VIRTUAL ECONOMICS

ISSN 2657-4047 *(online)*

Research article

AI LIKE CHATGPT, USERS LIKE US: HOW CHATGPT DRIVERS AND AI EFFICACY AFFECT CONSUMER BEHAVIOUR

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Abstract. Since OpenAI first unveiled ChatGPT, an artificial intelligence-based chatbot service, to the public, expectations for high utility and various possibilities have attracted researchers, industry, and consumers. The current study identified the influencing factors of consumer acceptance of ChatGPT that approached transformational innovation. For research purposes, 251 innovative consumers who use ChatGPT were recruited online, and the research model was tested by employing PLS (partial least squares) analysis. The study demonstrated the impact of consumers' perceptions of the two AI features (human-like characteristics and performance characteristics) on their intention to use AI through their efficacy in AI services and service satisfaction. Moreover, the serendipity experience could lead to positive use intention. Considering that few empirical studies investigated actual user behaviour since ChatGPT services are still in the early stages of the market, this study might provide several implications for researchers and practitioners.

Keywords*:* ChatGPT; AI; AI services; intention to use; serendipity experience.

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Citation: Lee, W. J., Lee, H. S., & Cha, M. K. (2023). AI Like ChatGPT, Users Like Us: How ChatGPT Drivers and AI Efficacy Affect Consumer Behaviour. *Virtual Economics, 6*(4), 44–59. https://doi.org/10.34021/ve.2023.06.04(3)

Received: September 17, 2023. Revised: December 10, 2023. Accepted: December 25, 2023.

1. Introduction

On November 30, 2022, OpenAI unveiled an AI-based chatbot named ChatGPT. It quickly attracted the attention of researchers and scholars to artificial intelligence [1]. The launch of ChatGPT has also generated widespread public interest as consumers worldwide are eager to experience innovation and evaluate its capabilities. Its monthly active users are estimated to have reached 100 million in just two months since its opening, meaning it is the fastest-spreading consumer application in history [2]. After application services using ChatGPT's API have emerged, and various GPT (Generative Pre-trained Transformers)-based AI services, such as Bing Chat and Google's BARD, have emerged, some argue that they have reached AI's singularity [3].

Corporate marketing is also heavily influenced by AI. Traditionally, marketing has developed and utilized Mar-tech while rapidly absorbing technological development. The Marketing Science Research Institute argues that it will significantly impact future marketing strategies, functions, and manager competencies [4]. In particular, with an intelligent chatbot that can replace past call centres [5], companies and researchers have become interested in algorithm-based automated marketing [6; 7]. The use of AI in marketing raises the need to adapt to a new task environment when traditional marketing is rapidly transitioning into online and digital. Therefore, it is essential to understand how AI is recognised and accepted by consumers and expect how it will change consumer behaviour.

The latest AI-related research in marketing mainly sheds light on chatbots in various services (e.g., voice assistants at home, healthcare, and hospitality). The previous research argued that the use of chatbots revolutionised the way consumers interact with companies and participate in consumption activities [5; 8; 9]. However, we are facing that ChatGPT has experienced exponential growth in the adoption of consumers and practitioners. Research needs to comprehensively address the impact of consumers' perceptions of recently launched technologies on consumer evaluation. The succulent study aims to fill this gap between the theory and phenomenon. Customers tend to evaluate AI services to a higher standard than other technologies [10]. Therefore, it is difficult to explain the full acceptance of AI services with existing technology acceptance models. Prior research reveals that social evidence from the experiences of others and the perceived intelligence of AI play an important role in shaping consumers' decision to adopt technology [11; 12]. This study focused on the effect of users' AI efficacy on technology acceptance.

However, in some cases, consumers can develop a positive attitude toward the technology and participate in the service without the perceived technological efficacy. It is the widespread adoption of smartphones and their applications that utilize complex technologies but are accessible to individuals of various ages and knowledge levels. This study noted that in services such as ChatGPT, general consumers who do not know complex prompt engineering can ask simple questions and achieve surprising results. In other words, the intention to use can increase through experiences of unexpected satisfaction, enjoyment, and flow [13; 14]. Despite its recent emergence, ChatGPT has sparked technical debates and garnered significant attention regarding its potential social influence. With a keen eye on its future trajectory, the public and media are showing considerable interest in how ChatGPT will affect culture and society. However, few academic studies have explored the effects of ChatGPT on marketing.

The current study identifies how consumers perceive the characteristics of ChatGPT and how it affects their intention to use it. The characteristics of AI perceived by consumers are classified into two main categories: performance characteristics and human-like characteristics. It is assumed that sub-factors of these two characteristics could affect consumers' intention to use through self-efficacy toward AI and satisfaction. In particular, human-like characteristics are fundamental technical characteristics that researchers should consider because they are benefits that advanced levels of AI can pursue [15]. In addition, this study also has a new perspective in that the research model contains both AI efficacy and the effects of serendipity, which are individual factors of technology acceptance that seem contradictory. A few researchers have recently begun to deal with serendipity experiences in consumer research [13; 14]. Thus, results might provide new insights into AI-related consumer behaviour.

2. Literature Review

2.1. Research Framework

The concept of technology self-efficacy has gained significant attention in research and practice as technological advancements continue to shape various aspects of our lives. Technology efficacy refers to individuals' beliefs and perceptions about the effectiveness and capabilities of technology in achieving desired outcomes [16]. Since self-efficacy is related to actual behaviour, it is vital to understand whether consumers will likely use ChatGPT to support their daily work. The efficacy of AI can be influenced by various factors. Among these are two key drivers of AI efficacy: the expected performance of AI and its human-like characteristics.

First, the performance of AI is important to make people feel confident in using AI services. Customers tend to evaluate AI services with a higher standard, and this is evident in the case of driverless vehicles, where customers prioritize the flawless performance and safety of AI [10]. Several factors influence consumers' adoption of AI technology. For instance, the ease of use of AI services, and the perceived AI intelligence play crucial roles in shaping consumers' technology adoption decisions and subsequent behaviours [12; 17].

Second, the human-like aspect of technology has gained prominence in the acceptance of AI. The Computers are Social Actors (CASA) paradigm explains the phenomenon in which individuals treat computer technologies as if they were real people. Studies have indicated that customers may exhibit reluctance to use AI services because they perceive these technologies as lacking the emotional capability to perform tasks for humans [18; 19]. Understanding these drivers of AI efficacy can inform the design and development of AI services that effectively meet users' expectations and enhance their adoption and usage. Further, the serendipity experience would have a positive influence on users' behaviour. Figure 1. illustrates the research framework based on the literature review.

2.2. Hypotheses

Prior studies provide empirical evidence supporting the relationship between perceived humanness and AI self-efficacy. Balakrishnan et al. conducted a study examining the impact of the anthropomorphic design of AI chatbot systems on users' self-efficacy and attitude toward AI technologies [20]. The findings revealed that when AI chatbots were designed to exhibit perceived anthropomorphism, individuals developed a higher level of self-efficacy and formed a positive attitude toward using AI technologies. In a similar vein, studies investigated the effects of verbal and psychological anthropomorphic features, such as synthesized speech quality, personality, and autonomy, on self-efficacy and social connection [21].

H1. Perceived humanness (PH) affects AI self-efficacy (AI) positively.

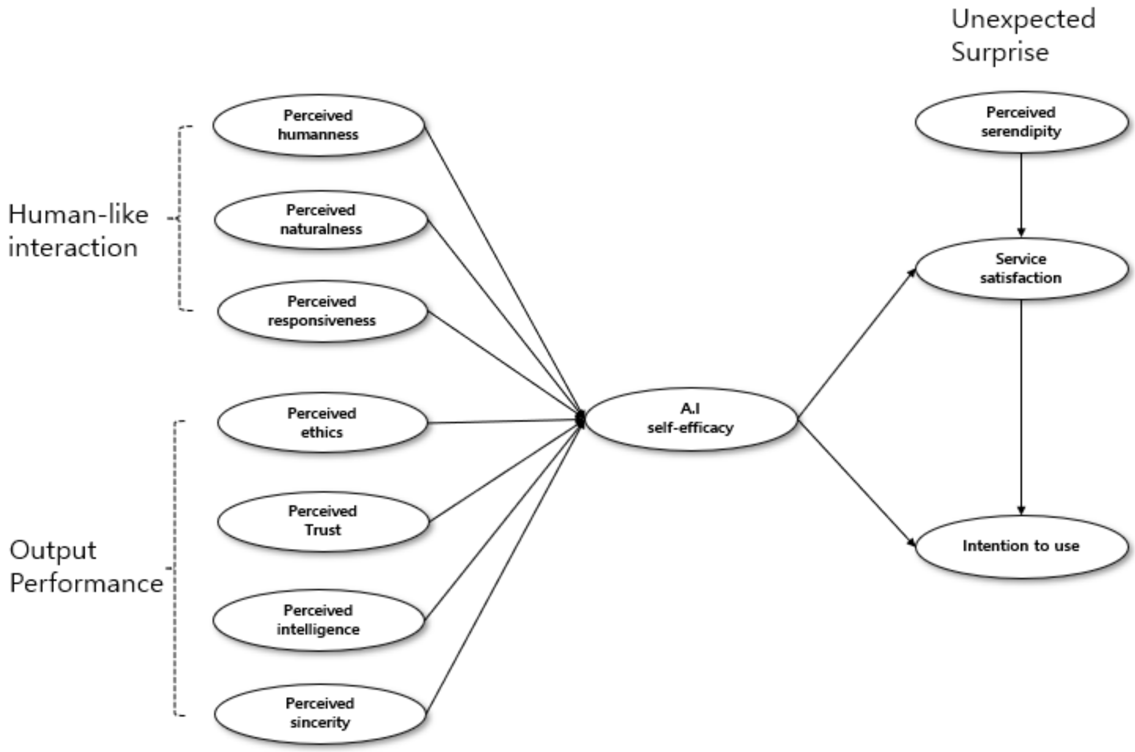

Figure 1. Research Model
Source*:* developed by the authors.

A previous study proposed that naturalness judgment can influence how people perceive sincerity in chatbot communication. It shows that perceived naturalness is one of the components of AI humanness. Chandra et al. claimed that perceived naturalness motivates users to continue using the technology for their interactions [22]. One might expect that users feel more confident in their ability to use and benefit from the technology when AI systems are perceived as natural as they expected.

H2. Perceived naturalness (PN) affects AI self-efficacy (AI) positively.

Several studies provide evidence supporting the relationship between perceived responsiveness and AI self-efficacy. Deng and Fei suggested that individuals' perceptions of information technology and their levels of self-efficacy [23]. They showed that participants who perceived a higher level of responsiveness from the technology reported higher levels of self-efficacy in using the technologies. One might conclude that people develop greater confidence in their ability to use technology when they receive prompt and helpful responses from technology. In the context of smart cities, Lee and Lee found that the responsiveness of smart city systems improves users' experience. Participants reported enhanced overall satisfaction and engagement with the technology when they perceived the smart city systems as responsive to their needs [24]. Thus, the responsiveness of AI services, specifically in providing timely and accurate information or assistance, might increase users' AI self-efficacy.

H3. Perceived responsiveness (PR) affects AI self-efficacy (AI) positively.

Perceived ethics, which refers to individuals' perceptions of the moral and ethical behaviour of systems or the organizations behind them, is a factor that can influence AI self-efficacy [25]. Users' confidence in using AI technologies may be influenced by their perceptions of the ethical implications associated with AI. Kwak et al. proposed that AI ethics awareness affects the self-efficacy of using AI-based healthcare technology [26]. Results suggest that individuals who are more aware of the ethical considerations and practices in AI may develop higher levels of self-efficacy in utilizing AI-based healthcare technology. Thus, the ethical behaviour of AI systems and organizations can enhance users' confidence in their ability to engage with AI technologies effectively.

H4. Perceived ethics (PE) positively affect AI self-efficacy (AI).

Several studies support the hypothesis that perceived trust positively affects AI self-efficacy. In the study, perceived trust refers to individuals' beliefs and confidence in AI systems' reliability, dependability, and competence. This mainly means cold-capability beliefs, which means that the performance requested by the user will be achieved without errors. When individuals trust AI systems, it is likely to contribute to higher levels of self-efficacy in using and interacting with them [27, 28]. Balakrishnan et al. also identified users' perceptions of chatbot assistants and their self-efficacy in interacting with chatbot systems [20]. Therefore, users might be more likely to be confident in interacting effectively with the ChatGPT when they trust the system.

H5. Perceived trust (PT) affects AI self-efficacy (AI) positively.

Studies have provided substantial evidence supporting that perceived intelligence positively impacts AI self-efficacy. Perceived intelligence refers to individuals' subjective perceptions of AI systems as possessing high levels of intelligence, knowledge, and capability to perform complex tasks [20]. It implies that users develop greater self-efficacy in using AI systems when perceiving them as highly intelligent. Schuetz and Venkatesh investigated the factors influencing users' acceptance of cognitive computing technologies and found that perceived intelligence significantly influenced users' self-efficacy [29]. They emphasize the importance of AI systems' intelligence in shaping user confidence in using technologies. One might expect that individuals' perceptions of AI systems' intelligence contribute significantly to their satisfaction with AI services.

H6. Perceived intelligence (PI) affects AI self-efficacy (AI) positively.

The existing body of research supports the hypothesis that perceived sincerity positively impacts AI self-efficacy. Perceived sincerity refers to individuals' subjective perceptions of AI systems as genuine, honest, and faithful in their interactions, while trust is based on the competence belief [30]. A previous study on human-robot trust has also distinguished performance trust and sincerity [31]. When individuals perceive AI systems as sincere, it enhances their self-efficacy in using and relying on these systems.

H7. Perceived sincerity (PS) affects AI self-efficacy (AI) positively.

A prior study found that users' satisfaction with AI chatbot services was affected by their self-efficacy in AI technology [20]. They suggest that individuals with higher self-efficacy in utilizing AI chatbots will likely experience greater satisfaction with the service. Cao et al. also investigated the impact of technology self-efficacy on service satisfaction in live-streaming commerce [32]. The study revealed that users with higher self-efficacy in utilizing live commerce platforms expressed higher satisfaction.

H8. AI self-efficacy (AI) affects service satisfaction (SA) positively.

Serendipity refers to the emotional response elicited by a chance encounter with a product, service, or experience the consumer did not deliberately choose [14]. This phenomenon can occur when the consumer is indifferent to the search outcome or diverges from the initial search goal [33; 34]. Research investigated that consumers' serendipity experience can lead to service satisfaction in various online contexts, including online shopping and social network sites [35]. Similarly, serendipity has been shown to enhance consumer satisfaction. These findings suggest that serendipitous encounters and experiences significantly shape consumers' satisfaction with online services.

H9. Serendipity experience (SX) positively affects service satisfaction (SA).

The positive relationship between self-efficacy and behavioural intention has been explored in various studies. Kumar et al. conducted a study focusing on mobile learning and found that self-efficacy positively influences behavioural intention [36]. Hong examined the effects of AI self-efficacy on the intention to use AI technologies across different domains, including smart homes, chatbots, music recommendations, and AI voice assistance [37]. These findings underscore the significance of self-efficacy in promoting user acceptance of AI technologies.

H10. AI self-efficacy (AI) affects the intention to use (IN) positively.

Extensive research proved the positive relationship between service satisfaction and the intention to use in the context of service industries, including AI services. Studies showed that higher satisfaction levels significantly influenced users' intention to continue using AI systems [38]. Kim et al. [39] also revealed that higher levels of user satisfaction significantly influenced users' intention to continue using AI-based virtual assistants. Thus, the following hypothesis can be established.

H11. Service satisfaction has positive effects on the intention to use (IN).

3. Empirical Research

3.1. Data Collection

An online survey was administered to ChatGPT users at a University in Korea in April 2023. The survey was conducted over two weeks, during which participants were employed to complete a questionnaire through an email invitation containing a link to the survey site. The sample was drawn from a relatively young generation to obtain a representative sample of innovative internet service users. In addition, to ensure that respondents had sufficient experience and knowledge of ChatGPT, they were required to respond to screening questions about their experience with the service.
A total of 251 users completed the questionnaire and information on the sample characteristics can be found in Table 1.

Table 1. Sample Characteristics

Classification	Description
1. Gender	Male (55.8%), female (46.2%)
2. Age	22.22 years
3. Frequency of Use	2.38 times/week
4. The purpose of use	Information search (55.8%), language translation (4.0%), program coding (3.6%), content generation (4.8%), casual conversation (21.5%), report preparation (4.0%), scheduling (0.8%), text summarization (1.2%), others (4.4%)

Source*:* developed by the authors.

3.2. Measurement Items

The initial validity of the questionnaire items was ensured by borrowing from previous studies, followed by face validity testing by two marketing academicians. However, common method variance potentially threatens the accuracy of the relationships between constructs [40]. Various preventive measures were implemented to overcome this issue, such as using clear and concise wording, conducting a pretest, and including reverse scale items to identify extreme and acquiescence response styles [42]. Table 2 presents the resulting constructs, variable definitions, and measurement items, all rated on a five-point Likert scale.

Table 2. Construct and Item

Constructs	Items	Source
Perceived Humanness	1. ChatGPT can accurately comprehend what I mean 2. ChatGPT can understand my intention 3. The understanding ability of ChatGPT is similar to that of a human being	[41]
Perceived Naturalness	1. ChatGPT is organic 2. ChatGPT is natural 3. ChatGPT is not awkward	[43]
Perceived Responsiveness	1. ChatGPT processes service accurately 2. ChatGPT answers quickly when I ask a question 3. ChatGPT delivers orders as promised	[41]

Constructs	Items	Source
Perceived Ethics	1. In general, ChatGPT is fair 2. Overall, I consider that ChatGPT follows a moral code 3. Overall, I consider ChatGPT to be ethical in its dealing with users	[25]
Perceived Trust	1. ChatGPT is trustworthy 2. ChatGPT is reliable 3. ChatGPT has integrity 4. ChatGPT will perform to the users' utmost benefit	[44]
Perceived Intelligence	1. ChatGPT can completer tasks quickly 2. ChatGPT is smart enough to understand my command 3. ChatGPT can provide me with a useful answer 4. ChatGPT is overall intelligent	[45; 46]
Perceived Sincerity	1. ChatGPT is sincere 2. ChatGPT is genuine 3. ChatGPT is faithful	[43]
AI Self- Efficacy	1. I feel confident using ChatGPT to complete tasks 2. I can use ChatGPT to accomplish what I need to do 3. I am comfortable troubleshooting ChatGPT problems on my own 4. I can use ChatGPT to solve problems	[47]
Serendipity Experience	1. ChatGPT has often provided unexpectedly good information 2. ChatGPT has often provided helpful information by accident 3. ChatGPT has often provided unexpected new information	[34])
Satisfaction	1. I am satisfied with ChatGPT 2. ChatGPT is a successful experience 3. ChatGPT has met my expectation 4. I believe using ChatGPT is a good choice	[48]
Intention to Use	1. I will continue to use ChatGPT in the future 2. I will continue to use ChatGPT in the future 3. I will recommend ChatGPT to my acquaintances 4. I will continue to use ChatGPT even if ChatGPT becomes paid	[49]

Source: developed by the authors.

3.3. Reliability and Validity

To ensure the internal consistency of measurement items, several statistical measures were used, including Cronbach's α, composite reliability, and average variance extracted (AVE), while confirmatory factor analysis was employed to assess construct validity [50]. The goodness-of-fit of the confirmatory factor analysis (CFA) model was deemed satisfactory, considering the model's complexity. The model yielded a chi-square value of 1203.306 with 610 degrees of freedom ($p < 0.001$). The absolute-fit measures, including the comparative fit index (CFI) of 0.922, goodness-of-fit index (GFI) of 0.807, root mean square error of approximation (RMSEA) of 0.062, and standardized root mean square residual (SRMR) of 0.062, demonstrated acceptable fit indices. The incremental fit measures, such as the normed fit index (NFI) of 0.855 and the Tucker-Lewis index (TLI) of 0.910, indicated a satisfactory fit for the CFA model.
The Cronbach's α ranged from 0.810 to 0.938 (> 0.70). Composite reliability coefficients ranged from 0.832 to 0.935 (> 0.60), suggesting that the measurement items exhibited high internal consistency [51]. The convergent validity was evaluated by examining the individual

factor loading of each item of constructs, which exceeded the recommended threshold of 0.70 [52]. Furthermore, the AVE values for each construct exceeded the recommended threshold of 0.5, indicating that the constructs had satisfactory convergent validity in Table 3.

Table 3. Reliability and Validity Test

Construct	Items	Factor loading	Cronbach's α	CR	AVE
Perceived Humanness (PH)	a1	0.823	0.814	0.889	0.727
	a2	0.766			
	a3	0.720			
Perceived Naturalness (PN)	b1	0.857	0.890	0.832	0.820
	b2	0.863			
	b3	0.842			
Perceived Responsiveness (PR)	c1	0.911	0.938	0.961	0.890
	c2	0.958			
	c3	0.876			
Perceived Ethics (PE)	d1	0.783	0.810	0.886	0.722
	d2	0.716			
	d3	0.810			
Perceived Trust (PT)	e1	0.952	0.883	0.920	0.743
	e2	0.942			
	e3	0.735			
	e4	0.673			
Perceived Sincerity (PS)	f1	0.900	0.868	0.920	0.792
	f2	0.915			
	f3	0.693			
Perceived Intelligence (PI)	g1	0.790	0.843	0.895	0.681
	g2	0.792			
	g3	0.812			
	g4	0.645			
AI Self-efficacy (AI)	h1	0.876	0.910	0.937	0.787
	h2	0.897			
	h3	0.788			
	h4	0.820			
Serendipity Experience (SX)	i1	0.771	0.844	0.906	0.763
	i2	0.896			
	i3	0.760			
Satisfaction (SA)	j1	0.892	0.907	0.935	0.782
	j2	0.847			
	j3	0.836			
	j4	0.808			
Intention to Use (IN)	k1	0.959	0.814	0.917	0.737
	k2	0.967			
	k3	0.745			

Source: developed by the authors.

The Fornell and Larcker test in Table 4 reveals the presence of discriminant validity.

Table 4. Fornell-Larcker Test

	AI	PE	PH	PT	IN	PN	PR	SA	SX	PS	PT
AI	0.887										
PE	0.368	0.850									
PH	0.463	0.410	0.853								
PT	0.445	0.416	0.375	0.890							
IN	0.627	0.229	0.268	0.377	0.859						
PN	0.513	0.407	0.748	0.429	0.334	0.905					
PR	0.319	0.339	0.355	0.446	0.239	0.365	0.944				
SA	0.685	0.358	0.459	0.512	0.808	0.500	0.369	0.884			
SX	0.494	0.306	0.361	0.485	0.422	0.351	0.398	0.495	0.873		
PS	0.559	0.503	0.711	0.501	0.382	0.662	0.389	0.557	0.525	0.825	
PT	0.530	0.543	0.472	0.455	0.484	0.438	0.316	0.631	0.465	0.613	0.862

Source*:* developed by the authors.

3.4. Hypothesis Test

A PLS (partial least squares) analysis was employed to investigate the causal relationships among constructs in the research model. Previous studies have found that PLS is particularly effective when the research has a small sample size, nonnormal data, and little prior theoretical foundation [52; 53]. Given that ChatGPT is a relatively new area with limited prior research and experienced users are few, PLS is deemed an appropriate method for this study. A bootstrapping sampling method (a simulation with 500 replications) was employed to test the hypothesized relationships. Table 5 reveals that most hypotheses, except H1, H3, and H4, were supported at a significance level of 0.05. In addition, the r^2 analysis demonstrated that the research model explained a substantial amount of variance in the outcome variables, with AI (AI self-efficacy), SA (satisfaction), and IN (intention to use) having r^2 values of 0.416, 0.501, and 0.661, respectively.

Table 5. Hypothesis Test

Hypotheses	path	SD	t	p
H1. PH → AI	-0.020	0.077	0.260	0.795
H2. PN → AI	0.222	0.079	2.822	0.005*
H3. PR → AI	0.034	0.059	0.578	0.564*
H4. PE → AI	-0.022	0.057	0.394	0.693
H5. PT → AI	0.262	0.064	4.093	0.000*
H6. PI → AI	0.197	0.080	2.467	0.014*
H7. PS → AI	0.134	0.066	2.040	0.042*
H8. AI → SA	0.582	0.060	9.731	0.000*
H9. SX → SA	0.208	0.057	3.663	0.000*
H10. AI → IN	0.318	0.058	2.386	0.017*
H11. SA → IN	0.714	0.052	13.825	0.000*

Note : r^2 (adj. r^2): AI=0.416 (0.399), SA=0.501 (0.497), IN=0.664 (0.661)
Source*:* developed by the authors.

4. Conclusions

This study expanded the traditional technology acceptance theory to demonstrate the effect of users' perception of ChatGPT on consumers' intention to use it through self-efficacy. The results are as follows. First, the user's AI self-efficacy plays an essential role in forming consumer satisfaction and intention to use. Second, the consumer's perception of the performance of AI has a positive effect on the consumer's intention to use it. Specifically, the performance characteristics of ChatGPT were significant, except for ethics. Perceived trust, intelligence, and sincerity positively impacted AI self-efficacy. Third, unexpectedly, several human-like characteristics of ChatGPT did not significantly affect user intention to use. The effects of humanness and responsiveness were not significant, while naturalness was significant. Finally, consumers' serendipity experience has a direct impact on consumer satisfaction and intention to use.

First, the theoretical framework posits that antecedents of AI self-efficacy comprise variables that elucidate both the human interaction characteristics and performance characteristics of ChatGPT. Specifically, users need to perceive that ChatGPT can enable them to attain their goals and that the service is as seamless and effortless as engaging in communication. This result highlights the essential qualities that AI-based services should possess to gain user acceptance. AI services should present a reliable performance and provide a smart solution that strives to produce optimal results [28; 31]. Interestingly, users do not appear to prioritize the ethical aspects of search results. While ethical considerations are undoubtedly critical for future AI development, there is a possibility that users may wish to refrain from having their search results subjected to ethical standards enforced by external entities [54]. The result is in the same vein as Borenstein and Howard's claim that it is unclear whether AI ethics regulations are making substantial changes, including industry practices [55]. Siau and Wang also argued that understanding and addressing ethical and moral issues related to AI is still in the infancy stage [56].

Second, it should be noted that naturalness was found to be a significant variable in explaining the human-like characteristics of ChatGPT. Contrary to the expectations, the effects of humanness and responsiveness were not significant. Results suggest re-examining the old belief that AI should closely resemble humans in all aspects. Users may not necessarily desire a perfect and personal relationship with ChatGPT if it can only deliver improved performance or results. One might perceive it as a tool that simplifies life, akin to a hammer, car, and simple devices until the ChatGPT technology is fully developed. Prior studies also suggested that ChatGPT still lacks human-like psycholinguistic properties, which makes it difficult for users to perceive that they have responsiveness or humanness, even though they perform the function of human-like summarization [57].

Third, self-efficacy for AI must be formed in advance to accept and spread the new technology service when the users' technology readiness to apply AI services has yet to be sufficiently formed. The results align with prior research on innovative technologies and consumer responses [32]. AI self-efficacy plays a mediating role for individuals to accept the characteristics of ChatGPT, and it affects service satisfaction and intention to use. Thus, AI services should be developed, prioritizing user experience.

Fourth, the serendipity experience directly impacted user satisfaction with ChatGPT. This direct relationship suggests that the ability of ChatGPT to surpass prompt human skills is another critical factor in promoting user satisfaction and usage of the service. For instance, in Midjourney, an AI-based drawing service, more simple prompts often result in more complete and satisfactory outcomes. If AI can generate results that occasionally exceed human expectations and anticipate user intentions to create relevant results, it has the potential to become a special service for everyone. In the Internet age, digital literacy created a divide between those who could and could not use the Internet. In the AI era, however, practitioners should have serendipity experiences that could bridge this divide and enable anyone to use AI services.

Finally, users' satisfaction with ChatGPT positively impacted their intention to use it as in other technology services. Therefore, practitioners should satisfy users in the early stages of market penetration for ChatGPT to emerge as a transformative service that revolutionizes the future. It is essential to address the issues and challenges that ChatGPT users face, such as connectivity problems and the provision of erroneous information. Swift resolution of these problems, along with communication with customers, is essential to enhance user satisfaction and promote the adoption of ChatGPT as a reliable and efficient AI-based service.

This study provides avenues for further research. First, the sample was collected in April 2023. The number of proficient ChatGPT users was still limited, considering ChatGPT was made available to the public in late 2022. Their knowledge and experience may have been inadequate. Therefore, it would be prudent to conduct further research when more skilled ChatGPT users are available. Second, a broader investigation of ChatGPT users is also needed. While the sampling method in this study was based on the rationale that users in their 20s are typically early adopters and influential users of information technology services, including artificial intelligence, it is essential to recognize that the user base of ChatGPT is expanding rapidly, particularly in the business domain. Hence, future research should be conducted to encompass diverse age groups and business user segments to obtain a comprehensive understanding of the perceptions and experiences of ChatGPT users. Last, results may only reflect user experiences encountering the current level of AI services. As ChatGPT has already advanced to version 4.0 with plans for future upgrades, the level of user experience is likely to change following these technological advancements. It is necessary to conduct additional research in line with the continuous advancements in AI services in the future [58].

Author Contributions: Conceptualization and data analysis, W.J. L., data curation and writing – review and editing, H.S. L.; writing – original draft preparation, M.K. C. All authors have read and agreed to the published version of the manuscript.

Data Availability Statement: Data cannot be shared due to ethical or privacy constraints.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Rivas, P. & Zhao, L. (2023). Marketing with ChatGPT: Navigating the Ethical Terrain of GPT-Based Chatbot Technology. *AI*, 4(2), 375–384. https://doi.org/10.3390/ai4020019
2. Hu, K. (2023). ChatGPT Sets Record for Fastest-Growing User Base - Analyst Note. *Reuters*, https://www.reuters.com/technology/chatgpt-sets-record-fastest-growing-user-base-analyst-note-2023-02-01
3. Teubner, T., Flath, C.M., Weinhardt, C., van der Aalst, W., & Hinz, O. (2023). Welcome to the Era of ChatGPT et al. The Prospects of Large Language Models. *Business & Information Systems Engineering*, 65, 95–101. https://doi.org/10.1007/s12599-023-00795-x
4. Marketing Science Institute (2020). Research priorities: 2020-2022 report. https://www.msi.org/wp-content/uploads/2021/07/MSI-2020-22-Research-Priorities-final.pdf-WORD.pdf
5. Malodia, S., Kaur, P. Ractham, P., Zakashita, M., & Dhir, A. (2022). Why Do People Avoid and Postpone the Use of Voice Assistants for Transactional Purposes? A Perspective from Decision Avoidance Theory. *Journal of Business Research*, 146, 605–618. https://doi.org/10.1016/j.jbusres.2022.03.045
6. Go, E., & Sundar, S. S. (2019). Humanizing Chatbots: The Effects of Visual, Identity and Conversational Cues on Humanness Perceptions. *Computers in Human Behavior*, 97, 304–316. https://doi.org/10.1016/j.chb.2019.01.020
7. Kumar, P, Kumar, S., & Dutot, V. (2023). Artificial Intelligence (AI)-Enabled CRM Capability in Healthcare: The Impact on Service Innovation. *International Journal of Information Management*, 69, 102598. https://doi.org/10.1016/j.ijinfomgt.2022.102598
8. Hoy, M.B. (2018). Alexa, Siri, Cortana, and More: An Introduction to Voice Assistants. *Medical Reference Services Quarterly*, *37*(1), 81–88. https://doi.org/10.1080/02763869.2018.1404391
9. Mann, J. A., MacDonald, B.A., Kuo, I.H., Li, X., & Broadbent, E. (2015). People Respond Better to Robots than Computer Tablets Delivering Healthcare Instructions. *Computers in Human Behavior*, 43, 112–117.
10. Gray, K. (2017). AI Can Be a Troublesome Teammate. *Harvard Business Review*, https://hbr.org/2017/07/ai-can-be-a-troublesome-teammate.
11. Tussyadiah, I. & Miller, G. (2019). Perceived Impacts of Artificial Intelligence and Responses to Positive Behaviour Change Intervention. In J. Pesonen, J. Neidhardt (Eds), *Information and Communication Technologies in Tourism 2019*. Springer.
12. McLean, G., Osei-Frimpong, K., & Barhorst, J. (2021). Alexa, Do Voice Assistants Influence Consumer Brand Engagement? Examining the Role of AI Powered Voice Assistants in Influencing Consumer Brand Engagement. *Journal of Business Research*, 124, 312–328. https://doi.org/10.1016/j.jbusres.2020.11.045
13. Bao, Z. & Yang, J. (2022). Why Online Consumers Have the Urge to Buy Impulsively: Roles of Serendipity, Trust and Flow Experience. *Management Decision*, *60*(12), 3350–3365. https://doi.org/10.1108/MD-07-2021-0900
14. Kim, A., Affonso, F.M., Laran, J. & Durante, K.M. (2021). Serendipity: Chance Encounters in The Marketplace Enhance Consumer Satisfaction. *Journal of Marketing*, *85*(4), 141–157. https://doi.org/10.1177/00222429211000344
15. Pelau, C., Dabija, D.C., & Ene, I. (2023). What Makes an AI Device Human-Like? The Role of Interaction Quality, Empathy and Perceived Psychological Anthropomorphic Characteristics in the Acceptance of Artificial Intelligence in the Service Industry. *Computers in Human Behavior*, 122, 106855. https://doi.org/10.1016/j.chb.2021.106855
16. Huffman, A.H., Jason Whetten, and William H. Huffman (2013). Using Technology in Higher Education: The Influence of Gender Roles on Technology Self-Efficacy. *Computers in Human Behavior*, *29*(4), 1779–1786. https://doi.org/10.1016/j.chb.2013.02.012
17. Weinmann, M., Schneider, C., & vom Brocke, J. (2016). Digital Nudging. *Business & Information Systems Engineering*, 58, 433–436. . https://doi.org/10.1007/s12599-016-0453-1
18. Nass, C. & Moon, Y. (2000). Machines and Mindlessness: Social Responses to Computers. *Journal of Social Issues*, 56, 81–103. https://doi.org/10.1111/0022-4537.00153
19. Castelo, N., Schmitt, B. & Sarvary, M. (2018). Human or Robot? The Uncanny Valley in Consumer Robots. In A. Gershoff, R. Kozinets, & T. White (Eds.), *Advances in Consumer Research*, (pp. 183–187), Association for Consumer Research.
20. Balakrishnan, J., Abed, S.S., & Jones, P. (2022). The Role of Meta-UTAUT Factors, Perceived Anthropomorphism, Perceived Intelligence, and Social Self-Efficacy in Chatbot-Based Services? *Technological Forecasting and Social Change*, 180, 121692. https://doi.org/10.1016/j.techfore.2022.121692

21. Cao, C., Zhao, L., & Hu, Y. (2019). Anthropomorphism of Intelligent Personal Assistants (IPAs): Antecedents and Consequences. *PACIS*.
22. Chandra, S., Shirish, A., & Srivastava, S.C. (2022), To Be or Not to Be…. Human? Theorizing the Role of Human-Like Competencies in Conversational Artificial Intelligence Agents. *Journal of Management Information Systems*, *39*(4), 969–1005. https://doi.org/10.1080/07421222.2022.2127441
23. Deng, G. & Fei, S. (2023). Exploring the Factors Influencing Online Civic Engagement in A Smart City: The Mediating Roles of ICT Self-Efficacy and Commitment to Community. *Computers in Human Behavior*, 143, 107682. https://doi.org/10.1016/j.chb.2023.107682
24. Lee, J. & Lee, H. (2014). Developing and Validating a Citizen-Centric Typology for Smart City Services. *Government Information Quarterly*, 31, S93–S105. https://doi.org/10.1016/j.giq.2014.01.010
25. Limbu, Y.B., Wolf, M., & Lunsford, N.D. (2012). Perceived Ethics of Online Retailers and Consumer Behavioral Intentions: The Mediating Roles of Trust and Attitude. *Journal of Research in Interactive Marketing*, *6*(2), 133–154. https://doi.org/10.1108/17505931211265435
26. Kwak, Y., Ahn, J.W. & Seo, Y.H. (2022). Influence of AI Ethics Awareness, Attitude, Anxiety, and Self-Efficacy on Nursing Students' Behavioral Intentions. *BMC nursing*, *21*(1), 1–8.
27. Hmoud, B. I. & László, V. (2020). Artificial Intelligence in Human Resources Information Systems: Investigating Its Trust and Adoption Determinants. *International Journal of Engineering and Management Sciences*, *5*(1), 749–765. https://doi.org/10.21791/IJEMS.2020.1.65
28. Rahman, M., Ming, T.H., Baigh, T.A., & Sarker, M. (2021). Adoption of Artificial Intelligence in Banking Services: An Empirical Analysis. *International Journal of Emerging Markets*, *18*(10), 4270-4300. https://doi.org/10.1108/IJOEM-06-2020-0724
29. Schuetz, S. & Venkatesh, S. (2020). The Rise of Human Machines: How Cognitive Computing Systems Challenge Assumptions of User-System Interaction. *Journal of the Association for Information Systems*, *21*(2), 460–482. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3680306
30. White, J. & Ahern, E. (2022). Self-efficacy, Sympathy, and Attributions: Understanding Helping Intentions towards Disclosers of Mental Health Concerns on Social Media. *Journal of Applied Social Psychology*, *53*(4), 275–286. https://doi.org/10.1111/jasp.12938
31. Malle, B.F. & Ullman, D. (2021). A Multi-dimensional Conception and Measure of Human-Robot Trust. In C. S. Nam and J. B. Lyons (eds.), *Trust in human-robot interaction: research and applications* (pp. 3–25). Elsevier.
32. Cao, D., Sun, Y., Goh, E., Wang, R., & Kuiavska, K. (2022). Adoption of Smart Voice Assistants Technology Among Airbnb Guests: A Revised Self-Efficacy-Based Value Adoption Model (SVAM). *International Journal of Hospitality Management*, 101, 103124. https://doi.org/10.1016/j.ijhm.2021.103124
33. e Cunha, M.P. (2006). Serendipity: Why Some Organizations Are Luckier Than Others. *Nova SBE Working Paper Series* wp472, Universidade Nova de Lisboa, Nova School of Business and Economics.
34. McCay-Peet, L. & Toms, E. (2010). Measuring the Dimensions of Serendipity in Digital Environments. *Information Research: An International Electronic Journal*, *16*(3), 1–6.
35. Lutz, C., Hoffmann, C.P., & Meckel, M. (2017). Online Serendipity: A Contextual Differentiation of Aantecedents and Outcomes. *Journal of the Association for Information Science and Technology*, *68*(7), 1698–1710. https://doi.org/10.1002/asi.23771
36. Kumar, J.A., Bervell, B., Annamalai, N., & Osman, S. (2020). Behavioral Intention to Use Mobile Learning: Evaluating the Role of Self-Efficacy, Subjective Norm, and WhatsApp Use Habit. *IEEE Access*, 8, 208058–208074. https://ieeexplore.ieee.org/document/9258902
37. Hong, J.W. (2022). I Was Born to Love AI: The Influence of Social Status on AI Self-Efficacy and Intentions to Use AI. *International Journal of Communication*, 16, 20. https://ijoc.org/index.php/ijoc/article/view/17728
38. Cheng, Y. & Jiang, H. (2020). How Do AI-Driven Chatbots Impact User Experience? Examining Gratifications, Perceived Privacy Risk, Satisfaction, Loyalty, and Continued Use. *Journal of Broadcasting & Electronic Media*, *64*(4), 592–614. https://doi.org/10.1080/08838151.2020.1834296
39. Kim, Y., Myeong, S., & Ahn, M.J. (2023). Living Labs for AI-Enabled Public Services: Functional Determinants, User Satisfaction, and Continued Use. *Sustainability*, *15*(11), 8672. https://doi.org/10.3390/su15118672
40. Rodríguez-Ardura, I. & Meseguer-Artola, A. (2020). Editorial: How to Prevent, Detect and Control Common Method Variance in Electronic Commerce Research. *Journal of Theoretical and Applied Electronic Commerce Research*, *15*(2), 1–5.

41. Hsu, C.-L. & Lin, J. C.-C. (2023). Understanding the User Satisfaction and Loyalty of Customer Servicechatbots. *Journal of Retailing and Consumer Services*, 71, 103211. https://doi.org/10.1016/j.jretconser.2022.103211
42. Baumgartner, H. & Steenkamp, J.B.E.M. (2001). Response Styles in Marketing Research: A Cross-National Investigation. *Journal of Marketing Research*, 38 (2), 143–156. https://doi.org/10.1509/jmkr.38.2.143.18840
43. Zhang, J., Zhu, Y., Wu, J., & Yu-Buck, G.F. (2023). A Natural Apology is Sincere: Understanding Chatbots' Performance in Symbolic Recovery. *International Journal of Hospitality Management*, 108, 103387. https://doi.org/10.1016/j.ijhm.2022.103387
44. Agag, G. M., & El-Masry, A.A. (2017). Why Do Consumers Trust Online Travel Websites? Drivers and Outcomes of Consumer Trust toward Online Travel Websites. *Journal of Travel Research*, *56*(3), 347–369. https://doi.org/10.1177/0047287516643185
45. Moussawi, S. & Koufari, M. (2019). Perceived Intelligence and Perceived Anthropomorphism of Personal Intelligent Agents: Scale Development and Validation. *Proceedings of the 52nd Hawaii International Conference on System Sciences*. http://hdl.handle.net/10125/59452
46. Lee, W. & Shin, S. (2018). Effects of Product Smartness on Satisfaction: Focused on the Perceived Characteristics of Smartphone. *Journal of Theoretical and Applied Electronic Commerce Research*, *13*(2), 1–14. https://doi.org/10.4067/S0718-18762018000200102
47. Compeau, D.R. & Higgins, C.A. (1995). Application of Social Cognitive Theory to Training for Computer Skills. *Information Systems Research*, *6*(2), 118–143. https://doi.org/10.1287/isre.6.2.118
48. Lin, H.-H. & Wang (2006). An Examination of the Determinants of Customer Loyalty in Mobile Commerce Context. *Information & Management*, *43*(3), 271–282. https://doi.org/10.1016/j.im.2005.08.001
49. Kim, M.J., & Hall, C.M. (2019). Can Climate Change Awareness Predict Pro-Environmental Practices in Restaurants? Comparing High and Low Dining Expenditure. *Sustainability*, *11*(23), 6777. https://doi.org/10.3390/su11236777
50. Lam, L. W. (2012). Impact of Competitiveness on Salespeople's Commitment and Performance. *Journal of Business Research*, *65*(9), 1328–1334. https://doi.org/10.1016/j.jbusres.2011.10.026
51. Fornell, C. & Larcker, D.F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research*, *8*(1), 39–50. https://doi.org/10.1177/002224378101800l
52. Hair Jr, J.F., Sarstedt, M., Hopkins, L., & Kuppelwieser, V.G. (2014). Partial Least Squares Structural Equation Modeling (PLS-SEM): An Emerging Tool in Business Research. *European Business Review*, *26*(2), 106–121. https://doi.org/10.1108/EBR-10-2013-0128
53. Wong, K. K-K. (2016). Technical Note: Mediation Analysis, Categorical Moderation Analysis, and Higher-order Constructs Modeling in Partial Least Squares Structural Equation Modeling (PLS-SEM): A B2B Example Using SmartPLS. *Marketing Bulletin*, 26, 1–22.
54. Ashok, M., Madan, R., Joha, A. & Sivarajah, U. (2022). Ethical Framework for Artificial Intelligence and Digital Technologies. *International Journal of Information Management*, 62, 102433. https://doi.org/10.1016/j.ijinfomgt.2021.102433
55. Borenstein, J. & Howard, A. (2021). Emerging Challenges in AI and The Need for AI Ethics Education. *AI Ethics*, 1, 61–65. https://doi.org/10.1007/s43681-020-00002-7
56. Siau, K. & Wang, W. (2020). Artificial Intelligence (AI) Ethics: Ethics of AI and Ethical AI. *Journal of Database Management*, *31*(2), 74–87. https://doi.org/10.4018/JDM.2020040105
57. Seals, S. M. and Shalin, V.L. (2023). Long-Form Analogies Generated by ChatGPT Lack Human-Like Psycholinguistic Properties. *Computation and Language*, https://arxiv.org/abs/2306.04537
58. OpenAI. (2023). GPT-4 is OpenAI's Most Advanced System, Producing Safer and More Useful Responses. https://openai.com/research/gpt-4