경영학 석사학위 논문

Evaluating the Current State of ChatGPT and its Disruptive Potential: An Empirical Study of Korean Users

챗GPT의 수용에 대한 현 상태 평가 및
파괴적 혁신으로서의 잠재력에 대한 실증적 연구:
한국 사용자들의 사용 경험 중심으로

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서울대학교 대학원
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이 논문을 경영학 석사 학위논문으로 제출함

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Abstract

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This study investigates the perception and adoption of ChatGPT, a large language model (LLM)-based chatbot created by OpenAI, among Korean users, and assesses its potential as the next disruptive innovation. Drawing on previous literature, the study proposes perceived intelligence and perceived anthropomorphism as key differentiating factors of ChatGPT from earlier AI-based chatbots. Four individual motives (perceived usefulness, ease of use, enjoyment, and trust) and two societal motives (social influence and AI anxiety) were identified as antecedents of ChatGPT acceptance. A survey was conducted with members from two Korean online communities related to artificial intelligence. The findings confirm that ChatGPT is being used for both utilitarian and hedonic purposes, with perceived usefulness and enjoyment positively impacting behavioral intention to adopt the chatbot. However, unlike prior expectations, perceived ease of use was not shown to have a significant influence on behavioral intention. Trust was not found to be a significant influencer to behavioral intention, while social influence played a substantial role in adoption intention and perceived usefulness. AI anxiety did not show a significant effect. The study confirmed that perceived intelligence and perceived anthropomorphism are constructs that influence the individual factors that influence behavioral intention to adopt and highlights the need for future research to deconstruct and explore the factors that make ChatGPT "enjoyable" and "easy to use" and to better understand its potential as a disruptive technology. Service developers and LLM providers are advised to design user-centric applications, focus on user-friendliness, acknowledge that building trust takes time, and recognize the role of social influence in adoption.

Keywords: ChatGPT, conversational artificial intelligence, disruptive innovation, technology acceptance model (TAM), dual purpose information systems, AI anxiety

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1. Introduction

Disruptive innovation, a concept introduced by Clayton Christensen (1997), refers to a new product, service, or technology which starts as a niche offering but eventually disrupts established markets and competitors. Such innovations may initially underperform in comparison to existing solutions but improve over time, eventually displacing incumbents and transforming industries (Christensen, 1997). Recent developments after the launch of OpenAI's ChatGPT (OpenAI, 2022) suggest it could be a disruptive innovation, akin to personal computers and smartphones (Wunker, 2023).

ChatGPT has exhibited rapid user growth, reaching 100 million users in just two months (Milmo, 2023), while the next fastest growing platform, TikTok, took approximately nine months to reach the same number (Hu, 2023). Since the release of ChatGPT, not only has the number of services adopting the ChatGPT API increased at an exponential rate (Pariseau, 2023), but some government agencies are considering adopting ChatGPT or similar chatbots to automate workflows (Myatt, 2023), even in Korea (S. Lee, 2023). Additionally, a current survey reported that business professionals found ChatGPT to be substantially helpful in enhancing productivity (Nielsen, 2023). Although the current capabilities of ChatGPT is seen as a "jack of all trades, but master of none" (Kocoń et al., 2023), these recent developments indicate the potential for ChatGPT to become the next disruptive technology.

Since it has been only half a year since ChatGPT's release, it is currently difficult to evaluate the extent to which technology has penetrated our lives and where it lies in the adoption process as defined by Everett Rogers (1962). However, there is a growing interest and excitement surrounding the technology, with some arguing that it is “overhyped” (Marks, 2022) and comparing its popularity to that of Metaverse and NFTs (Rosenbaum, 2023). On the other hand, some see it as a hope, with potential applications in various parts of society (Shinn et al., 2023).

In Information Systems (IS) literature, understanding individual acceptance and use of information systems has been regarded as important in studying the dissemination of technology which has been one of the primary topics of IS research (Venkatesh et al., 2007). User acceptance and confidence are crucial for the further development of a new technology (Taherdoost, 2018). Ultimately, acceptance has been regarded as a function of user involvement in the system (Venkatesh et al., 2012).

Given that it has been only a short timeframe since ChatGPT was released, it is crucial to examine user experiences and feedback during this initial period to assess its potential as a disruptive innovation. Feedback from the users who have adopted ChatGPT within this timeframe can provide valuable insights into the technology’s strengths and weaknesses. Not only will this help to understand the current trajectory of the new chatbot, but this will also assist relevant service developers to refine the technology and address its limitations to further its adoption by the rest of society.

Various research exists on consumer adoption of Artificial Intelligence (AI)-based novel technology regarding chatbots and robots, such as voice-based intelligent personal assistants (IPA) (Han & Yang, 2018; Fernandes & Oliveira, 2021; Moussawi et al., 2021), text-based chatbots (Pillai & Sivathanu, 2020; Sheehan et al., 2020; L. Li et al., 2021), and AI-powered robots (Belanche et al., 2019; Latikka et al., 2019; J. Kim et al., 2021). However, there has been little detailed research conducted on the context of adoption of ChatGPT and similar large language model (LLM)-based conversational AIs. ChatGPT (and next-generation LLMs forthcoming) is different in its capabilities compared to previous chatbots, and some opine that preceding chatbots have “lost the race” (Chen et al., 2023). Research has shown that early users are voicing out their opinions on Twitter (Haque et al., 2022), expressing that they are “disruptive” and “entertaining” and expressing their prospects of the technology. However, not much has been explored on the technological acceptance of ChatGPT.

Within the context of ChatGPT as a disruptive technology, user feedback could help to identify problems and fix issues to improve the experience of the technology further widen its adoption to the rest of society (Haque et al., 2022). There are already large online communities and networks being formed to share information about ChatGPT (Han, 2023), which is a beneficial opportunity to hear what they have to say about their current experiences with using the emerging technology.

Considering these recent developments and the increasing prominence of ChatGPT, this study aims to answer the following research questions:

1. **What are the differentiating factors of ChatGPT from previous AI-based chatbots?**

2. **What are the main individual and societal antecedents of acceptance of ChatGPT?**

3. **What obstacles does the current state of ChatGPT present, and what implications does it have for service developers or providers of LLM?**

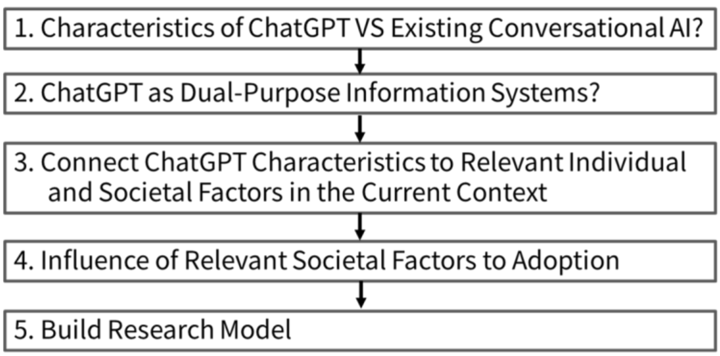
By addressing these research questions, this study contributes to the existing body of knowledge on AI-based conversational agents and their potential as disruptive innovations. Furthermore, the findings can help service developers and providers of LLMs to better understand user experiences, identify areas for improvement, and ultimately expand the adoption of ChatGPT and similar technologies.

The importance of this study lies not only in its potential to provide valuable insights into the current state of ChatGPT adoption, but also in its implications for the broader field of LLM-based conversation agents. As the technology continues to evolve and reshape the way we communicate, work, and interact, understanding the factors that influence its adoption and use will prove critical. By examining the experiences of Korean users, this study aims to shed light on the potential of ChatGPT as a disruptive innovation, ultimately contributing to the advancement of conversational AI and its broader impact on society.

2. Theoretical Background

To assess the current potential of the newly emerging ChatGPT's likelihood as the next disruptive innovation, we take a procedural approach in this section to build a relevant research model, structured as follows. First, relevant literature on conversational AI is explored to identify the distinguishing characteristics of ChatGPT and how it compares to existing chatbots. Second, borrowing from a myriad of technology acceptance literature, we identify ChatGPT as a dual-purpose information system (IS), and start constructing the theories on the Technological Acceptance Model (Davis, 1989) which has been frequently utilized to explore dual purpose IS. Thirdly, the section identifies the potential individual factors that are relevant to ChatGPT adoption in the current context and explore how they have been researched in technology acceptance literature and investigate how the characteristics of ChatGPT may influence these factors. Fourth, we identify some additional societal factors in terms of social influence and AI anxiety that is highly relevant and potentially influential in the current atmosphere influencing adoption. Finally, we combine the factors together – characteristics of ChatGPT, individual and societal factors - to create a model to conduct a comprehensive exploration of the current context of ChatGPT adoption.

Figure 1. Theoretical Development Procedure



2.1. Identifying the Characteristics of ChatGPT

As a new potential disruptive technology, it is important to first identify what makes the newly emerging technology potentially “disruptive”. This section explores the literature to identify the distinct characteristics of ChatGPT compared to existing AI-based chatbots.

ChatGPT can be classified as an extension of conversational artificial intelligence (AI), specifically, chatbots (Chen et al., 2023). Conversational chatbots are AI agents based on Natural Language Processing (NLP) and Machine Learning (ML) technology, which mimic humans while conversing (Meshram et al., 2021). Conversational AI learns to automate communications that were originally carried out by human beings using natural language processing and generation (Guzman & Lewis, 2020).

By technology, chatbots can be classified as legacy rule-based chatbots, which use a predefined set of rules to provide answers to user queries, and AI-based chatbots, which learn the patterns of human conversation based on specific keywords to provide responses to user queries (Chen et al., 2023). Major applications of chatbots include text-based chatbots, which are text-to-text based conversational agents and are usually utilized in the service industry to automate customer relationship management (CRM), and voice-based assistants, which use speech-to-text and automatic speech recognition technology to automate the human-like conversation process, such as Apple Siri, Google Assistant, and Amazon Alexa (MIT, 2021).

The new ChatGPT and existing conversational AI agents share similarities, such as the use of NLP and ML-based technology, and the capability of human-like dialogue by taking human input and outputting human-like text (Chen et al., 2023)

However, there are notable differences between the two. Existing conversational AI systems are basically “command and control” systems, understanding a finite list of questions from a keyword database (Chen et al., 2023) and thus are relatively limited in context awareness, scale, and generation ability (Koubaa et al., 2023). Conversely, LLM-based ChatGPT provides different answers every time it is generated and is not confined to certain rules or keywords like existing AI-based chatbots, making it capable of more intelligent tasks (Dwivedi et al., 2023; Koubaa et al., 2023) such as content generation, writing and fixing code, writing journal articles, summarizing documents, and multilingual translations (Shahriar & Hayawi, 2023).

Why is ChatGPT considered different and more capable than existing conversational chatbots? ChatGPT was trained using a similar concept to Reinforcement Learning with Human Feedback (RHLF) (Stiennon et al., 2020). ChatGPT’s predecessor, InstructGPT (Lowe & Leike, 2022) and was created to optimize the already intelligent GPT 3.5 to follow instructions by human users, but it was not the most optimized for human conversations. Eventually, InstructGPT was trained with a large corpus of human-rated conversational data, resulting in a ChatGPT more optimized for dialogue interface (OpenAI, 2022). In short, the vanilla GPT 3.5 model that was optimized to follow human-given instructions (InstructGPT) was further optimized for human dialogue contexts (ChatGPT).

The result of this process created emergent behavior markers for ChatGPT. such as more anthropomorphic and human-like conversation and behaviors (Dwivedi et al., 2023), detailed prompting allowing users to provide task explanations or examples in order to derive better ChatGPT outputs (Koubaa et al., 2023; Shahriar & Hayawi, 2023) in a manner similar to few-shot learning, and chain-of-thought (CoT) prompting, in which ChatGPT provides intermediate reasoning steps and reasons for its output (Wei et al., 2023).

Due to these ChatGPT's emergent behaviors, it can be theorized that users may perceive ChatGPT as possessing "higher intelligence" and anthropomorphism compared to traditional AI chatbots. This has resulted in an exploding number of users, reaching 100 million within just two months after its launch (Milmo, 2023).

How can we define ChatGPT's "intelligence" and "human-likeness" as perceived by its users? Existing literature has explored the adoption of AI-based tools based on the AI-based on their intelligent and anthropomorphistic characteristics.

2.1.1. Perception of Intelligence in AI

Research on intelligence and capabilities of AI and its influence on human adoption have been explored as early as the 1960s through research on intelligent systems. Early intelligent systems were designed to solve complex problems that posed difficulty for humans, such as mathematical theorems or playing chess (McCarthy & Hayes, 1969). With continued advancements in computing power and NLP technology, supercomputers such as IBM's Watson (Ferrucci et al., 2010) have been developed capable of not only answering complex questions, but also social skills capable of human like interactions.

This complexity has led to a confusion in relevant research on how to define the degree of intelligence in AI; whether to define intelligence in computers in terms of human-like behaviors regardless of capabilities to solve complex problems, or intelligence defined by rationality and logical behaviors with the only purpose of maximizing the outcomes requested by humans. Conversely, the perspective focusing on human-like cognitive intelligence and behavior is based on cognitive modeling and the Turing test methodologies (Turing, 1950), which offered a practical definition of intelligence. Traditionally, a computer is considered “intelligent” if the human questioner cannot discern whether the answers to certain inquiries posed by them came from a computer or an individual, irrespective of the accuracy or utility of those responses (Russell & Norvig, 2010).

With these noticeable advancements in AI technology in the last 2 decades, more efforts have been made to define Intelligence in AI in more modern terms. Legg & Hutter (2007) defined intelligence in AI includes concepts, such as goal achievement, problem-solving, speed, flexibility, learning, and environmental awareness. In human-robot interaction literature, perceived intelligence depends on a robot’s competence, measured by users’ ratings of knowledge, responsibility, and sensibleness (Bartneck et al., 2009). Furthermore, Moussawi et al. (2019) defined perceived intelligence as the perception of the AI’ behavior as efficient and autonomous with the ability to process and produce natural language and deliver effectual output.

Following the roots of the literature defining intelligence in AI, this study proposes a definition of perceived intelligence for ChatGPT adapted from the preceding literature: the user’s perception of intelligence of ChatGPT relates to its apparent understanding and awareness of the context and the underlying intent provided by the user and its ability to autonomously provide natural and logical human-like language, which assists users in fulfilling their goals. (Legg & Hutter (2007), Bartneck et al., (2019), and Moussawi et al. (2019))

2.1.2. Anthropomorphism in AI

Anthropomorphism is the user’s attribution of human-like characteristics to non-human agents (Chandler & Schwarz, 2010; Araujo, 2018). While anthropomorphism has been traditionally derived from anthropomorphic cues (such as facial expressions, body movements, voice) from embodied agents (with physical characteristics such as robots), research has shown that humans can perceive anthropomorphism from disembodied agents, as well (Araujo, 2018). Users can have a perception of mindless anthropomorphism, where they automatically attach human-like characteristics to computers, knowing that they are not humans, through the interface or the response the computers give (Y. Kim & Sundar, 2012). Schuetzler et al., (2021) emphasized the importance of understanding what makes non-human things anthropomorphic in the context of chatbot design.

Research has indicated that increased anthropomorphic qualities are linked to increased adoption of chatbots (Pillai & Sivathanu, 2020; Sheehan et al., 2020) through increased perception of conversational quality (Chung et al., 2020). Unlike existing AI-based chatbots that rely on keywords from databases, ChatGPT was trained and optimized especially for human dialogue contexts, thus it can be hypothesized that ChatGPT may be perceived as more anthropomorphic than existing AI-based chatbots.

Following recent literature, in the context of this research, it is proposed that perceived anthropomorphism for ChatGPT be defined as the user's perception that ChatGPT shows human-like and social characteristics and is capable of high-quality conversations while acknowledging that ChatGPT is a non-human conversational agent. (Definition is adopted from Y. Kim & Sundar (2012) and Schuetzler et al. (2021).

2.1.3. Distinguishing Perceived Intelligence and Anthropomorphism

Although systems that appear anthropomorphic may be perceived as intelligent (Waytz et al., 2014), perceived intelligence and perceived anthropomorphism can be differentiated (Moussawi et al., 2021). For example, Google Search might be considered intelligent by providing smart search results, but users don't see it as human or cognitively impose human-like features on it (Moussawi et al., 2021). Humanoids, like Ameca (Engineered Arts, 2022), may be considered anthropomorphic because they mimic human expressions, but people know that their answers are programmed and pre-written (i.e., not intelligent).

In the case of ChatGPT, elements of anthropomorphism and intelligence can be present on different levels. Perceived intelligence of ChatGPT might include providing logical and detailed chain-of-thought (CoT) reasoning based on the context provided by the user, while the perceived anthropomorphic features of ChatGPT might include pragmatic expressions, such as apologizing to the user when the user has stated that it has not given sufficient results.

This study investigates the intelligence and anthropomorphism of ChatGPT as perceived by current Korean users.

2.2. ChatGPT as a Dual-Purpose Information Systems

Now that we have identified the differentiating characteristics of the newly emerging technology in the previous section, the sections henceforth will focus on connecting ChatGPT to existing theoretical model and connecting the antecedents for ChatGPT adoption.

2.2.1. Dual Purpose Information Systems

In technology acceptance studies, IS acceptance has been readily approached from a dual-purpose perspective. An individual's motives for adoption of an IS can usually be utilitarian or hedonic, depending on the user's motivation (Venkatesh & Brown, 2001; B. Kim & Han, 2011; Gerow et al., 2013; Wakefield & Whitten, 2006; Wu & Lu, 2013). Utilitarian motives are mostly related to external motivation, while hedonic motives are usually seen as intrinsic motivations (Gerow et al., 2013). Utilitarian motivations for IS acceptance and use are more task-oriented, providing an instrumental value to the user, such as added productivity and efficiency (Gerow et al., 2013), while hedonic motives are usually intrinsic, related to fun, entertainment, and social purposes (B. Kim & Han, 2011; Van Der Heijden, 2004).

Dual-purpose systems are both utilitarian and hedonic, and most of their use is not reduced to a single purpose (Wu & Lu, 2013), and in some cases, the boundaries have been blurred (Köse et al., 2019). IS literature has readily applied the Technology Acceptance Model (TAM) (Davis, 1989) to dual-purpose information systems theories (Köse et al., 2019). Pillai et al. (2011) explored user motivation for accepting social networking sites (SNS) which seems intuitively hedonic in nature but revealed utilitarian motives. Köse et al. (2019) proposed a research model to gauge the utilitarian and hedonic motivation of users to adopt an IS where the motives may be blurred due to gamification elements. These studies have shown that users' motivations may be a mix of utilitarian and hedonic purposes.

2.2.2. ChatGPT is also Dual-Purpose?

In this research context, ChatGPT may also be considered a dual-purpose system as people have been using ChatGPT for both utilitarian and hedonic purposes. Examples of utilitarian uses of ChatGPT include process automation, content creation, and writing code. Marketing professionals, lawyers, teachers, and designers are using ChatGPT for their work. (Hoff & Zinkula, 2023). There are already various sources online websites, such as YouTube, which offer content videos explaining how to use ChatGPT effectively to achieve goals and increase work productivity. At the same time, some people use ChatGPT for hedonic uses or purposes, like planning trips abroad, receiving dating advice, and writing stories, telling jokes, or creating music. An early look at ChatGPT adopters' responses on Twitter indicate that they use ChatGPT for both utilitarian (software development, business, future career opportunities) and hedonic purposes (entertainment and exercising creativity) (Haque et al., 2022). Therefore, in the context of this study, ChatGPT will be approached from the lens of a dual purpose IS, applying TAM as the base model framework.

2.3. Individual Factors

2.3.1. Utilitarian Motives and Hedonic Motives

In the context of technology acceptance research, perceived usefulness (PU) and perceived ease of use (PEOU) was found to be the dominant antecedents for utilitarian motivations (Wakefield & Whitten, 2006). PU refers to the degree to which a person believes that using a particular system would enhance his or her job performance while PEOU is the degree to which a consumer believes a system is easy to use and free from effort (Davis, 1989). Research has also found that PU was felt stronger for functional AI (utilitarian use) than for social AI (hedonic use) (Kim et al., 2021).

The perceived intelligence of ChatGPT may have an influence on the PU and PEOU of ChatGPT. Its higher capabilities, compared to previous conversational chatbots, may help users perceive ChatGPT as having higher intelligence, which may, in turn, influence them to feel that ChatGPT is useful (PU) and easy to use (PEOU).

On the other hand, previous literature shows that antecedents for hedonic motivations include intrinsic motivations such as perceived enjoyment and other beliefs like perceived playfulness (Wakefield & Whitten, 2006). In particular, perceived enjoyment (PE) has been defined as the degree to which the activity of using a specific system is perceived to be enjoyable, aside from any performance consequence resulting from the system use (Venkatesh & Morris, 2000). The literature shows that increased humanness and conversational quality leads to higher perceived enjoyment and customer satisfaction using AI chatbots (Chung et al., 2020).

In the context of this research, the perceived anthropomorphism of ChatGPT may have an influence on users' perceived enjoyment. Users may feel ChatGPT is more human-like due to its capabilities compared to traditional chatbots, which may increase the perceived enjoyment towards ChatGPT.

2.3.2. Perceived Trust Towards AI

Trust has been a frequently studied construct in AI acceptance research (Bawack & Desveaud, 2022). Perceived trust (PT) can be defined as the extent to which consumers perceive a system as capable, credible, and reliable in risky and uncertain situations (You et al., 2018; Pillai & Sivathanu, 2020). For example, when consumers feel that a robot is safe, they perceive the robot as more trustworthy, leading to a stronger user intention to adopt service robots (You et al., 2018).

What are the antecedents of trust towards a system? Previous literature shows that perceived intelligence and anthropomorphism may be potential antecedents to trust. Although research on users' perceived intelligence of intelligent systems, such as AI, is lacking in information system studies, the relationship between the quality of service and trust has been investigated in other fields. In the field of service marketing, technical and functional service quality elements positively impact overall evaluations, including credibility and trust towards an organization (Eisingerich & Bell, 2008). In marketing literature, service quality has been found to have a positive relationship with trust in the brand (Chiou, 2006;

Sharma & Patterson, 1999). Although the context of these studies may not exactly match with that of AI-based tool adoption, the end goal remains the same: to have a better relationship with the service provider (ChatGPT) and the customer (user). Perceived intelligence of ChatGPT, relating to the quality of the chatbot's response, can be correlated with the service quality mentioned in the context of service providers (organizations/brands).

In the context of AI, anthropomorphism has been investigated frequently in IS literature, and studies have shown that anthropomorphic characteristics in robots, chatbots, and autonomous vehicles have a positive relationship with trust in AI (Chung et al., 2020; Blut et al., 2021; Belanche et al., 2019; de Visser et al., 2016; Sheehan et al., 2020). Therefore, ChatGPT's higher intelligence and anthropomorphic characteristics may positively influence users' trust in the chatbot.

Moreover, perceived trust has been shown to be a strong antecedent for behavioral intention in AI adoption (Fernandes & Oliveira, 2021; Panagiotopoulos & Dimitrakopoulos, 2018; Zhang et al., 2019; Pillai & Sivathanu, 2020). Increased trust in digital voice assistants leads to increased acceptance of automated technologies in service counters (Fernandes & Oliveira, 2021). For example, high initial trust in automated vehicles positively influences behavioral intentions to adopt them in China (Zhang et al., 2019). Increased trust in chatbots has also been shown to have a positive impact on the behavioral intention to adopt chatbots in tourism services (Pillai & Sivathanu, 2020). In light of the existing literature, it may be hypothesized that high perceived trust may result in a higher intention to adopt ChatGPT.

2.4. Societal Factors

Societal factors can significantly impact the acceptance and adoption of AI technologies like ChatGPT. Two critical and relevant societal factors influence the adoption of ChatGPT: social influence and AI anxiety.

2.4.1. Social Influence

For the last few months, AI and ChatGPT has been all over the news mentioning its capabilities and how it can be used to improve the knowledge workers' productivity. Many companies are apprehensive to apply it at their workplaces to automate work processes (Tellez, 2023). For example, the digital media company Buzzfeed placed a large bet on ChatGPT to automate its content creation processes to facilitate an "AI-assisted" creative process (Westfall, 2023). Similarly, the renowned management consulting firm Bain & Company made a special partnership with OpenAI to integrate ChatGPT into their management system to automate research and processes (Bain & Company, 2023).

This active movement by many organizations and society have naturally led to the human agents to feel a pressure to learn how to use ChatGPT "to stay ahead" at their workplace (Richardson, 2023). Anu Madgavkar from McKinsey Institute said that "So one way or the other people are going to have to learn to work with AI" (Greenhouse, 2023). As such, there is social influence affecting the adoption of ChatGPT.

Social Influence (SI) refers to the degree to which an individual perceives that important others believe he or she should use the system (Venkatesh et al., 2003). Social Influence includes subjective (social) norms of the affiliated group and the group's culture (Venkatesh et al., 2003).

Existing studies focused on the extensions of the Technology Acceptance Model (TAM) have shown that social influence impacts the users' perceived usefulness of an IS (Venkatesh & Morris, 2000; Davis, 1989). For example, Lewis et al. (2003) extended TAM studies to include social and institutional contexts, finding that social beliefs and norms influence the perceived usefulness of information technology. A meta-analysis conducted by Wu & Lu (2013) showed that voluntariness in the affiliated group moderates the perceived usefulness, hence influencing the behavioral intention to use new information system.

Moreover, social influence may also impact the user's behavioral intention to adopt an IS. Studies based on the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) have shown that social influence impacts consumer trial, continuous use, and economic benefits of retail service innovations, such as personal shopping assistants (Kasilingam, 2020) and blogs (Hsu & Lin, 2008). In the context of AI-based tools, Kasilingam (2020) found that social influence and norms have a direct impact on shopping chatbot adoption, while Cao et al. (2021) discovered that social and peer influence influences the behavioral intention to use artificial intelligence at the organizational level. Consequently, the social influence surrounding ChatGPT may impact users' behavioral intentions to adopt and use the technology, even if their personal views may be different.

2.4.2. AI Anxiety

AI anxiety can be an essential factor in users' adoption and use of ChatGPT. IS literature has explored a relevant concept of technological anxiety which refers to the feeling of fear or apprehension that might be felt using of technology (Meuter et al., 2005). This anxiety has been discussed as an important antecedent of technology adoption (Meuter et al., 2005) and could lead to confusion regarding tasks to be performed, decreased motivation levels, or avoidance of new tech tools (Mani & Chouk, 2018), and ultimately has a negative influence on technology adoption (Evanschitzky et al., 2015).

In the context of this study and AI, notable tech leaders, including Bill Gates, Elon Musk, and the late Stephen Hawking, have expressed concerns about the potential for AI to get out of control and result in disastrous outcomes for humanity (Johnson & Verdicchio, 2017; Future of Life Institute, 2015). With the rapid dissemination of ChatGPT and related services recently, these concerns have been echoed by industrial tech leaders who have signed an open letter calling for a pause on large-scale AI experiments using GPT-4 due to worries about the "profound risks to human society" (Future of Life Institute, 2023).

Adapting to the definition proposed by Johnson & Verdicchio (2017), this study defines AI anxiety to refer to the feelings of apprehension or unease that arise due to concerns that AI could become uncontrollable and have harmful consequences for individuals and society (Johnson & Verdicchio, 2017). Several studies have attempted to measure and validate AI anxiety using different scales (J. Li & Huang, 2020; Y.-Y. Wang & Wang, 2022).

3. Theoretical Model and Hypothesis Development

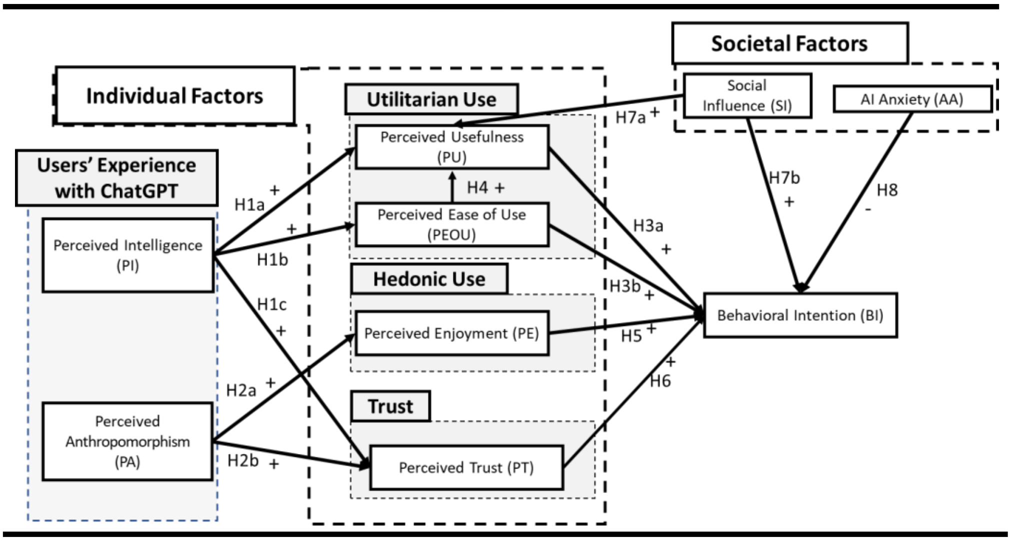
3.1. Research Model

Following the routes of technology adoption studies, this research also adopts fundamental theory of the Technology Acceptance Model (TAM) proposed by Davis (1989). Researchers utilized the TAM model to traditionally investigate utilitarian uses of IS (Davis et al., 1989; Venkatesh & Morris, 2000; Xiao & Benbasat, 2007). However, over the years, increasing number of studies have started to apply the TAM model to examine the adoption of IS for hedonic motives as well (Van Der Heijden, 2004; Wu & Lu, 2013).

The model has been utilized to inspect additional constructs influencing the adoption of technology, including cognitive absorption (Agarwal & Karahanna, 2000), the output quality of information systems (Wixom & Todd, 2005), trust towards a system (Gefen & Straub, 2003), and the perceived enjoyment (Van Der Heijden, 2004; Koufaris, 2002). IS adoption studies have also investigated the adoption of dual- (or multi-) purpose systems (Van Der Heijden, 2004; Köse et al., 2019) in relation to personal computers at home (Venkatesh & Brown, 2001), social networking platforms (Koufaris, 2002), and intelligent personal assistants (Moussawi et al., 2021). The model has been also utilized to investigate the influence of social influence on perceived usefulness (Lewis et al., 2003), and social factors on behavioral intentions to adopt a system (Kasilingam, 2020; Hsu & Lin, 2008).

Moreover, TAM has been utilized in investigating potential disruptive technologies (or have already disruptive each respective sectors) and extended and adapted for each specific domains including smart mobile wallets in the hotel industry (Lew et al., 2020), AI-based CRM software in the banking industry (Omoge et al., 2022), mobile payment in the service sector (Schmidthuber et al., 2020), and

Figure 2. Research Model and Hypotheses



wireless internet (Lu et al., 2003). This research also extends these studies to investigate the potential of the newly emerging ChatGPT as the next disruptive technology.

3.2. Hypothesis Development

The research model employed in this study is informed by existing literature on technology adoption and utilizes constructs to assess users' overall experiences within the initial months of engaging with the new chatbot. This paper examines how users' perceptions of ChatGPT's quality, encompassing perceived intelligence and anthropomorphism, subsequently affect individual factors such as utilitarian (perceived usefulness and perceived ease of use) and hedonic (perceived enjoyment) motivations, in addition to the perceived trust in ChatGPT. Beyond these individual factors, the study also explores societal factors, incorporating social influence and users' felt anxiety towards artificial intelligence. Through the application of this model, the study seeks to conduct a comprehensive analysis of the individual and societal factors that contribute to people's behavioral beliefs regarding ChatGPT. Please refer to Figure 2 for the complete research model.

3.2.1. Influence of Perceived Intelligence

Perceived intelligence (PI) refers to the user's perception that ChatGPT understands and is aware of the underlying intent provided by the user and feels that ChatGPT is capable of providing context-aware, natural, logical human-like language which can assist the user in fulfilling their goals (Legg & Hutter, 2007; Bartneck et al., 2019; Moussawi et al., 2019). It is anticipated that there will be a positive correlation between perceived intelligence and perceived usefulness. Perceived usefulness (PU) refers to the degree to which a person believes that using ChatGPT would enhance his or her job performance (Davis, 1989). The superior performance of ChatGPT in comparison to existing AI-driven chatbots such as Siri and Alexa are expected to foster the impression that the chatbot possesses greater intelligence, resulting in higher quality output (i.e., more logical, and well-reasoned conversations), which in turn contributes to the perception of usefulness.

Approaching the issue from a procedural perspective, previous studies have shown that when a decision support system (DSS) is developed with the goal of reducing task complexity and accelerating task completion (thereby enhancing perceived intelligence), the cognitive load experienced by the user is alleviated. This, in turn, leads to the perception that the DSS is more useful (Kamis et al., 2008). Examining the matter from an outcome-focused standpoint, it has been demonstrated that a user's perceived performance and output quality in association with an Online Analytical Processing (OLAP) system have a positive influence on the system's perceived usefulness (Hart & Porter, 2004). This line of reasoning can also be applied to the context of an advanced ChatGPT implementation.

We contend that the heightened intelligence of ChatGPT may contribute to the perception that its more sophisticated outputs assist users in achieving their objectives. Consequently, we propose the following hypothesis:

H1a: User's perceived intelligence of ChatGPT will have a positive influence on the perceived usefulness of the chatbot.

In addition, it is anticipated that a user's perceived intelligence of ChatGPT will exert a positive influence on the chatbot's perceived ease of use. Perceived ease of use (PEOU) is the degree to which the user expects the system will be easy to use and free from effort (Davis, 1989). This expectation is substantiated by empirical evidence demonstrating that when a DSS is less complex for a given task, users perceive it to be easier to use (Kamis et al., 2008). In the context of healthcare AI adoption among government employees in Dubai, the quality of information furnished by AI has been identified as having a positive impact on perceived ease of use (Al Shamsi et al., 2022). We argue that within the context of ChatGPT, the more intelligent and sophisticated outputs generated by the system will lead users to perceive it as easier to use. Consequently, we put forth the following hypothesis:

H1b: User's perceived intelligence of ChatGPT will have a positive influence on the perceived ease of use of the chatbot.

The perceived intelligence of ChatGPT is also expected to have a positive influence on the perceived trust towards the chatbot. Perceived trust (PT) refers to the degree to which a person believes that using ChatGPT's responses are credible and reliable in the context of uncertainty (Pillai & Sivathanu, 2020; You et al., 2018; J. D. Lee & See, 2004).

Trust is an important foundation for a successful adoption in IS studies and it has been a frequently investigated in relation to AI as an important factor for behavioral intention for adoption (Bawack & Desveaud, 2022). We propose that perceived intelligence of AI has a positive correlation to the perceived trust. The concept of perceived intelligence is lacking in the field of IS, but similar context has been studied in other fields of management. In the field of service marketing, technical and functional service quality elements positively impact overall evaluations, including credibility and trust towards the organization (Eisingerich & Bell, 2008). Furthermore, service quality has been found to have a positive relationship with trust in the brand (Chiou, 2006; Sharma & Patterson, 1999). Although the context of these studies may not exactly match with that of AI-based tool adoption, the end goal remains the same: to have a better relationship with the service provider (ChatGPT) and the customer (user). Perceived intelligence of ChatGPT, relating to the quality of the chatbot's response, can be correlated with the service quality mentioned in the context of service providers (organizations/brands). Given this information, we propose:

H1c: User's perceived intelligence of ChatGPT will have a positive influence towards perceived trust of the chatbot.

3.2.2. Influence of Perceived Anthropomorphism

Perceived anthropomorphism (PA) refers to the degree to which a person perceives ChatGPT as possessing human-like and social characteristics capable of high-quality conversations under the knowledge that ChatGPT is a non-human conversational agent (Kim & Sundar, 2012; Schuetzler et al., 2021). This study expects that the users' perceived anthropomorphism of ChatGPT will have a positive influence on the perceived enjoyment and trust towards the chatbot.

Research in cognitive psychology has discovered that when individuals anthropomorphize an object, they ascribe social attributes to it, effectively forming a ‘relationship’ with the object, which has the potential to enhance the overall quality of their experience by rendering it more positive and enjoyable (Chandler & Schwarz, 2010). This phenomenon has been observed in the Information Systems (IS) literature, where it has been demonstrated that human interactions with systems are similarly affected. For instance, when human-like attributes were introduced to retail websites through the incorporation of avatars, there was a noticeable increase in users’ perceived enjoyment, arousal, and pleasure (Wang et al., 2007). Likewise, in the realm of artificial intelligence, the introduction of anthropomorphic features in recommendation agents, such as humanoid embodiment and voice-based communication, led to heightened user perceptions of enjoyment (Qiu & Benbasat, 2009).

In the case of ChatGPT, we postulate that since the system has been specifically trained and optimized for human dialogue contexts, similar outcomes can be anticipated. Therefore, we propose the following hypothesis:

H2a: The user’s perceived anthropomorphism of ChatGPT will have a positive influence on the user’s perceived enjoyment of using ChatGPT.

We also anticipate that perceived anthropomorphism of ChatGPT may positively influence the perceived trust towards the chatbot. This relationship has been found in recent AI related literature. Cheng et al. (2022) showed that increased anthropomorphic characteristics in text-based chatbots, such as perceived warmth and communal relationship, positively impacted trust in chatbots. Additionally, Waytz et al. (2014) found that incorporating anthropomorphic characteristics like voice and gender into autonomous vehicles increased users’ perceived trust towards those vehicles. Furthermore, de Visser et al. (2016) conducted three experiments that revealed anthropomorphic elements as strong influencers in increasing trust resilience for human users.

During the user's experience with ChatGPT, it is expected that users will likely feel a sense of trust towards ChatGPT. While it was not explicitly 'trained' to show emotions, the chatbot is capable of showing signs of human-like social and emotional cues during the conversation. For example, apologizing to the user when the user has expressed discontent for the conversation, or ChatGPT showing empathy. Based on the previous literature, we propose the following hypothesis:

H2b: The user's perceived anthropomorphism of ChatGPT will have a positive influence on the user's perceived trust towards ChatGPT.

3.2.3. Influence of Utilitarian Motivations

Behavioral intention has consistently emerged as the most robust predictor of future continued usage of an IS (Davis, 1989; Davis et al., 1992; Venkatesh et al., 2003; Venkatesh & Brown, 2001; Venkatesh et al., 2012). In the context of this research, the user's behavioral intention serves as an indicator of the extent to which an individual is inclined to adopt ChatGPT. Factors both internal and external to the user can influence their behavioral intention. Given the current usage of ChatGPT and the recent advancements in AI, we propose four individual factors and two societal (external) factors as potential antecedents that shape the user's behavioral intention.

Perceived usefulness and ease of use represent an individual's utilitarian motives to use the system. We posit that the perceived usefulness (PU) of ChatGPT will exert a positive influence on adoption intention. The relationship between a system's perceived usefulness and the behavioral intention to adopt has been extensively corroborated across various contexts, such as online e-learning environments (S.-H. Liu et al., 2005), web-based stores (Koufaris, 2002), and decision support systems (Kamis et al., 2008). In the specific context of AI chatbots, PU has been demonstrated to positively impact behavioral intentions in industries such as tourism (Pillai & Sivathanu, 2020) and service counters (Fernandes & Oliveira, 2021). Given the capabilities attributed to ChatGPT, users may perceive the chatbot as beneficial in helping them attain their objectives, leading us to propose the following hypothesis:

H3a: User's perceived usefulness of ChatGPT will have a positive influence on their behavioral intention to use ChatGPT.

It is probable that users will perceive ChatGPT as easy to use, given that they obtain results by entering simple human-like, natural language text into the chatbot interface. This perceived ease of use is likely to foster positive intentions towards the continued utilization of the system. The positive association between perceived ease of use (PEOU) and behavioral intentions has been established in a variety of contexts, including productivity software (Venkatesh & Morris, 2000), personal workstations (Moore & Benbasat, 1991), and business-to-consumer (B2C) services (Gefen & Straub, 2003). In the domain of AI-based tools, PEOU has been demonstrated to exert a positive influence on behavioral intentions in the context of autonomous vehicles (Panagiotopoulos & Dimitrakopoulos, 2018; Zhang et al., 2019) and tourism chatbots (Pillai & Sivathanu, 2020). Consequently, we put forth the following hypothesis:

H3b: User's perceived ease of use of ChatGPT will have a positive influence on their behavioral intention to use ChatGPT.

Perceived ease of use serves as an indicator of the cognitive effort required to operate a system (Davis, 1989; Gefen & Straub, 2003). As the cognitive effort needed to utilize ChatGPT diminishes, the perceived benefits of the chatbot may correspondingly increase. Users might experience the sensation of effortlessly obtaining valuable outcomes by simply inputting text into the ChatGPT interface. The positive influence of PEOU on PU has been substantiated in diverse contexts, including Online Analytical Processing (OLAP) usage (Hart & Porter, 2004) and decision support systems (Kamis et al., 2008). In the realm of AI, this relationship has been empirically validated in gamified driving AI systems (Köse et al., 2019) and autonomous vehicles (Zhang et al., 2020; Panagiotopoulos & Dimitrakopoulos, 2018). In light of these findings, we propose the following hypothesis:

H4: User's perceived ease of use of ChatGPT has a positive influence on its perceived usefulness.

3.2.4. Influence of Hedonic Motivation

Perceived Enjoyment (PE) refers to the user perceiving the activity of using ChatGPT as fun and enjoyable, aside from any performance consequences resulting from the system use (Davis et al., 1992; Venkatesh & Morris, 2000). Perceived enjoyment represents the hedonic motivation to use ChatGPT.

Extant IS literature has demonstrated that deriving enjoyment from using an information system exerts a positive impact on users' behavioral intentions to adopt the system across various contexts, such as web-based stores (Koufaris, 2002) and decision support systems (Kamis et al., 2008). Within the domain of AI, heightened enjoyment has been observed to positively affect behavioral intention in AI-powered language e-learning systems (Lin et al., 2022) and voice assistants (Pitardi & Marriott, 2021). Pertaining to the context of this study, users may perceive ChatGPT as enjoyable through experimentation with the chatbot, which could consequently increase their intention to adopt ChatGPT. In light of these findings, we put forth the following hypothesis:

H5: The user's Perceived Enjoyment (PE) of using ChatGPT will have a positive influence on the user's behavioral intention to adopt ChatGPT.

3.2.5. Influence of Trust

The role of trust having a positive impact on the adoption intention of a system has been empirically supported in various IS contexts, such as B2C e-services (Gefen & Straub, 2003) and recommendation agents (Qiu & Benbasat, 2009). In the context of artificial intelligence-based tools, the positive influence between perceived trust (PT) and behavioral intention to adopt has been demonstrated for voice assistants (Pitardi & Marriott, 2021), autonomous vehicles in China (Zhang et al., 2020), social chatbots (Cheng et al., 2022), and the tourism industry (Pillai & Sivathanu, 2020).

In the current context of ChatGPT, the current state of ChatGPT is full of uncertainty and risks (Gow, 2023) as it is still in its initial stages (McKnight et al., 2002). If users have formed a perception of trust towards ChatGPT, they may have formed a stronger behavioral intention to use it. Based on the literature relevant to trust in IS and AI, we propose the following hypothesis:

H6: The user's Perceived Trust (PT) towards ChatGPT will have a positive influence on the user's behavioral intention to adopt ChatGPT.

3.2.6. Influence of Societal Factors

This study explores two main societal factors: social influence and AI anxiety. Social influence (SI) is defined as the degree to which an individual perceives that important others believe he or she should use ChatGPT (Venkatesh et al., 2003). Social influence includes subjective (social) norms of the affiliated group and the group's culture (Venkatesh et al., 2003).

In the context of this study, it could be said that there is a social influence to adopt ChatGPT into people's everyday lives work and personal lives. Companies are on the move to adopt ChatGPT in their workplaces (Tellez, 2023; Westfall, 2023; Bain & Company, 2023), and people feel a pressure to use ChatGPT just to "stay ahead" (Richardson, 2023; Greenhouse, 2023).

Previous literature based on TAM (Davis, 1989) has shown that social influence has a positive impact on perceived usefulness in various contexts, such as knowledge workers' technology adoption (Lewis et al., 2003) and online shopping (Bonn et al., 2016). In the context of AI voice assistants, subjective norm was found to be an influential factor for perceived usefulness (Moriuchi, 2021; Song, 2019). With the recent "hype" about ChatGPT, the social influence may have an influence on the user's perception of its usefulness, we propose the following hypothesis:

H7a: Social Influence (SI) will have a positive impact on the user's perceived usefulness to adopt ChatGPT.

Social influence has also been shown to have a direct influence on behavioral intention in previous technology acceptance studies based on UTAUT (Venkatesh et al., 2003; Venkatesh et al., 2012). For example, it has influenced the intention to accept mobile banking solutions (Yu, 2012; Zhou et al., 2010), mobile app purchases (Hsu & Lin, 2016), novel technology introduced in organizations (Venkatesh & Davis, 2000), and blog adoption (Hsu & Lin, 2008). In the context of AI, social influence was found to have a significant influence on the behavioral intentions for the adoption of social robots in college classrooms (Guggemos et al., 2020). Therefore, in this research context we also hypothesize that:

H7b: Social Influence (SI) will have a positive impact on the user's behavioral intention to adopt ChatGPT.

AI anxiety (AA) is defined as the degree to which the user feels a sense of apprehension that AI will get out of control (Meuter et al., 2003; Johnson & Verdicchio, 2017). Users who actively seek information might be more vulnerable to media opinions on ChatGPT and AI in general and could be more exposed to news that incites AI anxiety. The higher AI anxiety could negatively impact their intention to use ChatGPT. Previous literature has shown that technical anxiety can be a barrier to acceptance in the context of consumer self-service technologies (Meuter et al., 2005) and the Internet of Things (Mani & Chouk, 2018). In the context of AI chatbots for travel planning, technological anxiety was found to have a negative influence on adoption intention (Pillai & Sivathanu, 2020). AI anxiety was also shown to have a negative relationship with individuals' readiness for change in AI adoption (Suseno et al., 2022).

In the context of this study, it could be said that there is a sense of anxiety towards AI based on speed and pace it's evolving, even by industry leading tech leaders (Johnson & Verdicchio, 2017; Future of Life Institute, 2015; Future of Life Institute, 2023). Based on these recent developments, an anxiety may have been formed by the users and may pose a negative influence towards the behavior to adopt ChatGPT as reflected by previous literature on technology anxiety, thus we propose the following hypothesis:

H8: AI Anxiety (AA) will have a negative impact on the user's behavioral intention to adopt ChatGPT.

4. Research Methodology

4.1. Description of the Subject for Survey

The aim of this research is to gather a comprehensive understanding of user experiences with ChatGPT, with the intention of identifying the most influential antecedents in their behavioral intention to continue utilizing the service and deriving significant insights about the technology's future trajectory, thus providing important insights for business developers. To accomplish this, it was crucial to obtain feedback and viewpoints from Korean individuals who had engaged with ChatGPT to a degree that allowed them to form their overall impressions and who were willing to share their experiences with others. Opportunely, online communities centered on the usage of ChatGPT and generative AI have been emerging in Korea (Kim, 2023). Members of these communities actively interact with other virtual participants they encounter online, exchanging recommendations for optimally employing this technology and discussing the rapidly changing news and trends in the field of artificial intelligence.

The subjects of our research were drawn from two of the most prominent communities associated with ChatGPT and Generative AI: AI Korea Community[1] and ChatGPTers[2]. The AI Korea Community, the larger of the two, was founded in early January 2023, and boasts over 6,000 members (as of late April 2023) who share information about generative AI at large. ChatGPTers was founded in late December 2022, and has about 3,500 members (as of late April 2023). Both communities are characterized by their high level of activity, vibrancy, and continuous growth, with

[1] https://www.aikoreacommunity.com
[2] https://www.chatgpters.org/home

various discussion rooms dedicated to different types or applications of AI (such as language models and image models) and various use cases (ranging from research and business applications to creative uses in music, art, and writing). Each community promotes active online engagement through a variety of online and offline events, thereby increasing the homophily of its membership.

These online communities provided an excellent opportunity for conducting our research and selecting optimal subjects for our study. Online communities are, primarily, virtual forums where information providers and information seekers congregate to interact, exchange information, and offer advice within a specific product category (Brown et al., 2007). The community members fulfill various roles (Yang et al., 2019). Information providers primarily disseminate up-to-date news about the product category in question, while information seekers actively pursue information about the product to inform their decision-making process (Cotten & Gupta, 2004; Brown et al., 2007). As the information providers have already formed their opinions about ChatGPT, information seekers — who constitute the majority of community members — are expected to have formed perceptions and evaluations about ChatGPT due to their active engagement. Collecting feedback and opinions from these communities increases the likelihood of obtaining responses that genuinely reflect perceptions of ChatGPT.

Furthermore, online communities serve as hubs for Word-of-Mouth (WoM) effects, amplifying user voices from these communities to the broader market (Kozinets et al., 2010; Brown et al., 2007). Considering their establishment in late December (ChatGPTers) and early January (AI Korea Community) — prior to ChatGPT's broad publicization in the media in February 2023 — these communities represent potential sources of the initial WoM surrounding ChatGPT in Korea and provide an important source of opinion for service providers.

4.2. Instrument Development

The survey items were all adapted from previous studies and measured 10 constructs, as follows: perceived intelligence (PI) items were adapted from Moussawi et al. (2021) and Pillai & Sivathanu (2020); perceived anthropomorphism (PA) from Moussawi et al. (2019); perceived usefulness (PU) from Moore & Benbasat (1991) and Venkatesh (2022); perceived ease of use (PEOU) from Moore & Benbasat (1991) and Venkatesh et al. (2012); perceived enjoyment (PE) from Davis et al., (1992), Kamis et al. (2008), and Gerow et al. (2013), perceived trust (PT) from Xu et al. (2019), Moussawi et al. (2021), and Pillai & Sivathanu (2020); social influence (SI) from Venkatesh et al. (2012); AI anxiety (AA) from Meuter et al. (2005), Li & Huang, (2020), and Pillai & Sivathanu (2020), behavioral intention (BI) from Venkatesh et al. (2012). All survey items were measured using reflective

Table 1. Definition of Constructs

Construct	Definition	Adapted from
Perceived Intelligence (PI)	The user's perception that ChatGPT understands and is aware of the underlying intent provided by the user, and feels that ChatGPT is capable of providing context aware, natural, logical human-like language which can assist in user fulfilling its goals	Legg et al. (2017), Bartneck et al. (2019), Moussawi et al. (2019),
Perceived Anthropomorphism (PA)	The degree to which a person perceives ChatGPT as possessing human-like and social characteristics capable of high-quality conversations under the knowledge ChatGPT is a non-human conversational agent	Kim et al. (2012), Schuetzler et al. (2021)
Perceived Usefulness (PU)	The degree to which a person believes that using ChatGPT would enhance his or her job performance	Davis et al. (1989)
Perceived Ease of Use (PEOU)	The degree to which a person believes that ChatGPT is easy to use and free from effort.	Davis et al. (1989)
Perceived Enjoyment (PE)	The user perceives the activity of using the system (ChatGPT) as fun and enjoyable, aside from any performance consequence resulting from the system use.	Davis et al. (1992) Venkatesh et al. (2000)
Perceived Trust (PT)	The degree to which a person believes that using ChatGPT's responses are credible and reliable in the context of uncertainty.	Pillai et al. (2020), You et al. (2018), Lee et al. (2004)
Social Influence (SI)	The degree to which an individual perceives that important others believe he or she should use ChatGPT	Venkatesh et al. (2003)
AI Anxiety (AI)	The degree to which the user feel a sense of apprehension that AI will get out of control.	Meuteret al. (2003), Johnson et al. (2017)
Behavioral Intention (BI)	A person’s subjective probability that he or she will perform a given behavior.	Davis et al. (1989)

constructs, and all the wording of the questions was adapted to fit the context of ChatGPT use. The questions were initially written in English and rtranslated into Korean. All items were measured using a 5-point Likert scale with anchors being “Strongly Disagree” for 1 and “Strongly Agree” for 5. The complete list of the definition of constructs and the survey questionnaire can be found on Tables 1 and 2.

Table 2. Complete Survey Items

Cons.	Survey Items	Adapted from
PI	PI1. ChatGPT accurately interprets the context and intent of my questions or statements. PI2. ChatGPT provides coherent and contextually relevant responses to my inquiries. PI3. I think ChatGPT's responses are logical, and it consistently helps me achieve my goals. PI4. I think ChatGPT demonstrates a strong understanding of the subject matter in our conversations.	Moussawi et al. (2021), Pillai et al. (2020)
PA	PA1. ChatGPT displays human-like emotions in its conversations. *PA2. ChatGPT is capable of adapting its conversation style to match my preferences. PA3. While interacting with ChatGPT, I often feel as if I'm conversing with a human. PA4. ChatGPT demonstrates an understanding of social norms during our interactions.	Waytz et al. (2010), Pillai et al. (2020), Moussawi et al. (2021)
PU	PU1. Using ChatGPT has improved my job performance. PU2. ChatGPT enables me to accomplish tasks more effectively. PU 3. I find ChatGPT to be a valuable tool in my work. PU 4. ChatGPT helps me to enhance my productivity.	Moore et al., (1991) Venkatesh et al., (2012); Pillai et al. (2020)
PEOU	PEOU1. Overall, I believe that ChatGPT is easy to use. PEOU 2. It requires minimal cognitive effort to learn how to use ChatGPT. PEOU 3. It is easy to get ChatGPT to do what I want to do. PEOU 4. Interacting with ChatGPT feels intuitive and natural.	Venkatesh et al. (2012), Moore et al. (1991)
PE	PE 1. I find using ChatGPT to be fun. PE 2. ChatGPT adds a sense of enjoyment to my tasks in my personal and daily life. PE 3. I feel the interaction with ChatGPT to be interesting. PE 4. The experience of interacting with ChatGPT is inherently enjoyable.	Davis et al. (1992), Kamis et al. (2008), Gerow et al. (2013)
PT	PT1. I feel that conversation and response provided by ChatGPT are honest and authentic. PT2. I feel that ChatGPT's answers are clear opinions which are reliable. PT3. I feel confident in ChatGPT's abilities to provide credible information. PT4. I feel that ChatGPT has the necessarily abilities to achieve my intended goals.	Xu & Zhang et al. (2018), Moussawi et al. (2021), Pillai et al. (2020)
SI	SI1. People who are important to me think that I should use ChatGPT. SI2. People who influence my behavior think that I should use ChatGPT. SI3. People whose opinions that I value encourage the use of ChatGPT. *SI4. I feel pressure from the people that I deem as important to use ChatGPT	Venkatesh et al. (2012)
AA	AA1. I worry that AI systems like ChatGPT might become uncontrollable. AA2. I feel uneasy about the potential risks associated with using AI systems like ChatGPT. *AA3. I am concerned that AI technologies might have negative consequences on society. AA4. The rapid development of AI systems like ChatGPT makes me anxious.	Meuter et al. (2005), Li et al. (2020), Pillai et al. (2020)
BI	BI1. I intend to continue using ChatGPT in the future. BI2. I will always try to use ChatGPT in my daily life. BI3. I will plan to continue to use ChatGPT more frequently. BI4. I am willing to invest time and effort in learning how to use ChatGPT more effectively.	Venkatesh et al., (2012)

Notes: * Omitted from the final model due to low factor loadings and high cross loadings.

4.3. Execution of Survey and Data Collection Process

The survey was formulated using a Google Forms document and distributed through Kakao Talk, the main messenger service of choice for Koreans. It is also the primary medium of communication for both online communities. Through Kakao, these communities actively exchange AI-related information, tips, and tricks among the members in real-time.

While it would have been optimal to receive a larger number of samples from the majority of the members, there were some limitations in the data collection process: (1) due to the different policies existent in each community, a limit was imposed on the total duration for which the survey could be conducted within these communities, (2) due to the real-time nature of the instant messaging platform on which these communities were running, a single message post for the survey was likely to be quickly overwhelmed by other messages during active times of the day, and (3) given the immense size of the community, with 3,000+ members in each chatroom, it was difficult for many members to check the messages all the time.

Given these constraints in data collection, potential biases could have been introduced to the study. The limitations in the total duration for the survey could potentially lead to a time-based bias, with only those who were present and active during the survey period having the opportunity to participate. Furthermore, the transient nature of the messaging platform and the difficulty for many members to consistently check messages might have resulted in a convenience bias, where only the most active or engaged members, or those who were online at the right time, contributed to the study. These limitations could have resulted in a sample that is not entirely representative of the larger community, thus possibly affecting the generalizability of the results.

The survey was conducted over a period of 8 days, from April 17 to 25, 2023. Incentives were provided to the participants, with 10% of them being randomly selected and given Starbucks Coffee coupons. As a result, 205 samples were collected. Although this is small compared to the overall scale of the community, this sample size meets the recommendation of current literature, which suggests a minimum R-squared of 0.1 at a 5% significance level with six arrows pointing to a construct (Cohen, 1992).

4.4. Research Model

The variance based Partial Least Squares - Structural Equation Model (PLS-SEM) approach was chosen to evaluate our model. The widely used SmartPLS4 (Ringle et al., 2022) was used to conduct the analysis.

PLS-SEM has been frequently used in IS studies (Ringle et al., 2012) is a suitable approach suitable for this research for the following reasons:

1. The objective of our analysis is prediction (Hair et al., 2019). The variance-based PLS-SEM approach is more appropriate than the covariance-based CB-SEM for identifying and predicting key drivers in structural model evaluation (Ringle et al., 2012). In this research, we aim to determine the stronger antecedents for the behavioral intention to adopt ChatGPT. Our model reports the coefficient of determinant (R-squared) values to assess the model's ability explain and predict the endogenous variable.
2. PLS-SEM should be selected when the model complex includes many constructs, indicators, and model relationships (Hair et al., 2019). The goal of this study is to explore influence of different relationship of 10 constructs between (1) the perceived quality of ChatGPT service in terms of perceived intelligence and anthropomorphism. (2) individual factors (PU, PEOU, PE,

PT), and societal factors (SI and AA), and (3) ultimately the behavioral intentions.

3. PLS-SEM also offers high prediction accuracy which is restricted in small sample size (Hair et al., 2019). While the community of interest had over 9,000 members in total, there were limitations in collecting samples as only a one-time posting of the survey was allowed due to each community's policies. As a result of the survey sample collection, 205 samples were gathered. Despite a small sample size, this fits the minimum requirement for the recommended sample size as recommended by (Cohen, 1992).
4. PLS-SEM also offers high prediction accuracy which is restricted in small sample size (Hair et al., 2019). While the community of interest had over 9,000 members in total, there were limitations in collecting samples as only a one-time posting of the survey was allowed due to each community's policies. As a result of the survey sample collection, 205 samples were gathered. Despite a small sample size, this fits the minimum requirement for the recommended sample size as recommended by (Cohen, 1992).

4.5. Check for Common Method Bias

As an initial check of the validity of the model, we checked the existence of common method bias (CMB) in our model. According to Sharma & Patterson (1999), our measure of the perception towards and usage of ChatGPT essentially consists of behavior-anchored scales that may be subject to relatively high common method variance, that is, high item characteristic effects. The existence of a common method variance may cause biases, commonly referred to as "common method bias" (CMB) (Kock, 2015). Using questionnaires answered on Likert-type scales constitutes an integral part of an SEM study's measurement method, and CMB is a phenomenon caused by the measurement method used in an SEM study (Kock, 2015).

Harmon’s single factor test is one of the most widely used techniques to address the issue of common method bias (Podsakoff et al., 2003). Harmon’s single factor test is usually conducted before the evaluation of measurement model, however, may face some problems in which models that pass the convergent and discriminant validity may still be “contaminated” by CMB (Kock, 2015). As an alternative, Kock (2015) proposes a solution to check for common method bias. An occurrence of Variation Inflation Factors (VIF) greater than 3.5 is proposed as an indication of pathological collinearity, and an indication that model may be contaminated by common method bias. Kock (2015) mentions that if all the VIFs in the inner model resulting from a full collinearity test are equal or lower than 3.3 the model can be considered free of common method bias. As suggested by Kock (2015), the check for CMB would be conducted after the measurement model had been evaluated.

4.6. Measurement Model Evaluation

For reflective measurement models the evaluation procedures include (1) check of outer loadings, (2) internal consistency reliability, (3) convergent validity, and (4) discriminant validity. First, the outer loadings - the estimates of the relationships between the latent variables and the indicators (the survey questions / manifest variables) - were checked. It is recommended the all the factor loadings are higher than 0.708 (Hair et al., 2019). While most of the outer loadings were well above 0.708, three indicators (PA2, SI4, AA3) were below the recommended value, so they were deleted from the model. The cross-loadings can be found in Table 3.

Internal consistency reliability refers to the degree to which the indicators measure the same latent variable and are coordinated with each other. Table 3 shows the composite reliability (Joreskog, 1971) measures. While Cronbach’s alpha is another popular metric to report the internal consistency reliability, it produces lower values than composite reliability (Hair et al., 2019), and therefore Joreskog's composite reliability is considered as a better measure. All the composite reliability measures were over 0.86 which are considered "satisfactory to good" (Hair et al., 2019). Table 3 shows the internal consistency reliability measure (ρ_c) of each latent variable.

Table 3. Measurement Model Factor and Cross-Loadings, Internal Consistency Reliability (Composite Reliability (ρ_c)), and Convergent Validity (Average Variance Extracted (AVE))

Constructs		PI	PA	PU	PEOU	PE	PT	SI	AA	BI
Perceived Intelligence ρ_c = 0.854 AVE = 0.595	**PI1**	**0.721**	0.340	0.345	0.209	0.246	0.275	0.033	0.070	0.110
	PI2	**0.740**	0.389	0.339	0.187	0.249	0.330	0.089	0.080	0.139
	PI3	**0.819**	0.313	0.434	0.265	0.373	0.476	0.011	0.111	0.211
	PI4	**0.801**	0.471	0.302	0.208	0.283	0.438	0.030	0.155	0.128
Perceived Anthropo-morphism ρ_c = 0.878 AVE = 0.707	**PA1**	0.424	**0.879**	0.059	0.132	0.085	0.280	0.125	0.102	0.076
	PA3	0.424	**0.748**	0.090	0.071	0.075	0.269	0.090	0.078	0.042
	PA4	0.385	**0.887**	0.070	0.227	0.166	0.347	0.156	0.157	0.084
Perceived Usefulness ρ_c = 0.940 AVE = 0.797	**PU1**	0.386	0.094	**0.870**	0.321	0.518	0.469	0.281	0.018	0.461
	PU2	0.395	0.063	**0.902**	0.281	0.457	0.440	0.180	0.021	0.345
	PU3	0.440	0.086	**0.890**	0.266	0.560	0.452	0.299	0.066	0.461
	PU4	0.432	0.061	**0.909**	0.298	0.503	0.465	0.246	0.024	0.452
Perceived Ease of Use ρ_c = 0.887 AVE = 0.663	**PEOU1**	0.192	0.140	0.230	**0.736**	0.299	0.220	0.086	0.067	0.068
	PEOU2	0.193	0.143	0.154	**0.820**	0.285	0.229	0.134	0.089	0.049
	PEOU3	0.254	0.146	0.292	**0.858**	0.352	0.326	0.194	0.106	0.181
	PEOU4	0.265	0.158	0.335	**0.837**	0.328	0.330	0.135	0.138	0.115
Perceived Enjoyment ρ_c = 0.923 AVE = 0.751	**PE1**	0.367	0.112	0.457	0.352	**0.837**	0.405	0.215	0.076	0.419
	PE2	0.269	0.075	0.541	0.340	**0.904**	0.400	0.291	0.053	0.512
	PE3	0.367	0.109	0.542	0.335	**0.845**	0.465	0.249	0.050	0.411
	PE4	0.332	0.175	0.453	0.338	**0.880**	0.498	0.293	0.102	0.462
Perceived Trust ρ_c = 0.860 AVE = 0.606	**PT1**	0.410	0.387	0.230	0.296	0.348	**0.751**	0.189	0.019	0.183
	PT2	0.367	0.214	0.380	0.237	0.382	**0.810**	0.136	0.028	0.206
	PT3	0.341	0.341	0.268	0.201	0.303	**0.807**	0.222	0.034	0.235
	PT4	0.429	0.185	0.654	0.335	0.515	**0.744**	0.244	0.020	0.399
Social Influence ρ_c = 0.918 AVE = 0.789	**SI1**	0.026	0.099	0.270	0.139	0.319	0.240	**0.892**	0.07	0.307
	SI2	0.039	0.097	0.196	0.116	0.244	0.193	**0.907**	0.117	0.305
	SI3	0.002	0.196	0.287	0.199	0.245	0.253	**0.865**	0.153	0.326
AI Anxiety ρ_c = 0.880 AVE = 0.711	**AA1**	0.151	0.162	0.071	0.103	0.107	0.007	0.120	**0.956**	0.176
	AA2	0.042	0.065	0.059	0.122	0.006	0.104	0.072	**0.801**	0.025
	AA4	0.078	0.050	0.028	0.137	0.011	0.045	0.125	**0.761**	0.073
Behavioral Intention ρ_c = 0.890 AVE = 0.671	**BI1**	0.202	0.059	0.510	0.204	0.398	0.262	0.219	0.089	**0.773**
	BI2	0.166	0.083	0.451	0.100	0.451	0.323	0.327	0.105	**0.906**
	BI3	0.098	0.060	0.330	0.109	0.424	0.246	0.360	0.122	**0.867**
	BI4	0.182	0.064	0.300	0.043	0.440	0.279	0.241	0.183	**0.717**

Notes: 3 indicators (PA2, SI4, and AA3) were deleted due to their low loading and high cross-loadings.

Convergent validity refers to the degree to which the indicators of a single latent variable are related and is assessed with the average variance extracted (AVE) values, which are the mean of the squared loadings of each indicator in a construct (Hair et al., 2019). All the AVE values are over 0.59 which means that the indicators well converge to the latent constructs. Table 3 shows the convergent validity of the measurement model.

Discriminant validity refers to the extent to which a construct is empirically distinct from other constructs in the model (Hair et al., 2019). The popular method to evaluate discriminant validity are Fornell-Larcker criterion (Fornell & Larcker, 1981). It states that the square root of the AVE for each construct needs to be higher than its correlation with other constructs. Table 4 shows the Fornell-Larcker criterion

Table 4. Discriminant Validity (Fornell Larcker Criterion and Heterotrait Monotrait Ratio Criterion)

	PI	PA	PU	PEOU	PE	PT	SI	AA	BI
PI	**0.771**								
PA	0.484 (0.633)	**0.841**							
PU	0.464 (0.544)	0.086 (0.101)	**0.893**						
PEOU	0.285 (0.339)	0.180 (0.209)	0.327 (0.354)	**0.814**					
PE	0.381 (0.455)	0.135 (0.154)	0.574 (0.633)	0.393 (0.450)	**0.867**				
PT	0.503 (0.623)	0.360 (0.454)	0.512 (0.580)	0.351 (0.408)	0.509 (0.597)	**0.778**			
SI	-0.003 (0.075)	0.150 (0.174)	0.286 (0.312)	0.173 (0.194)	0.304 (0.343)	0.260 (0.305)	**0.888**		
AA	0.137 (0.129)	0.139 (0.142)	0.037 (0.070)	-0.128 (0.170)	0.081 (0.073)	-0.019 (0.083)	0.131 (0.141)	**0.843**	
BI	0.197 (0.240)	0.082 (0.114)	0.486 (0.553)	0.138 (0.173)	0.523 (0.607)	0.340 (0.406)	0.353 (0.412)	0.151 (0.150)	**0.819**

Notes: 1. The values in diagonal cells are the square root of the AVEs for the corresponding latent constructs.
2. All the off-diagonal cells are the correlations between the corresponding constructs
3. The values in parentheses show the HTMT ratio.

for the data. All square roots of the AVEs were greater than the correlations with the latent variable in our model, indicating sufficient discriminant validity. We also checked the heterotrait-monotrait (HTMT) ratio of the correlations (Henseler et al., 2015) which was proposed as an alternative to the Fornell-Larcker criterion (Fornell & Larcker, 1981). It was proposed that a threshold value of 0.9 or below to meet the discriminant validity. A high value of HTMT signifies that constructs may not be discriminant but rather similar. The values in parentheses in Table 4 signifies the HTMT ratio for each of the constructs, and all values were below the suggested threshold of 0.9. Therefore, the discriminant validity was met.

4.7. Structural Model Evaluation and Hypothesis Testing

In preparation for the structural model analysis, we initially examine potential collinearity issues within the model through the assessment of variance inflation factors (VIFs). The VIFs not only serve as an indicator for multicollinearity, but also in identifying the presence of common method bias (CMB) (Kock, 2015).

Table 5. Collinearity Statistics (Variation Inflation Factors - VIFs)

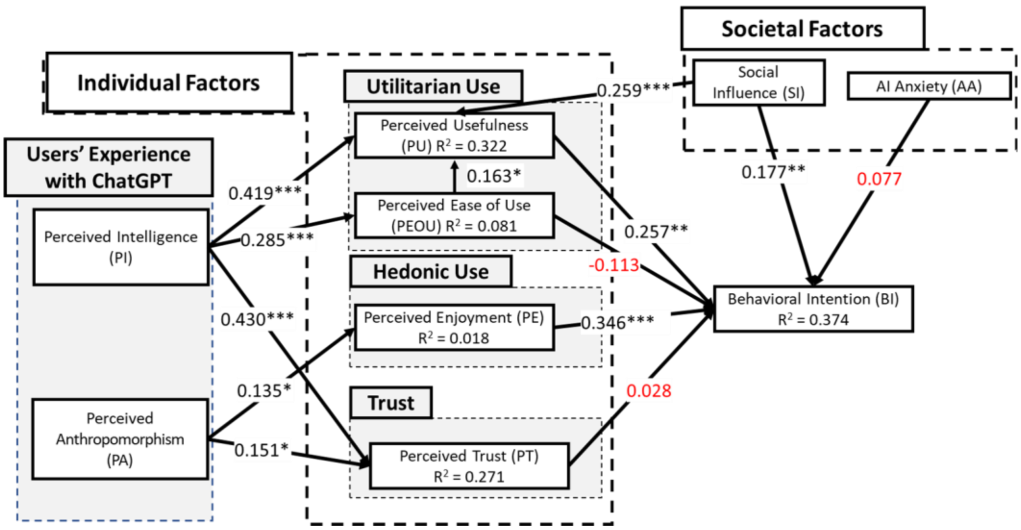
	PI	PA	PU	PEOU	PE	PT	SI	AA	BI
PI			1.092	1.000		1.306			
PA					1.000	1.306			
PU									1.682
PEOU			1.126						1.273
PE									1.774
PT									1.549
SI			1.034						1.154
AA									1.058
BI									

Notes: All VIFs were under 3.3, which means that collinearity as well as common variance method bias (CMB) was not an issue (Kock, 2015).

The collinearity statistics reported in Table 5 reveal VIF values below 3.3, indicating that neither CMB (Kock, 2015) nor collinearity concerns are prevalent in the model.

To determine the statistical significance of path coefficients, we employ a bootstrapping technique, as suggested by (Chin, 2010). The outcomes of hypothesis testing are illustrated in Figure 3. Hypotheses H1a, H1b, and H1c evaluate the positive associations between perceived intelligence and perceived usefulness (H1a), perceived ease of use (H1b), and perceived enjoyment (H1c). For H1a, H1b, and H1c, the respective path coefficients and p-values are as follows: $\beta = 0.322, p = 0.000$; $\beta = 0.284, p = 0.000$; and $\beta = 0.430, p = 0.000$. All three hypotheses are supported. Hypotheses H2a and H2b assess the positive effects of perceived anthropomorphism on perceived enjoyment (H2a) and perceived trust (H2b). The path coefficients and p-values for H2a ($\beta = 0.135, p = 0.041$) and H2b ($\beta = 0.151$, $p = 0.043$) indicate support for both hypotheses.

Figure 3. Results of the Research Model



Notes: 1. *p<0.05, **p<0.01, ***p<0.001, others are non-significant
2. Bootstrapping method was used as suggested by Chin (2010)

Hypotheses H3a and H3b investigate the positive influence of utilitarian motives—namely, perceived usefulness and perceived ease of use—on the behavioral intention to adopt ChatGPT. H3a, with $\beta = 0.257$ and $p = 0.004$, is supported. In contrast, H3b presents a path coefficient of $\beta = -0.113$ and a p-value of $p = 0.073$, which was not only statistically non-significant at the 0.05 significance level, but also demonstrates a direction opposite to the expected path, and therefore H3b is not supported. Hypothesis H4 examines the relationship between utilitarian motives, specifically the positive influence of perceived ease of use on perceived usefulness, as explored in traditional TAM studies. H4 is supported, with $\beta = 0.163$ and $p = 0.012$.

Hypothesis H5 explores the impact of the hedonic motive of perceived enjoyment on the behavioral intention to adopt and is supported by a path coefficient of $\beta = 0.346$ and a p-value of $p = 0.000$. Hypothesis H6 evaluates the influence of trust on behavioral intentions to adopt, a factor frequently investigated in previous research. However, contrary to initial expectations, H6 is not supported due to a lack of statistical significance.

Hypotheses H7a, H7b, and H8 examine the effects of societal factors. H7a evaluates the positive association between social influence and perceived usefulness and is supported with $\beta = 0.259$ and $p = 0.000$. H7b assesses the positive relationship between social influence and the behavioral intention to adopt and is also supported, with $\beta = 0.177$ and $p = 0.003$. H8 investigates the potential negative association between AI anxiety and the behavioral intention to adopt but is not statistically significant, nor supported, with path coefficients moving in a direction opposite to expectations.

Table 6. Hypothesis Testing Results

Hypotheses		Results
1a	User's perceived intelligence (PI) of ChatGPT will have a positive influence on the perceived usefulness of the chatbot.	Supported
1b	User's perceived intelligence (PI) of ChatGPT will have a positive influence on the perceived ease of use of the chatbot.	Supported
1c	User's perceived intelligence (PI) of ChatGPT will have a positive influence towards perceived trust of the chatbot.	Supported
2a	The user's perceived anthropomorphism (PA) of ChatGPT will have a positive influence on the user's perceived enjoyment of using ChatGPT.	Supported
2b	The user's perceived anthropomorphism (PA)of ChatGPT will have a positive influence on the user's perceived trust towards ChatGPT.	Supported
3a	User's perceived usefulness of ChatGPT (PU) will have a positive influence on their behavioral intention to use ChatGPT.	Supported
3b	User's perceived ease of use of ChatGPT (PEOU) will have a positive influence on their behavioral intention to use ChatGPT.	Not Supported
4	User's perceived ease of use (PEOU) of ChatGPT has a positive influence on its perceived usefulness.	Supported
5	The user's Perceived Enjoyment (PE) of using ChatGPT will have a positive influence on the user's behavioral intention to adopt ChatGPT.	Supported
6	The user's Perceived Trust (PT) towards ChatGPT will have a positive influence on the user's behavioral intention to adopt ChatGPT.	Not Supported
7a	Social Influence (SI) will have a positive impact on the user's perceived usefulness to adopt ChatGPT.	Supported
7b	Social Influence (SI) will have a positive impact on the user's behavioral intention to adopt ChatGPT.	Supported
8	AI Anxiety (AA) will have a negative impact on the user's behavioral intention to adopt ChatGPT.	Not Supported

Figure 3 shows the R-squared values in each endogenous variable, which measure the variance explained by each endogenous construct, serving as an indicator of the model's explanatory power (Shmueli & Koppius, 2011). R-squared is also known as the in-sample predictive power (Rigdon, 2012). General guidelines suggest that R-squared values of 0.75, 0.50, and 0.25 are deemed substantial, moderate, and weak, respectively (Hair et al., 2019). However, acceptable R-squared values depend on the context, with some disciplines considering values as low as 0.1 to be satisfactory. R-squared is also influenced by the number of predictor constructs, with a greater number typically resulting in higher R-squared values (Hair et al., 2019). It is crucial to interpret R-squared values in relation to the study's context.

In this model, some constructs exhibit notably low R-squared values, even falling below the 0.25 "rule" recommended by Hair et al. (2019). Specifically, the R-squared values for perceived ease of use (PEOU) and perceived enjoyment (PE) are 0.081 and 0.018, respectively. Nevertheless, a significant positive relationship was identified between perceived enjoyment and behavioral intention to adopt. As discussed in greater detail in the subsequent discussion section, these R-squared values should be considered within the context of this study (Hair et al., 2019), and with an open mind. The rationale is that research on ChatGPT adoption is relatively limited at this stage, and the relationship between perceived anthropomorphism and enjoyment is relatively new, making it characteristic of exploratory research. Perceived ease of use and perceived enjoyment might even be interconnected from the context of a dual-purpose information systems. The relationship between these variables is further examined in an extended study and elaborated upon in the discussions section.

In summary, the structural model analysis provides support for most of the proposed hypotheses, with the exception of H3b, H6, and H8. These results are summarized in Table 6. The findings suggest that perceived intelligence, perceived anthropomorphism, utilitarian motives, hedonic motives, and social influence positively affect user adoption and acceptance of ChatGPT, whereas perceived ease of use and AI anxiety do not demonstrate a statistically significant relationship with the behavioral intention to adopt. Moreover, trust, while expected to be a crucial factor, was found not to be statistically significant in this model.

5. Discussions

The goal of the study was to explore the current state of ChatGPT, specifically, how it has been perceived by Korean users over the last few months and assess its potential as the next disruptive technology. To do so, this research did the following: (1) identify the characteristics of ChatGPT in relation to the existing literature from the context of conversational AI and consider how ChatGPT may be perceived different from existing ones from the perspective intelligence and anthropomorphism, (2) explore how these qualitative characteristics may influence the individual's motivations to use ChatGPT in terms of utilitarian or hedonic uses, (3) and conduct a comprehensive investigation of how individual and societal factors influence the behavioral intention to adopt the new chatbot.

Our empirical study showed that perceived intelligence and anthropomorphism are two key characteristics that influence the utilitarian and hedonic motivations for ChatGPT use, as well as trust towards the chatbot. Additionally, our results show that for Korean users, perceived usefulness and perceived enjoyment positively impact the intention to adopt a PIA. Together the two constructs (perceived usefulness and enjoyment) indicate that the ChatGPT is being used for both utilitarian and hedonic uses, and they both shape the user's intention to adopt the chatbot. These results are in line with prior findings in the context of the theory of dual-purpose information systems (Wu & Lu, 2013; Köse et al., 2019). Moreover, it was found that social influence of ChatGPT shapes the individuals' perception of its usefulness as well as the behavioral intention to adopt.

However, did not find support for a few constructs – perceived ease of use, perceived trust, and AI anxiety – to be significant determinants for the behavioral intention to adopt ChatGPT. A few discussions are noteworthy.

5.1. Perceived Ease of Use with Behavioral Intention

While it was initially expected that the perceived ease of use will have a positive influence on the behavioral intention to adopt ChatGPT, this was not supported, even though a myriad other literature supported this relationship in IS research (Venkatesh & Morris, 2000; Moore & Benbasat, 1991; Gefen & Straub, 2003), even in the specific context of AI (Panagiotopoulos & Dimitrakopoulos, 2018; Zhang et al., 2019), and chatbots (Pillai & Sivathanu, 2020). Not only was it statistically non-significant, but also the direction of path coefficient was opposite (negative) than the expected.

A possible explanation for the unexpected result may be due to the complexity of using ChatGPT due to the flexibility and the range of possibilities with prompting. That is, how users design their input prompts may result in infinitely differently "generated" results. For people first approach ChatGPT, they may be amazed by ChatGPT's capabilities, being able to output a higher-than-expected quality answer with just a few lines of natural human language. This is the "magical experience" as pointed out by (Blagic, 2022), hence being referred to as a "game changer" by some early users (Haque et al., 2022) and leading to an explosion of the number of users (Milmo, 2023). However, as they try to utilize ChatGPT for more advanced purposes with detailed prompts, they may not easily get the "detailed results" as expected. This is because ChatGPT, being a generative AI, will give different results based on how the prompt is given. There is a whole field of prompt engineering (P. Liu et al., 2021), and OpenAI even provides official guidelines for prompting for better results (Shieh, 2023), and an official course for developers (Fulford & Ng, 2023).

Simply put, ChatGPT may be "easy to use" at first, but also "not so easy to use" for more advanced uses. This may be explained by the Duning Kruger effect

(Kruger & Dunning, 1999) which refers to a cognitive bias that can lead you to overestimate your abilities and knowledge in a particular idea. First without sufficient experience of ChatGPT, they may think that ChatGPT will give satisfactory results in whatever prompt you put in. However, as your knowledge and experience with ChatGPT grows, you get to know that some work is required in the prompt to get better experiences. Sommer (2023) points out that knowledge workers are falling victim of the Dunning-Kruger effect due to ChatGPT.

While statistically non-significant, the negative results may signify that more people in this sample may deem the use of ChatGPT as difficult due to its prompt flexibility. Despite the subjects being from a community of information seekers, people from various social strata with different experiences in tech may gather. Because ChatGPT is disseminating at a fast rate, diverse people have become involved in it. These different prior experiences with technology could be referred to as "habit" (Venkatesh et al., 2012). Venkatesh et al. (2012) refers to habit as the degree to which people tend to perform behaviors automatically because of learning. Habit in the IS context is the accumulated experience of using similar technology. Future research can extend this by testing if everyday users with low experience (habit) find ChatGPT to be easier to use by learning simple prompting techniques.

5.2. Perceived Trust with Behavioral Intention

Our research did not demonstrate that perceived trust positively influenced the behavioral intention to adopt ChatGPT, as anticipated based on previous literature in the context of voice assistants (Pitardi & Marriott, 2021), autonomous vehicles (Zhang et al., 2020), social robots (Cheng et al., 2022), and the tourism industry (Pillai & Sivathanu, 2020). A potential reason for this is that ChatGPT is a pioneering technology, democratizing access to LLM-based chatbots for the general public and is relatively new. Users in the first five months of ChatGPT's service might not have had the opportunity to fully engage with the chatbot and develop trust in it. Research has shown that trust between customers and brands or services takes time to establish (Zak, 2017; Ha, 2004), and this process may be even longer for unproven, new offerings (Vadino, 2020). While users might have formed a "sense" of trust in ChatGPT based on its capabilities (intelligence and anthropomorphism), this trust may not have been strong enough to directly influence adoption.

This outcome can be attributed to the uncanny valley effect (UVE) (Destephe et al., 2015), a phenomenon where exposure to an almost authentic yet imperfect human representation creates unease for the user. Although ChatGPT exhibits disembodied anthropomorphism (Araujo, 2018), Brownell (2023) contends that the widespread use of ChatGPT is introducing a new uncanny valley for Language Generation models. Previous studies have discovered that the uncanny valley effect can result in negative trust towards a system (Shin et al., 2019). According to Shin et al. (2019), UVE triggered by visual realism discrepancies in embodied agents can cause eeriness and negatively impact perceived trust, thereby influencing adoption decisions. While our study identified a positive relationship between perceived trust and adoption intentions, future research could investigate the factors that contribute to trust in language generation chatbots and determine which aspects most strongly influence the behavioral intention to adopt ChatGPT. Familiarity has been proposed as a solution to the "uncanny valley" (S. W. Song & Shin, 2022). Prolonged exposure to ChatGPT and other LLM-based chatbots may increase familiarity, potentially leading to enhanced trust and positive adoption intentions. Future research could explore this possibility.

5.3. AI Anxiety with Behavioral Intentions

It was expected that anxiety towards artificial intelligence was negatively correlated to the adoption intention, however, our results showed it insignificant. A possible explanation is that there is currently a mix of both hope for the advancement of AI technology (low anxiety) and worrisome forecasts for this technology (high AI anxiety) coexisting in the community.

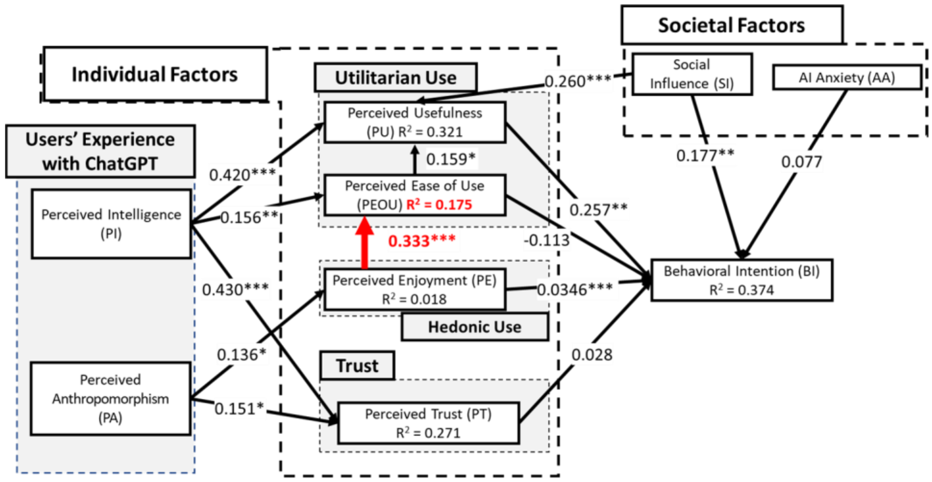
There is surely a coexistence of optimism and pessimism about the advancement of AI (Schmelzer, 2019). While there are reports about the transformative nature of potential AI (Chui et al., 2022; Rotman, 2023) which induces hope, there are also various news items causing anxiety (Johnson & Verdicchio, 2017; Future of Life Institute, 2015; Future of Life Institute, 2023). This social reaction offers possible explanations for the unexpected study results of the perceived ease of use and trust relationship with behavioral intention. Due to a rapid dissemination of ChatGPT to a wide population, a mix of those experienced and unexperienced users, along with those optimistic and pessimistic about AI, could be mixed in the current population of Korean ChatGPT users. It takes considerable time to become skilled in the use of a new technology (Venkatesh et al., 2012), and it takes time for one to build significant trust with the service (Zak, 2017; Ha, 2004), especially for a novel and potentially disruptive technology, like ChatGPT.

5.4. Extended study:

Disentangling Utilitarian and Hedonic Motivations

While not explicitly part of this study, another topic worthy of discussion and of future research is whether ChatGPT has a stronger characteristic as a utilitarian or hedonic information system. Both perceived usefulness and perceived enjoyment turned out to have positive influence on behavioral intention to adopt with

Figure 4. Extended Study 1: Testing for Stronger Utilitarian Motives for ChatGPT (Connecting PE → PEOU)

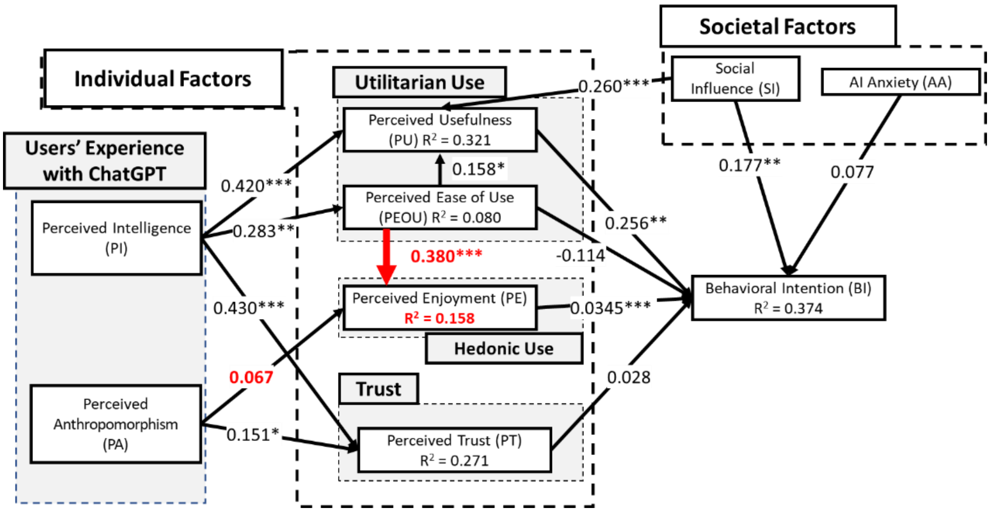


Notes: Following Sun & Zhang (2006) study, PE →PEOU connection was made to test for stronger utilitarian motives. The noticeable changes to the model results are marked in red. Connecting perceived enjoyment (PE) to perceived ease of use (PEOU), the path coefficient (β=0.333) turned out to be significant (***p<0.001), and the R^2 of PEOU increased from 0.081 to 0.175. An increase of 0.094.

statistical significance, however, the path coefficient of perceived usefulness ($\beta = 0.257$) turned out to be higher than perceived enjoyment ($\beta = 0.346$) towards behavioral intention. It might be intuitively expected that the utilitarian motives are stronger than the hedonic motive, but our study resulted in the other way around.

First of all, the R-squared for perceived enjoyment is very low at 0.02. While perceived anthropomorphism turned out to have a significant and positive relationship to perceived enjoyment, the low r-squared may signify that there may be many other unspecified variables than just anthropomorphism that influence what makes ChatGPT more enjoyable. A possible variable explored in previous literature is the concept of computer playfulness (Wakefield & Whitten, 2006; Venkatesh, 2000; Blut et al., 2016), which refers to the degree of spontaneity in microcomputer interactions (Venkatesh, 2000). Adapted to ChatGPT's terms, it could refer to the extent to which the user feels ChatGPT is playful from its random generated answers.

Figure 5. Extended Study 2: Testing for Stronger Hedonic Motives of ChatGPT (Connecting PEOU → PE)



Notes: Following Sun & Zhang (2006) study, PEOU →PEE connection was made to test for stronger hedonic motives. The noticeable changes to the model results are marked in red. Connecting perceived ease of use (PEOU) to perceived enjoyment (PE), the path coefficient (β=0.380) turned out to be significant (***p<0.001), and the R^2 of PEOU increased from 0.018 to 0.158. An increase of 0.14. However, the connection from perceived anthropomorphism (PA) to perceived enjoyment (PE) which previously turned out to be significant changed to insignificant, while the direction was still positive.

Further research could investigate other factors that influences perceived enjoyment, or addition of other hedonic motives for ChatGPT adoption.

Considering Sun & Zhang (2006)'s research, an extended study was conducted by connecting PEOU and PE in both directions, with the rest of the model remaining the same. Figure 4 tests for the potential stronger utilitarian uses by connecting PE → PEOU, and Figure 5 tests for the potential stronger hedonic uses by connecting PEOU → PE. The results showed that for PE → PEOU: $\beta = 0.333$ and $p = 0.000$ and for PEOU → PE: $\beta = 0.380$ and $p = 0.000$. Reflecting upon Sun & Zhang (2006) study, it could be interpreted that because the path coefficient for PEOU → PE ($\beta = 0.380$) is stronger than PE → PEOU ($\beta = 0.333$), utilitarian motives may not be as strong than hedonic motives to use ChatGPT, similar to the original test in which path coefficient for perceived usefulness ($\beta = 0.257$) was lower than the path coefficient for perceived enjoyment ($\beta = 0.346$) towards the behavioral intention to adopt. However, this preliminary test should also be taken with some caution because in the model of PEOU → PE, the originally significant path coefficient connecting perceived anthropomorphism to perceived enjoyment (PA → PE) became insignificant with $\beta = 0.067$ and $p = 0.255$, but at the same time, the R-squared for PE being increased from 0.018 to 0.158, signifying that there is a much more complex relationship between perceived enjoyment and perceived ease of use for ChatGPT, and perceived anthropomorphism could be related in a different manner to perceived enjoyment. As mentioned in the structural model analysis, these results should not be taken seriously because the context of this study has an exploratory characteristic (Hair et al., 2019). Further studies may be able to explore this relationship further.

The results of the original study and the extended study both signify that at the current state, hedonic motivations to adopt ChatGPT may be stronger than utilitarian motivations to do so. A possible explanation for this is that while many people have experienced ChatGPT due to the recent hype, in general, most people still use it for fun (hedonic use) than to use it to achieve their practical goals (utilitarian purposes).

This explanation is in line with the insignificant results for perceived ease of use, trust, and anxiety towards ChatGPT. This technology, while advanced, is still relatively new, but now it is being promoted to a wider audience than a novel technology typically would. For people that have used similar state-of-the-art chatbots previously, the experience using ChatGPT may be similar; however, for the wider public, this may not be the case. In other words, the accumulated experiences of using similar LLM-chatbot based technology may be high for early adopters of technology, but not as high for the general public. Venkatesh et al. (2012) called this “habit” and found that this was a significant moderating construct for antecedents for IS adoption. Not only can this explanation be applied for the insignificant results for trust and anxiety, but also for the results of stronger hedonic motivations than the utilitarian motivations. The “general public” currently use it more for hedonic purposes than utilitarian purposes.

5.5. Theoretical Contributions and Practical Implications

This research aims to examine the emergence of ChatGPT and Large Language Models (LLMs)-based chatbots as potential disruptive technologies. By exploring previous literature on conversational AI, chatbots, and robots, the study identifies potential characteristics of ChatGPT that may influence users’ motives for adoption. Based on a literature review and an analysis of ChatGPT’s training process, perceived intelligence and anthropomorphism are proposed as two key characteristics. The study then presents and tests a theoretical model to gain a comprehensive understanding of how these antecedents influence individuals’ utilitarian and hedonic motives for using ChatGPT, as well as its impact on perceived trust. The model also explores not only individual factors, but also societal factors, such as social influence and anxiety towards AI, which ultimately affect the behavioral intention to adopt ChatGPT.

This study is among the first to investigate the adoption of ChatGPT from a consumer and general level, building on existing research on conversational AI and chatbots. While numerous studies have been conducted on ChatGPT’s capabilities (Koubaa et al., 2023; Kocoń et al., 2023) and its potential impact on fields like education (Tlili et al., 2023) and academia (Xames & Shefa, 2023), this study is the first to specifically examine general user perception.

In the context of IT adoption and dual-purpose information systems, this study is the first to confirm that ChatGPT is utilized for both utilitarian and hedonic purposes. Prior research on information system adoption emphasized the need to account for holistic experience with IT (Agarwal & Karahanna, 2000). As a potential disruptive technology, this study verifies that ChatGPT serves both utilitarian and hedonic purposes in terms of perceived usefulness and ease of use.

This study is also among the first to explore the potential influence of societal factors on users' behavioral intention to adopt ChatGPT, focusing on social influence and AI anxiety as induced by media portrayals. This is highly relevant given the current hype surrounding ChatGPT (Rosenbaum, 2023; Marks, 2022) and the daily media coverage of AI advancements. The study finds that social influence plays a significant role in ChatGPT adoption, while AI anxiety is not a major factor.

These findings have practical implications for developers seeking to incorporate OpenAI's GPT application programming interface (API) into their services or develop other LLM-based chatbot services.

1. **Design services and applications with end users in mind, focusing on their primary purposes for using the technology.** Developers should carefully consider how users' cognitive perceptions will influence the adoption of the service. ChatGPT is used for various purposes, including accomplishing individual tasks (utilitarian) and entertainment (hedonic). LLM-based models can be improved through detailed prompt engineering, which has been shown to enhance ChatGPT performance (White et al., 2023) and is supported by public resources from OpenAI (Fulford & Ng, 2023; Shieh, 2023).

2. **Focus on making the service or application more user-friendly through preprogrammed prompts or user interface improvements.** The study's results indicate that ChatGPT is currently perceived as difficult to use, potentially due to the freedom and flexibility provided by the prompting system. Developers can create guidelines and user-friendly materials to make the system more intuitive and harness the power of AI.

3. **Understand that building trust in the service or application will take time, as the technology is relatively new**. Developers should recognize that trust will not be established immediately due to uncertainties surrounding the technology. Instead of rushing to market, it is recommended to focus on fostering trust over time.

4. **Acknowledge the role of social influence in adoption intentions and the perceived usefulness of the service.** Service and application developers should consider leveraging social influence by promoting their products within users' immediate social circles, targeting organizations, communities, and networks. This approach can lead to a word-of-mouth effect that ultimately contributes to the adoption of ChatGPT-based services and applications.

5.6. Limitations and Future Research

There are some limitations to the generalization of the study's findings. Firstly, there is a potential for bias in the data which. Certain constraints in data collection could have introduced biases, including (1) a time-based bias due to the limited duration for the survey, favoring those who were active during that period, and (2) a convenience bias arising from the transient nature of the messaging platform and difficulty in continuous message checking, likely skewing the sample towards the most active or engaged members. These conditions might compromise the representativeness of the sample and the generalizability of some of the results for example, not only has been trust been frequently recognized as an important factor for deciding AI adoption, it has been frequently mentioned as an important factor at the workplace and between knowledge workers. Future research may be conducted more deeply in these constructs in a more elaborate data collection procedure.

Second, this study was conducted from the perspective of Korean users. Previous research in Information Systems (IS) literature has shown that cultural differences can affect technology adoption (Lee et al., 2013; Im et al., 2011). Although not directly related to cross-cultural adoption of ChatGPT, a recent study by (Cao et al., 2023) confirmed that ChatGPT's outputs align with different cultural contexts due to its training on a vast multilingual corpus. This study provides initial insights into ChatGPT's cultural implications. Future research could explore the impact of different cultural backgrounds on the adoption of LLM-based chatbots.

Third, from a methodological standpoint, this cross-sectional study collected individuals' perceptions of ChatGPT and their intention to adopt it approximately six months after its dissemination. This might be why perceived trust and AI anxiety had insignificant relationships with behavioral intention. As technology is still relatively novel, it takes time to build trust and overcome anxiety. Future research could conduct a longitudinal study to investigate changes in trust and anxiety towards behavioral intention over time.

Fourth, while significant at the 5% level, the explanatory power (R-squared) of some variables, particularly perceived enjoyment and ease of use, was low—much lower than the typical threshold for 'low' explanatory power (Hair et al., 2019). This study examined the antecedents of individuals' motives to adopt ChatGPT from the perspective of perceived intelligence and perceived anthropomorphism, based on previous AI literature. However, the low explanatory power may indicate that ChatGPT's nature is more complex. Specifically, what makes ChatGPT "easy to use" and "enjoyable" could be more complicated than anticipated. Future research may investigate this further by deconstructing what makes ChatGPT and other LLM-based chatbots easy to use and enjoyable.

Fifth, while this study confirmed that ChatGPT is a dual-purpose information system used for both utilitarian (perceived usefulness) and hedonic (perceived enjoyment) purposes, it could not clearly determine which motive was stronger. The study was conducted with random participants from an AI user community, attempting to survey the "general public." However, utilitarian vs. hedonic motives may differ across professions and industries. Future studies may delve deeper into the characteristics of ChatGPT adoption with more detailed constructs.

Finally, while this study did investigate the potential of ChatGPT as the next disruptive technology, these results can't be applied for the next generation LLM-based chatbots overall. While ChatGPT was the first mover, there are competing chatbots coming out to the market, including Google's Bard based on PaLM, and Meta's open-source LlaMa model. This is just the beginning of the competition, and what the LLM-based chatbot market will look like years from now may look different from the current atmosphere where ChatGPT dominates the market as the first mover.

6. Conclusion

The aim of this study was to investigate the perception of Korean users towards ChatGPT in recent months and evaluate its potential as the next disruptive innovation. A survey was conducted with members from two Korean online communities related to artificial intelligence, both established after ChatGPT's launch. This study seeks to answer the research questions outlined in the introduction:

1. **How does ChatGPT differ from previous AI-based chatbots?**

Drawing on prior literature in the conversational AI context, the study proposed perceived intelligence and perceived anthropomorphism as potential characteristics of ChatGPT that could directly or indirectly affect individuals' motives for using the chatbot. Based on previous studies, the perceived intelligence for ChatGPT be defined as the user's perception that ChatGPT understands and is aware of the context and the underlying intent provided by the user and can autonomously provide natural and logical human-like language, which assists the user in fulfilling their goals. Perceived anthropomorphism for ChatGPT was defined as the user's perception that ChatGPT shows human-like and social characteristics, capable of high-quality conversations while acknowledging that ChatGPT is a non-human conversational agent.

2. **What are the key individual and societal antecedents of ChatGPT acceptance?**

The study identified four individual motives and two societal motives based on previous technology adoption literature. The individual motives were derived from the literature on dual-purpose information systems, with perceived usefulness and ease of use influencing utilitarian motives to adopt, and perceived enjoyment as the antecedent of hedonic motives to use ChatGPT. Trust was also proposed as a crucial factor. The two societal factors identified were social influence and AI anxiety.

The study's findings can be summarized as follows: ChatGPT was confirmed to be used for both utilitarian purposes, in terms of perceived usefulness, and hedonic motives, in terms of perceived enjoyment, both positively impacting the behavioral intention to adopt the chatbot. However, perceived ease of use was found to have a negative effect on the behavioral intention. A possible explanation could be the flexibility of ChatGPT's generated responses based on prompt design and the degree of prompt knowledge required for more advanced uses.

At this stage, trust was not found to be a significant influencer of behavioral intention to adopt ChatGPT, likely due to its early stages and rapid spread to a large audience. Regarding societal factors, social influence from groups and networks was found to significantly impact not only behavioral intention to adopt but also perceived usefulness of ChatGPT. AI anxiety did not have a significant effect.

It was recommended that future studies delve deeper into what makes ChatGPT enjoyable and easy to use. While perceived anthropomorphism was a statistically significant determinant of perceived enjoyment, the current model provided low explanatory power. The same was true for perceived ease of use. Future studies should dissect these two constructs and their relationships with other constructs in this study to gain a more comprehensive understanding of what makes ChatGPT more "adoptable."

3. What challenges does the current state of ChatGPT present, and what implications does it have for service developers or LLM providers?

The study revealed that the most significant obstacles to ChatGPT adoption in its current state are ease of use and perceived trust. This suggests that ChatGPT might be perceived as difficult to use for advanced applications. Although ChatGPT is seen as useful and enjoyable, it is not trusted enough to be a determinant for adoption.

The study's findings have implications for service or application developers, suggesting that they should (1) design services with the end user in mind, focusing on their primary purposes for using the technology and what cognitive perceptions will drive adoption, (2) concentrate on making services and applications more user-friendly through preprogrammed prompts or user interfaces, (3) acknowledge that building trust in the brand will take time, and (4) recognize that social influence plays a role.

Despite these obstacles, however, the bright side is that the behavioral intentions had a positive influence on actual usage behavior. Users are currently actively finding opportunities to incorporate ChatGPT in their personal and work lives.

Another but final question is, does this study indicate any new insights into the potential of ChatGPT as the next disruptive technology? Just like personal computers and smartphones have fundamentally changed industries and how we do business, ChatGPT will bring about another fundamental change in how we interact with technology itself.

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8. Appendix

I. Korean Survey (Distributed through Google Forms[3])

[설문 안내]

안녕하세요! 학술연구를 위한 설문에 응해주셔서 감사합니다!

1. 설문 배경과 목적:

본 설문의 목적은 국내 ChatGPT 사용자의 활용 경험과 ChatGPT 의 향후 사용(수용) 의향에 대한 상관관계 관련 연구를 진행하기 위함입니다.

혹시, ChatGPT 를 사용하며 놀라웠던 첫 경험, 기억하시나요?

2022 년 11 월 30 일, Open AI 가 ChatGPT 를 공개하였습니다. 우리가 자주 사용하는 애플 시리(Siri)와 구글 어시스턴트(Google Assistant)과는 다르게, 어떤 것을 던지더라도 웬만한 것은 뚝딱 잘 해내니. 그 놀라운 성능으로 인해 5 일 만에 100 만 사용자를 달성하였으며, 약 2 개월 만에 1 억명의 사용자를 모집하였다고 알려져 있습니다.

하지만 ChatGPT, 아직 완벽하진 않습니다.

그 유명한 '세종대왕의 맥북 던짐사건'처럼 ChatGPT 는 완벽하지 않습니다. 아직 헛소리도 하고, 간혹 우리 기대에 못 미치는 대답을 할 때 약간의 실망감을 느끼긴 합니다. 현재로써는 발전의 여지는 충분히 남아있으나, ChatGPT 를 비롯한 거대언어모델(LLM) 기반 챗봇, 더 나아가 생성 AI(Generative AI)가 우리 스마트폰처럼 일상적인 것이 되는 것은 시간문제입니다. 매일매일 GPT 기반 다양한 서비스들이 우후죽순으로 생겨나고 있는 것을 보면 향후 그 방향성을 짐작할 수 있습니다.

다음 파괴적 혁신?

다음 파괴적인 기술(Disruptive Technology)로 주목받고 있는 ChatGPT 와 LLM. 기술이 올바른 방향으로 발전하여 사회 나머지 구성원들까지 전파하기 위해서는 이를 사용해온 사용자들의 경험과 의견이 매우 중요합니다.

그 동안 여러분들의 경험은 어떠셨나요?

기술이 올바른 방향으로 발전을 위한 연구의 일환으로 잠시만의 시간을 할애하여 본 연구 설문에 참여해주시면 감사하겠습니다.

[3] https://forms.gle/tMx4S8K7MiHVhHbZ6

2. 설문 참여 대상:
지금까지 ChatGPT 를 활용해오신 사용자분들이 설문 대상입니다.

3. 설문의 내용 및 예상시간 :
약 50 개의 문항으로, 신기술에 대한 나의 수용 정도, ChatGPT 사용 시 느꼈던 ChatGPT 의 지적 수준, ChatGPT 의 유용성, 활용 용이성, 사용 의향 등 개인적인 경험에 대한 질문들이 포함되어 있습니다.

설문 예상 소요 시간은 6 분 이내 입니다.
연구 완료 후 추첨을 통해 응답자의 약 5%의 분들께 스타벅스 카페라떼 기프티콘을 지급하고자 합니다.

4. 설문 결과 활용 및 익명 처리
설문 응답 데이터는 **순수히 연구의 목적으로만 익명 처리되며 활용**되며 **제 3 자에게 공개 및 제공**되지 않습니다.

5. 설문 참여자들 대상 추첨 및 경품 지급
설문 데이터 수집 완료 후 응답자의 10% 대상으로 **스타벅스 카페라떼 기프티콘**을 지급할 예정입니다.
개인정보 수집 항목: 문자 수신이 가능한 국내 연락처
설문 완료 후 희망자에 한해서 경품을 지급할 예정이며, 경품 지급 후 파기 될 것입니다.

(1/5) ChatGPT 를 사용 시작 계기와 주요 활용 목적은 어떻게 되나요? 6 개 문항

1. ChatGPT 를 듣게 된 시기가 아닌, 직접적으로 사용하기 시작한 대략적인 시기를 선택해주세요.
○ 2023 년 1 월 또는 그 이전 (2022 년 12 월)
○ 2023 년 2 월
○ 2023 년 3 월
○ 2023 년 4 월

2. 어느 나이 대에 속하시나요? (만 나이 기준으로 선택해주세요)
○ 20 세 미만 ○ 20 세~24 세 ○ 25 세~29 세 ○ 30 세~34 세 ○ 35 세~39 세
○ 40 세~44 세 ○ 45 세~49 세 ○50 세 이상

3. ChatGPT 사용 간 주 활용 용도는 어떻게 되시나요? (중복 선택 가능)

□ 아이데이션(Ideation) 및 브레인스토밍(Brainstorming)

□ 문서 작성 (Document Writing)

□ 교육 및 학습 (Education and Learning)

□ 검색 및 자료 조사 (Search / Research)

□ 데이터 분석(Data Analaysis)

□ 번역 (Translation)

□ 컴퓨터 코딩 및 프로그래밍 (Computer Programming)

□ 재미 (For Fun)

4. 신기술이 나왔을 때 주변 지인 및 일반 대중들보다 더 일찍 기술을 활용해보는 편이라고 생각되시나요?

○ 예 ○ 아니오

5. 현재 유료(ChatGPT Plus)를 구독 중이신가요?

○ 예. 유료 버전을 구독 중입니다. ○ 아니오. 무료 버전만 이용 중입니다.

6. [유료 사용자 한해서] GPT-4 버전을 사용하고 계신가요?

○ 예. 필요시 사용하고 있습니다. ○ 아니오. 많이 사용하지 않습니다.

<u>(2/5) ChatGPT 와 상호작용 간 ChatGPT 의 응답에 대한 경험 - 8 개 문항</u>

ChatGPT 는 기존의 다양한 챗봇과 더불어 일상적으로 사용하는 애플 시리(Apple Siri), 구글 어시스턴트(Google Assistant), 삼성 빅스비(Samsung Bixby)등 기존 서비스들과는 다르게 지능이 더욱 뛰어나며 더 대화 형식이 인간과 유사하다는 점에서 주목받고 있습니다. ChatGPT 사용 시 ChatGPT 의 응답/대화의 품질에 대해 받은 종합적인 느낌에 대해서 상기해주시고 아래 8 개의 문항에 답해주세요.

1. ChatGPT 는 나의 질문의 맥락과 의도를 정확하게 파악한다고 생각한다. (PI1)

1 2 3 4 5

전혀 아니다 ○ ○ ○ ○ ○ 매우 그렇다

2. ChatGPT 는 내 질문에 대해 일관되며 상황에 맞는 대답을 제공한다고 생각한다. (PI2)

1 2 3 4 5

전혀 아니다 ○ ○ ○ ○ ○ 매우 그렇다

3. ChatGPT 의 응답은 논리적이며, 나의 목표를 달성하는 데 도움이 된다고 생각한다. (PI3)

1 2 3 4 5

전혀 아니다 ○ ○ ○ ○ ○ 매우 그렇다

4. ChatGPT 는 대화의 주제에 대한 깊은 이해를 하고 있다고 생각한다. (PI4)

1 2 3 4 5

전혀 아니다 ○ ○ ○ ○ ○ 매우 그렇다

5. ChatGPT 는 대화에서 인간과 유사한 감정과 사회적 인식을 보여준다고 생각한다. (PA1)

1 2 3 4 5

전혀 아니다 ○ ○ ○ ○ ○ 매우 그렇다

6. ChatGPT 는 상황에 맞춰 대화 스타일을 조절할 수 있다고 생각한다. (PA2)

1 2 3 4 5

전혀 아니다 ○ ○ ○ ○ ○ 매우 그렇다

7. ChatGPT 와 상호작용 중에 사회적 규범과 윤리에 대한 이해를 보여준다고 생각한다. (PA3)

1 2 3 4 5

전혀 아니다 ○ ○ ○ ○ ○ 매우 그렇다

8. 인공지능 챗봇이란 것은 알고 있지만, ChatGPT 와 상호작용하면서 종종 인간과 대화하는 것처럼 느껴진다. (PA4)

1 2 3 4 5

전혀 아니다 ○ ○ ○ ○ ○ 매우 그렇다

(3/5) ChatGPT 사용 경험 관련 종합 후기 관련 조사 - 16 개 문항

ChatGPT 는 기존의 다양한 챗봇과 더불어 일상적으로 사용하는 애플 시리(Apple Siri), 구글 어시스턴트(Google Assistant), 삼성 빅스비(Samsung Bixby)등 기존 서비스들과는 다르게 지능이 더욱 뛰어나며 더 대화 형식이 인간과 유사하다는 점에서 주목받고 있습니다.

ChatGPT 사용 시 ChatGPT 의 응답/대화의 품질에 대해 받은 종합적인 느낌에 대해서 상기해주시고 아래 8 개의 문항에 답해주세요.

1. ChatGPT 를 사용하면 나의 작업 성과가 향상된다고 생각한다. (PU1)

1 2 3 4 5

전혀 아니다 ○ ○ ○ ○ ○ 매우 그렇다

2. ChatGPT 를 사용하면 나의 업무를 보다 효율적으로 수행할 수 있다. (PU2)

1 2 3 4 5

전혀 아니다 ○ ○ ○ ○ ○ 매우 그렇다

3. 내 일을 하는데 있어 ChatGPT 가 매우 유용한 도구라고 생각된다. (PU3)

1 2 3 4 5

전혀 아니다 ○ ○ ○ ○ ○ 매우 그렇다

4. ChatGPT 는 나의 생산성을 높이는데 도움이 된다고 생각한다. (PU4)

1 2 3 4 5

전혀 아니다 ○ ○ ○ ○ ○ 매우 그렇다

5. 전반적으로 ChatGPT 는 사용하기 어렵지 않다고 생각한다. (PEOU1)

1 2 3 4 5

전혀 아니다 ○ ○ ○ ○ ○ 매우 그렇다

6. ChatGPT 를 사용하는 방법을 배우는데 큰 노력이 필요하지 않다고 생각한다. (PEOU2)

1 2 3 4 5

전혀 아니다 ○ ○ ○ ○ ○ 매우 그렇다

7. ChatGPT 에게 내가 원하는 바를 시키는 것이 어렵지 않다. (PEOU3)

1 2 3 4 5

전혀 아니다 ○ ○ ○ ○ ○ 매우 그렇다

8. ChatGPT 를 사용하는 것은 직관적이며 자연스럽다. (PEOU4)

1 2 3 4 5

전혀 아니다 ○ ○ ○ ○ ○ 매우 그렇다

9. 나는 ChatGPT 를 사용하는 것이 재미있다. (PE1)

1 2 3 4 5

전혀 아니다 ○ ○ ○ ○ ○ 매우 그렇다

10. ChatGPT 는 내 업무와 일상에 즐거움의 요소를 더한다. (PE2)

1 2 3 4 5

전혀 아니다 ○ ○ ○ ○ ○ 매우 그렇다

11. ChatGPT 과의 상호작용 경험은 흥미롭다. (PE3)

1 2 3 4 5

전혀 아니다 ○ ○ ○ ○ ○ 매우 그렇다

12. 나는 ChatGPT 와 대화하는 경험 자체가 즐겁다. (PE4)

1 2 3 4 5

전혀 아니다 ○ ○ ○ ○ ○ 매우 그렇다

13. 나는 ChatGPT 가 제공한 응답과 대화 내용이 솔직하다고 생각한다. (PT1)

1 2 3 4 5

전혀 아니다 ○ ○ ○ ○ ○ 매우 그렇다

14. 내가 도움을 요청한다면 ChatGPT 는 나를 돕기 위해 최선을 다할 것이다. (PT2)

1 2 3 4 5

전혀 아니다 ○ ○ ○ ○ ○ 매우 그렇다

15. ChatGPT 가 나를 대하는데 진실되게 대한다. (PT3)

1 2 3 4 5

전혀 아니다 ○ ○ ○ ○ ○ 매우 그렇다

16. ChatGPT 는 나의 목표를 달성하는데 능력이 있고 효과적이라고 생각한다. (PT4)

1 2 3 4 5

전혀 아니다 ○ ○ ○ ○ ○ 매우 그렇다

(4/5) ChatGPT 사용 관련 외부 요인들에 대한 조사 - 8 개 문항

ChatGPT 사용 동기 관련 외부 요인들에 대한 문항들입니다.

내가 속해있는 조직과 커뮤니티 뿐만 아니라 주변 지인들과 사회 뉴스에서도 ChatGPT 과 인공지능과 관련된 다양한 소식과 사용 사례들을 접할 수 있습니다.
내가 속한 조직과 커뮤니티에서 나누어지는 ChatGPT 의 이야기들과 본인이 뉴스에서 접하는 ChatGPT 관련 소식들을 기반으로 아래 8 개의 문항들에 대해서 답해주세요 .

1. 나에게 중요한 사람들은 내가 ChatGPT 를 사용해야 한다고 생각한다. (SI1)

1 2 3 4 5

전혀 아니다 ○ ○ ○ ○ ○ 매우 그렇다

2. 나의 행동에 영향을 주는 사람들은 내가 ChatGPT 를 사용해야 한다고 생각한다. (SI2)

1 2 3 4 5

전혀 아니다 ○ ○ ○ ○ ○ 매우 그렇다

3. 내가 의견을 자주 참고하는 사람들은 ChatGPT 의 사용을 장려한다. (SI3)

1 2 3 4 5

전혀 아니다 ○ ○ ○ ○ ○ 매우 그렇다

4. 내가 중요하게 생각하는 사람들로부터 ChatGPT 사용하도록 무언의 압박을 받는다. (SI4)

1 2 3 4 5

전혀 아니다 ○ ○ ○ ○ ○ 매우 그렇다

5. ChatGPT 와 같은 인공지능 시스템이 통제 불능이 될 수 있다고 걱정한다. (AA1)

1 2 3 4 5

전혀 아니다 ○ ○ ○ ○ ○ 매우 그렇다

6. ChatGPT 와 같은 인공지능 시스템을 사용하는 것에 대해 잠재적 위험에 불안을 느낀다. (AA2)

1 2 3 4 5

전혀 아니다 ○ ○ ○ ○ ○ 매우 그렇다

7. 인공지능 기술이 사회에 부정적인 영향을 미칠 수 있다고 걱정한다. (AA3)

1 2 3 4 5

전혀 아니다 ○ ○ ○ ○ ○ 매우 그렇다

8. 인공지능 시스템의 급속한 발전에 불안을 느낀다. (AA4)

1 2 3 4 5

전혀 아니다 ○ ○ ○ ○ ○ 매우 그렇다

(5/5) 향후 ChatGPT 사용 의향 및 의도 관련 조사 - 8 개 문항

마지막으로, ChatGPT 의 종합 사용 경험에 대한 문항입니다.

그간 ChatGPT 의 종합적인 경험으로 비추어 봤을 때 현재 및 향후 사용 의향 / 의도와 관련된 8 개의 문항에 대해 답해주세요.

1. 나는 향후에도 ChatGPT 를 계속 사용할 계획이다. (BI1)

1 2 3 4 5

전혀 아니다 ○ ○ ○ ○ ○ 매우 그렇다

2. 나는 ChatGPT 를 일상적으로도 사용하려고 시도할 것이다. (BI2)

1 2 3 4 5

전혀 아니다 ○ ○ ○ ○ ○ 매우 그렇다

3. 나는 ChatGPT 를 더 자주 사용하려고 노력할 것이다. (BI3)

1 2 3 4 5

전혀 아니다 ○ ○ ○ ○ ○ 매우 그렇다

4. 나는 ChatGPT 를 더 효율적으로 사용하는 법을 배우는 데 시간과 노력을 투자할 의향이 있다. (BI4)

1 2 3 4 5

전혀 아니다 ○ ○ ○ ○ ○ 매우 그렇다

5. 나는 현재 업무를 수행하기 위해 ChatGPT 를 자주 사용한다. (AUB1)

1 2 3 4 5

전혀 아니다 ○ ○ ○ ○ ○ 매우 그렇다

6. ChatGPT 는 내 업무 과정의 필수적인 부분이 되었다. (AUB2)

1 2 3 4 5

전혀 아니다 ○ ○ ○ ○ ○ 매우 그렇다

7. 나는 일과 중에 다양한 일에 도움을 받기 위해 ChatGPT 을 활용한다. (AUB2)

1 2 3 4 5

전혀 아니다 ○ ○ ○ ○ ○ 매우 그렇다

8. 내 일에서 ChatGPT 를 활용할 기회를 적극적으로 찾는다. (AUB4)

1 2 3 4 5

전혀 아니다 ○ ○ ○ ○ ○ 매우 그렇다

국문 초록

챗GPT의 수용에 대한 현 상태 평가 및 파괴적 혁신으로서의 잠재력 평가에 대한 실증적 연구: 한국 사용자들의 사용 경험 중심으로

서울대학교 경영대학원

최지웅

본 연구는 국내 인공지능 관련 온라인 커뮤니티 두 곳의 회원들을 대상으로 OpenAI가 개발한 대규모 언어 모델 LLM – Large Language Model 기반 챗봇 Chatbot 챗GPT에 대한 인식과 도입 현황을 조사하고, 챗GPT ChatGPT의 차세대 파괴적 혁신으로써 가능성을 평가한다. 대화형 인공지능 Conversational Artificial Intelligence 과 관련된 선행 연구를 바탕으로 인지된 지능 Perceived Intelligence 과 인지된 의인화 Perceived Anthropomorphism를 기존 인공지능 기반 챗봇과의 차별되는 챗GPT의 주요 특성이자 챗GPT의 품질을 평가할 수 두 가지 변수로 식별되었으며, 이를 바탕으로 챗GPT의 이용 의사 behavioral intention to adopt에 영향을 줄 수 있는 4가지 개인적 요인(인지된 유용성 Perceived Usefulness, 인지된 사용 용이성 Perceived Ease of Use, 인지된 즐거움 Perceived Enjoyment, 인지된 신뢰 Perceived Trust)와 2가지 사회적 요인(사회적 영향력 Social Influence, AI 불안감 AI Anxiety)를 챗GPT 이용의사의 선행 요인으로 제시하였다. 연구 결과, 인지된 유용성과 즐거움이 챗GPT의 이용 의사에 긍정적인 영향을 미치는 것으로 나타나 챗봇이 실용적 utilitarian 목적과 쾌락 hedonic의 목적를 위해 모두에서 사용되고 있는 것으로 확인되었다.

그러나 당초 예상과 달리 인지된 사용 용이성은 이용의사에 유의미한 영향을 주지 못하는 것으로 나타났으며, 신뢰 또한 이용의사에 유의미한 영향을 미치는 것으로 밝혀지지 않았다. 사회적 영향력은 이용의사와 인지된 유용성에 유의미한 영향을 미치는 것으로 나타난 반면 AI 불안감은 유의미한 영향을 미치지 않은 것으로 밝혀졌다. 본 연구는 인지된 지능 및 의인화가 챗 GPT 의 이용의사에 영향을 미치는 개인적 요인이라는 것을 확인을 하였으며, 어떤 것이 ChatGPT 를 '즐겁고 사용하기 쉽게 만드는 지', 그 요인을 해부하여 더 집중 탐구해야 하는 향후 연구의 필요성을 강조한다. 본 연구를 바탕으로 대규모 언어모델기반 챗봇을 이용한 서비스 및 응용프로그램 개발자들은 사용자 중심의 애플리케이션을 설계하고, 서비스 개발 시 사용자 편의성에 초점을 맞추어야 하며, 신기술을 이용한 서비스에 대한 신뢰를 구축하는 데 시간이 걸린다는 점을 인지하고, 채택에 있어 사회적 영향력의 역할을 인식하고 서비스를 개발해야 한다는 비즈니스 인사이트를 제공한다.

키워드: ChatGPT, 인공지능(AI) 챗봇, 파괴적 혁신, 기술 수용 모델(TAM), 이중 목적 정보 시스템(Dual Purpose Information System), AI 불안감