of technology use within the framework of the use and gratification theory.

LIMITATIONS

This study is not without limitations. First, our survey was distributed in July 2023 in order to target early adopters of ChatGPT and similar LLMs. While engaging early adopters offers valuable insights into functionality, usability, and technological barriers, it inherently restricts the representativeness of users and usage patterns among future adopters and long-term users. Second, data was collected from the USA. Therefore, further studies of ChatGPT are required to test and measure the users' information practices throughout diverse geographies. Moreover, incorporating diverse user experiences, including underrepresented communities and residents of the Global South can offer a more comprehensive and inclusive understanding of concerns, usage patterns, and impact.

GENERATIVE AI USE

We confirm that we did not use generative AI tools/services to author this submission.

AUTHOR ATTRIBUTION

Boryung Ju: conceptualization, data curation, formal analysis, methodology, validation, writing – original draft, and writing – reviewing and editing; Brenton Stewart: conceptualization, data curation, writing – original draft, and writing – reviewing and editing

REFERENCES

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179-211.

Alessa, A., & Al-Khalifa, H. (2023). Towards designing a ChatGPT conversational companion for elderly people. Proceedings of the 16th International Conference on PErvasive Technologies Related to Assistive Environments,

Arslan, S. (2023). Exploring the potential of chatGPT in personalized obesity treatment. *Annals of biomedical engineering*, *51*(9), 1887-1888.

Ashfaq, M., Yun, J., Yu, S., & Loureiro, S. M. C. (2020). I, Chatbot: Modeling the determinants of users' satisfaction and continuance intention of AI-powered service agents. *Telematics and Informatics*, *54*, 101473.

Baek, T. H., & Kim, M. (2023). Is ChatGPT scary good? How user motivations affect creepiness and trust in generative artificial intelligence. *Telematics and Informatics*, *83*, 102030.

Baron, S., Patterson, A., & Harris, K. (2006). Beyond technology acceptance: understanding consumer practice. *International Journal of Service Industry Management*, *17*(2), 111-135.

Bhaimiya, S. (2023, February 2). ChatGPT may be the fastest-growing consumer app in internet history, reaching 100 million users in just over 2 months, UBS report says. *Business Insider*. https://www.businessinsider.com/chatgpt-may-be-fastest-growing-app-in-history-ubs-study-2023-2

Bhattacherjee, A. (2001). Understanding information systems continuance: An expectation-confirmation model. *MIS quarterly*, 351-370.

Bodonhelyi, A., Bozkir, E., Yang, S., Kasneci, E., & Kasneci, G. (2024). User intent recognition and satisfaction with large language models: A user study with chatgpt. *arXiv preprint arXiv:2402.02136*.

Brandtzaeg, P. B., & Følstad, A. (2017). Why people use chatbots. Internet Science: 4th International Conference, INSCI 2017, Thessaloniki, Greece, November 22-24, 2017, Proceedings 4,

Cai, D., Li, H., & Law, R. (2022). Anthropomorphism and OTA chatbot adoption: a mixed methods study. *Journal of Travel & Tourism Marketing*, *39*(2), 228-255.

Chang, C.-C., Hung, S.-W., Cheng, M.-J., & Wu, C.-Y. (2015). Exploring the intention to continue using social networking sites: The case of Facebook. *Technological Forecasting and Social Change*, *95*, 48-56. https://doi.org/https://doi.org/10.1016/j.techfore.2014.03.012

Chen, N. H., & Huang, S. C. T. (2016). Domestic technology adoption: comparison of innovation adoption models and moderators. *Human Factors and Ergonomics in Manufacturing & Service Industries*, *26*(2), 177-190.

Cheng, Y., & Jiang, H. (2020). How do AI-driven chatbots impact user experience? Examining gratifications, perceived privacy risk, satisfaction, loyalty, and continued use. *Journal of Broadcasting & Electronic Media*, *64*(4), 592-614.

Choudhury, A., & Shamszare, H. (2023). Investigating the impact of user trust on the adoption and use of ChatGPT: Survey analysis. *Journal of medical Internet research*, *25*, e47184.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS quarterly*, 319-340.

Denecke, K., & Warren, J. (2020). How to evaluate health applications with conversational user interface? *Studies in health technology and informatics*, *270*, 976-980.

Elyoseph, Z., & Levkovich, I. (2023). Beyond human expertise: the promise and limitations of ChatGPT in suicide risk assessment. *Frontiers in psychiatry*, *14*, 1213141.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of marketing research*, *18*(1), 39-50.

Fu, C.-J., Silalahi, A. D. K., Shih, I.-T., Eunike, I. J., & Jargalsaikhan, S. (2024). Balancing Satisfaction and Clarity: Enhancing User Information Satisfaction with AI-Powered ChatGPT in Higher Education.

Gao, B. (2023). A uses and gratifications approach to examining users' continuance intention towards smart mobile learning. *Humanities and Social Sciences Communications*, *10*(1), 1-13.

Gazit, T. (2021). Key motivations for leading Facebook communities: a uses and gratifications approach. *Aslib Journal of Information Management*, *73*(3), 454-472.

Gosling, S. D., & Mason, W. (2015). Internet research in psychology. *Annual review of psychology*, *66*, 877-902.

Gu, W., Bao, P., Hao, W., & Kim, J. (2019). Empirical examination of intention to continue to use smart home services. *Sustainability*, *11*(19), 5213.

Gupta, A., Yousaf, A., & Mishra, A. (2020). How pre-adoption expectancies shape post-adoption continuance intentions: An extended expectation-confirmation model. *International Journal of Information Management*, *52*, 102094.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). *Multivariate data analysis* (7th ed.). Pearson.

Haleem, A., Javaid, M., & Singh, R. P. (2022). An era of ChatGPT as a significant futuristic support tool: A study on features, abilities, and challenges. *BenchCouncil transactions on benchmarks, standards and evaluations*, *2*(4), 100089.

Harahap, M. A. K., Junianto, P., Astutik, W. S., Risdwiyanto, A., & Ausat, A. M. A. (2023). Use of ChatGPT in Building Personalisation in Business Services. *Jurnal Minfo Polgan*, *12*(1), 1212-1219.

Hill, J., Ford, W. R., & Farreras, I. G. (2015). Real conversations with artificial intelligence: A comparison between human–human online conversations and human–chatbot conversations. *Computers in Human Behavior*, *49*, 245-250.

Ibrahim, R., Leng, N., Yusoff, R., Samy, G., Masrom, S., & Rizman, Z. (2017). E-learning acceptance based on technology acceptance model (TAM). *Journal of Fundamental and Applied Sciences*, *9*(4S), 871-889.

Joo, Y. J., Park, S., & Shin, E. K. (2017). Students' expectation, satisfaction, and continuance intention to use digital textbooks. *Computers in Human Behavior*, *69*, 83-90.

Ju, B., & Albertson, D. (2018). Exploring factors influencing acceptance and use of video digital libraries. *Information Research: An International Electronic Journal*, *23*(2), n2.

Ju, B., Stewart, J.B., Park, S., & Walker, J. (n.d.). An approach to information seeking: On social influence, trust, personalization, and conversational ability in adoption of AI chatbots [Unpublished manuscript].

Kamal, S. A., Shafiq, M., & Kakria, P. (2020). Investigating acceptance of telemedicine services through an extended technology acceptance model (TAM). *Technology in Society*, *60*, 101212.

Kasilingam, D. L. (2020). Understanding the attitude and intention to use smartphone chatbots for shopping. *Technology in Society*, *62*, 101280.

Keating, M., Rhodes, B., & Richards, A. (2013). Crowdsourcing: A flexible method for innovation, data collection, and analysis in social science research. In *Social media, sociality, and survey research* (pp. 179-201).

Kim, Y., & Adler, M. (2015). Social scientists' data sharing behaviors: Investigating the roles of individual motivations, institutional pressures, and data repositories. *International Journal of Information Management*, *35*(4), 408-418.

Koo, C., Wati, Y., Park, K., & Lim, M. K. (2011). Website quality, expectation, confirmation, and end user satisfaction: the knowledge-intensive website of the Korean National Cancer Information Center. *Journal of medical Internet research*, *13*(4), e1574.

Law, E. L.-C., Følstad, A., & Van As, N. (2022). Effects of humanlikeness and conversational breakdown on trust in chatbots for customer service. Nordic Human-Computer Interaction Conference,

Liao, L., Yang, G. H., & Shah, C. (2023). Proactive conversational agents in the post-chatgpt world. Proceedings of the 46th International ACM SIGIR Conference on Research and Development in Information Retrieval,

Limo, F. A. F., Tiza, D. R. H., Roque, M. M., Herrera, E. E., Murillo, J. P. M., Huallpa, J. J., Flores, V. A. A., Castillo, A. G. R., Peña, P. F. P., & Carranza, C. P. M. (2023). Personalized tutoring: ChatGPT as a virtual tutor for personalized learning experiences. *Przestrzeń Społeczna (Social Space)*, *23*(1), 293-312.

Luhmann, N. (1979). *Trust and Power*. John Wiley & Sons.

Mamun, M. R. A., Senn, W. D., Peak, D. A., Prybutok, V. R., & Torres, R. A. (2020). Emotional satisfaction and IS continuance behavior: reshaping the expectation-confirmation model. *International Journal of Human–Computer Interaction*, *36*(15), 1437-1446.

Marton, C., & Wei Choo, C. (2012). A review of theoretical models of health information seeking on the web. *Journal of Documentation*, *68*(3), 330-352.

Mathieson, K. (1991). Predicting user intentions: comparing the technology acceptance model with the theory of planned behavior. *Information systems research*, *2*(3), 173-191.

Mcknight, D. H., Carter, M., Thatcher, J. B., & Clay, P. F. (2011). Trust in a specific technology: An investigation of its components and measures. *ACM Transactions on management information systems (TMIS)*, *2*(2), 1-25.

McQuail, D. (2010). *Mass communication theory: An introduction* (pp. 420-430). SAGE Publications. ISBN 978-1849202923.

Nguyen, T. T., Nguyen, T. C. A. H., & Tran, C. D. (2022). Exploring individuals' adoption of COVID-19 contact-tracing apps: a mixed-methods approach. *Library Hi Tech*, *40*(2), 376-393.

Oliver, R. L. (1977). Effect of expectation and disconfirmation on postexposure product evaluations: An alternative interpretation. *Journal of applied psychology*, *62*(4), 480.

Park, E., & Gelles-Watnick, R. (2023). Most Americans haven't used ChatGPT; few think it will have a major impact on their job. *Pew Research Center, https://pewrsr*.

Paul, J., Ueno, A., & Dennis, C. (2023). ChatGPT and consumers: Benefits, pitfalls and future research agenda. In (Vol. 47, pp. 1213-1225): Wiley Online Library.

Pavone, G., Meyer-Waarden, L., & Munzel, A. (2019). The effect of communication styles on customer attitudes: a comparison of human-chatbot versus human-human interactions. 48th Annual EMAC Conference, Hamburg, May,

Rauniar, R., Rawski, G., Yang, J., & Johnson, B. (2014). Technology acceptance model (TAM) and social media usage: an empirical study on Facebook. *Journal of enterprise information management*, *27*(1), 6-30.

Ringle, Christian M., Wende, Sven, & Becker, Jan-Michael. (2024). SmartPLS 4. Manheim am Rhein: SmartPLS. Retrieved from https://www.smartpls.com

Rubin, A. M. (1981). An examination of television viewing motivations. *Communication research*, *8*(2), 141-165.

Schlebbe, K. (2023). Uses and gratifications of a tablet computer for children: an analysis of online customer reviews. *Online Information Review*, *47*(4), 714-731.

Skjuve, M., Brandtzæg, P. B., & Følstad, A. (2024). Why do people use ChatGPT? Exploring user motivations for generative conversational AI. *First Monday*, *29*(1).

Smith, T. (2022). Disruptive technology: definition, example, and how to invest. Investopedia. In.

Song, S., Zhao, Y. C., Yao, X., Ba, Z., & Zhu, Q. (2021). Short video apps as a health information source: an investigation of affordances, user experience and users' intention to continue the use of TikTok. *Internet Research*, *31*(6), 2120-2142.

Stone, R. W., & Baker-Eveleth, L. (2013). Students' expectation, confirmation, and continuance intention to use electronic textbooks. *Computers in Human Behavior*, *29*(3), 984-990.

Taylor, S., & Todd, P. (1995). Assessing IT usage: The role of prior experience. *MIS quarterly*, 561-570.

Thompson, R. L., Higgins, C. A., & Howell, J. M. (1991). Personal computing: Toward a conceptual model of utilization. *MIS quarterly*, 125-143.

Usakli, A., & Kucukergin, K. G. (2018). Using partial least squares structural equation modeling in hospitality and tourism: do researchers follow practical guidelines? *International Journal of Contemporary Hospitality Management*, *30*(11), 3462-3512.

Vannoy, S. A., & Palvia, P. (2010). The social influence model of technology adoption. *Communications of the ACM*, *53*(6), 149-153.

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management science*, *46*(2), 186-204.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS quarterly*, 425-478.

Verma, N., Fleischmann, K. R., Zhou, L., Xie, B., Lee, M. K., Rich, K., Shiroma, K., Jia, C., & Zimmerman, T. (2022). Trust in COVID-19 public health information. *Journal of the Association for Information Science and Technology*, *73*(12), 1776-1792. https://doi.org/https://doi.org/10.1002/asi.24712

Wang, S., Luo, C., & Jiang, P. (2018). Empirical study about the motivations for using multifunctional social media: Based upon the uses and gratifications theory.

Wu, X., Duan, R., & Ni, J. (2023). Unveiling security, privacy, and ethical concerns of chatgpt. *Journal of Information and Intelligence*.

Xie, C., Wang, Y., & Cheng, Y. (2024). Does artificial intelligence satisfy you? A meta-analysis of user gratification and user satisfaction with AI-powered chatbots. *International Journal of Human–Computer Interaction*, *40*(3), 613-623.