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Modeling Chatgpt Continuance Intention: The Role of Expectancy, Satisfaction, and Trust

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Abstract. The growth of digital technology has increased the use of online services, with AI tools like ChatGPT becoming widely used. This study examines the impact of user perceptions on their intention to continue using ChatGPT, emphasising performance expectancy, effort expectancy, satisfaction, and trust as moderating variables. Data were gathered from 200 ChatGPT users using an organised survey and analysed via Partial Least Squares, Structural Equation Modelling (PLS, SEM). Findings indicate that performance expectancy as well as effort expectancy significantly enhance satisfaction and directly affect continuance intention. Satisfaction serves as a mediating factor between the anticipation variables and the intention to continue use. Nonetheless, trust does not substantially influence the correlation between performance or effort expectancy and satisfaction. The findings indicate that users' perception of ChatGPT as beneficial and user-friendly enhances their pleasure, hence reinforcing their intention to continue utilising it. This emphasises the significance of utility and user-friendliness in fostering sustained engagement with AI services.
Keywords: Continuance Intention, Effort Expectancy, Performance Expectancy, Satisfaction, Trust.

BACKGROUND

The swift progression of technology has resulted in the creation of numerous internet-based services that enhance societal comfort. Individuals can access various facilities with the internet, including entertainment, communication, literature searches, and crucial sectors such as economics and business. The internet functions as a tool that improves efficiency and effectiveness, rendering it indispensable for enhancing performance and optimizing numerous jobs.

The emergence of artificial intelligence (AI) language models, particularly generative pre-trained transformers (GPTs), has revolutionized company operations and customer engagement. Their rapid adoption reshapes marketing strategies, enhances customer engagement, and redefines market dynamics. AI models have revolutionized communication by enabling human-like interactions between businesses and consumers. Chen et al. (2024) note the shift from rule-based AI to advanced language processing, driving significant marketing and customer service changes. AI-powered systems, such

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as service robots and chatbots, improve customer interactions by delivering adaptive and personalized experiences (Shah et al., 2023). Luo (2024) emphasizes the significance of AI in education, illustrating its capacity to enhance engagement, a phenomenon also observed in consumer interactions. Similarly, Raghulan and Jayanthi (2024) emphasize AI-driven marketing strategies that enhance brand loyalty through personalized communication and automation.

The rise of AI language models, such as ChatGPT, has significantly impacted customer engagement strategies. Businesses use ChatGPT to provide real-time, personalized responses, improving customer satisfaction and loyalty (Gala & Makaryus, 2023). Its ability to handle multiple queries simultaneously enhances efficiency, reducing wait times and improving service quality. Although Pack and Maloney (2024) investigated AI applications in education, additional study is required to assess its direct influence on marketing and sales engagement. Beyond customer interactions, ChatGPT supports market research by analyzing large datasets from online conversations, helping businesses understand consumer behaviour and trends (Pack & Maloney, 2023). Additionally, Tenakwah et al. (2023) highlight how AI accelerates data analysis, which can be leveraged to track market shifts and customer sentiment, keeping businesses competitive in dynamic environments.

The market potential for ChatGPT-integrated solutions extends beyond traditional applications, fostering a new ecosystem of AI-driven products and services. Khurana et al. (2022) highlight how ChatGPT's natural language processing capabilities have spurred innovations across industries, from content creation to language learning. Businesses are leveraging this technology to develop more innovative chatbots, personalized applications, and advanced educational tools, creating new AI-focused market segments. As competition intensifies, companies are not only striving for superior service execution but also enhancing AI-driven interactions to differentiate themselves. With the rapid growth of AI tools like ChatGPT, it has become essential to understand why people keep using these technologies over time (Venkatesh et al., 2012; Li et al., 2023). Although ChatGPT gained much attention initially, reports showed that user activity dropped noticeably around mid-2023 user activity dropped, monthly visits declined by nearly 10%, and average session time fell, raising questions about what influences people to continue using it or stop. The UTAUT2 model elucidates continuing usage by emphasizing elements such as the technology's utility (Performance Expectancy) and its usability (Effort Expectancy), with satisfaction being a pivotal element in this framework (Bhattacherjee, 2001; Hsu & Lin, 2015).

The Unified Theory of Acceptance and Use of Technology (UTAUT) identifies Performance Expectancy (PE) and Effort Expectancy (EE) as key predictors of behavioural intention (Venkatesh et al., 2003). PE refers to how much users believe the tool helps them perform better, while EE is about how easy it is to use. These beliefs affect satisfaction, shaping continuance intention (CI) (Bhattacherjee, 2001). Studies support this path: PE and EE contribute to satisfaction and CI (Chauhan & Jaiswal, 2016; Gupta et al., 2008). However, other studies offer contrasting findings. For example, Wang & Yang (2005) found PE had a weak effect on CI in some users, and Venkatesh et al. (2012) showed that EE's influence fades as users become more experienced.

To address this gap, recent studies suggest adding trust as a moderator. Trust means users believe the system is reliable and will not cause harm (McKnight et al., 2011). It enhances the impact of PE and EE on satisfaction and CI (Li, 2021; Alharbi, 2017). A meta-analysis conducted by Blut et al. (2022) further substantiates trust as a critical element in augmenting the UTAUT approach. However, trust is not always effective.

In some cases, like mandatory-use environments, its impact may be limited (Venkatesh et al., 2003). Too much trust could even reduce critical evaluation, lowering satisfaction over time (Li, 2021). In conclusion, while PE, EE, satisfaction, and trust form a strong framework, their effectiveness can change based on user experience, context, and technology type. To better understand ChatGPT's declining usage, it is essential to consider how trust interacts with user expectations in dynamic AI environments.

THEORETICAL STUDY

Academic research on consumer acceptance of technology is built on various hypotheses, with the UTAUT2 being a key framework. This study examines artificial intelligence (AI) application through the UTAUT framework, encompassing factors such as Performance Expectancy (PE), Effort Expectancy (EE), Satisfaction, and Continuance Intention. In this framework, external factors directly shape user perceptions of utility and usability, hence impacting their overall evaluations of technology.

Performance Expectancy (PE)

Performance Expectancy (PE) is the conviction that utilizing a system would enhance work performance (Venkatesh et al., 2003). It plays a key role in user adoption, especially when users feel the technology helps them work more efficiently or achieve goals more easily. Studies show that PE is one of the strongest predictors of continued use in traditional and AI technologies (Zhou et al., 2010; Venkatesh et al., 2016).In AI contexts such as ChatGPT, PE denotes the extent to which users see the tool as augmenting productivity, including idea generation, expedited writing, or problem-solving (Li, 2021; Alharbi, 2017). A greater perceived ease (PE) frequently results in increased pleasure and a more robust intention to utilize the instrument (Bhattacherjee, 2001).

Effort Expectancy (EE)

Effort Expectancy (EE), characterized as the apparent simplicity of utilizing a system (Venkatesh et al., 2003), is pivotal in the initial adoption of technology. When users find a system intuitive and straightforward, it lowers their cognitive effort and increases satisfaction, boosting their intention to continue using it (Bhattacherjee, 2001; Martín & Herrero, 2012).

However, as users become more experienced, EE's influence tends to decline, shifting the focus toward performance-based outcomes (Venkatesh et al., 2012). In AI tools like ChatGPT, EE refers to how easily users can engage with the interface, understand responses, and apply AI outputs in their tasks. A user-friendly design and smooth experience encourage regular use, especially for beginners or non-technical users (Huang et al., 2023). On the other hand, if users encounter complexity or inefficiency, it can reduce satisfaction and weaken their continuance intention. Thus, maintaining high EE is essential to retain users, particularly in a competitive and evolving AI landscape.

Satisfaction

Satisfaction is essential in assessing the extent to which the goods or services offered by a business fulfill or exceed consumer expectations. It measures how well a company's offerings align with customer anticipations, incorporating key aspects such as product quality, service efficiency, pricing, and overall user experience (Majiid et al., 2020; Fahira & Djamaludin, 2023). When consumers see that their expectations have been met or surpassed, they are likely to cultivate a favorable impression of the brand or service provider (Son et al., 2022). This assessment procedure is typically gauged using multiple indications, such as customer satisfaction ratings subsequent to their encounter with a product or service (Tudoran et al., 2012).

Trust

Trust in technology is defined as users' faith in the system's reliability, integrity, and competence (McKnight et al., 2011). It markedly amplifies the influence of Performance Expectancy (PE) and Effort Expectancy (EE) on user satisfaction. When users have confidence in AI technologies such as ChatGPT, they believe that the system will provide the anticipated advantages (PE) and that the effort needed to utilize it (EE) is warranted. This augmented trust improves happiness and motivates users to persist in their engagement with the technology (McKnight et al., 2011; Thatcher et al., 2004).

However, some research suggests that trust's moderating effect may vary depending on the context. In situations where technology use is mandatory or habitual, trust may have a reduced influence since users continue using the system regardless of their trust levels (Venkatesh et al., 2003). Moreover, excessive trust might lead users to become complacent, overlooking potential flaws or limitations of the system. This complacency can reduce users' critical evaluation and ultimately harm long-term satisfaction and sustained use (McKnight, Liu & Pentland, 2020).

Continuance Intention

Continuance intention denotes an individual's dedication or readiness to persist in utilizing a specific product, service, or system beyond the initial adoption stage. It emphasizes users' continued involvement with a technology or service informed by previous experiences. Ferreira et al. (2021). This concept is shaped by post-usage evaluations, where individuals assess their experiences against their initial expectations. Mao et al. (2023) compare continuance intention to repurchase intention in consumer behaviour, emphasizing its role in fostering long-term relationships between users and the products or services they adopt. Furthermore, the intention to continue is affected by user satisfaction and perceived effectiveness, highlighting the psychological factors that promote sustained engagement (Chiu et al., 2020).

Conceptual framework

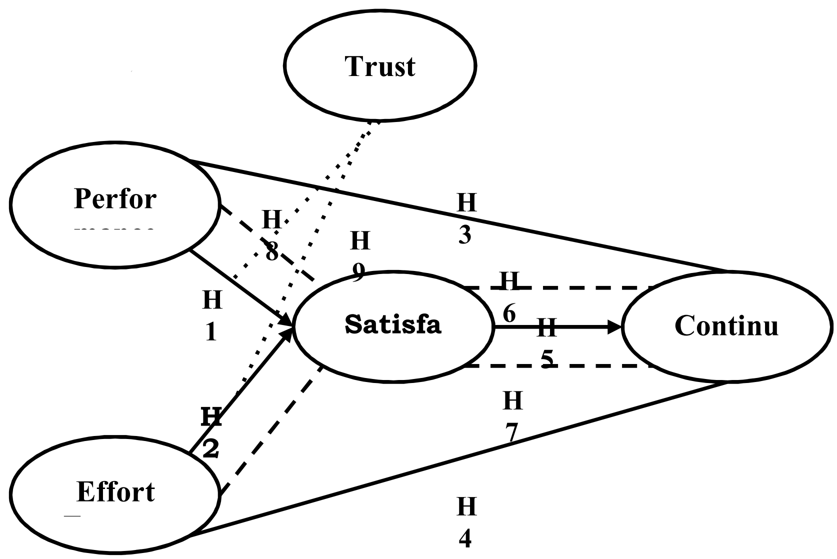

Figure 1. Research Framework

Based on the problem description and conceptual framework, the researcher posits the following study hypothesis:

H1: There is a relationship between performance expectancy and satisfaction.

H2: There is a relationship between performance expectancy and satisfaction.

H3: There is a relationship between performance expectancy and continuance intention.

H4: There is a relationship between effort expectancy and continuance intention.

H5: There is a relationship between satisfaction and continuance intention.

H6: Satisfaction mediates the relationship between performance expectancy and continuance intention.

H7: Satisfaction mediates the relationship between effort expectancy and continuance intention.

H8: Trust moderates the relationship between performance expectancy and satisfaction.

H9: Trust moderates the relationship between effort expectancy and satisfaction.

RESEARCH METHODS

This research is classified as quantitative. This investigation utilises questionnaires to collect data from a wider demographic sample. This study is categorised as causal associative research based on the level of explanation. This study will analyse the causal link among the factors under investigation. The data for this study was collected via Google Forms, which were distributed online through social media channels. The questionnaire utilised a Likert scale ranging from 1 to 5, including the following categories: Strongly Agree receives a score of 5; Agree receives a score of 4; Somewhat Agree receives a score of 3; Disagree receives a score of 2; Strongly Disagree receives a score of 1. The study's population comprises ChatGPT users. The employed sample technique is non-probability sampling, specifically purposive sampling, characterized by the following criteria: 1) Have utilized ChatGPT; 2) Aged over 15 years; 3) Residing in Indonesia. The sample size for this investigation was established using the Lemeshow formula method. This study necessitates a minimum of 100 respondents as a research sample due to the uncertainty around the overall population (Slamet & Aglis, 2020). The overall sample included in this research comprises 200 respondents. This study utilizes a causal methodology through Structural Equation Modeling (SEM) to evaluate its hypotheses, with data analyzed with SmartPLS version 4 employing the PLS-SEM technique.

RESULTS AND DISCUSSION

Result

Respondent Characteristic

Table 1. Respondents Characteristic

Category	Item	Frequency	Percentage (%)
Gender	Man	80	40
	Woman	120	60
	Total	200	100
Age	15-24 Years old	59	29.5
	25-34 Years old	110	55
	35-44 Years old	30	15
	45+ Years old	1	0.5
	Total	200	100
Last Education	Junior High School	8	4
	Senior High School	110	55
	Diploma/Bachelor's Degree	70	35
	Master's/Doctoral Degree	12	6

	Total	200	100
Work	Full-time worker	45	22.5
	Part-time worker	55	27.5
	Unemployed	19	9.5
	Students	31	15.5
	Others	50	25
	Total	200	100
Address	Sumatera	40	20
	Jawa	86	43
	Kalimantan	49	24.5
	Sulawesi	11	5.5
	Nusa Tenggara	4	2
	Bali	6	3
	Maluku	2	1
	Papua	2	1
	Total	200	100

Source: Data processed (2025)

Measurement Model

Table 2 presents the measurement model for the indicators of the four variables obtained using the PLS approach. The results include assessments of model fit and tests for validity and reliability.

Table 2. Loading Factor (LF), Cronbach's Alpha, Composite Reliability (CR), and Average Variance Extracted (AVE) value in Overall Model Fit

Variable	Indicator	LF	Cronbach Alpha	CR	AVE
Performance Expectancy	PE1	0.919	0.923	0.923	0.812
	PE2	0.914			
	PE3	0.887			

	PE4	0.885			
Effort Expectancy	EE1	0.912	0.928	0.928	0.822
	EE2	0.885			
	EE3	0.907			
	EE4	0.923			
Satisfaction	SAT1	0.936	0.906	0.907	0.842
	SAT2	0.909			
	SAT3	0.907			
Trust	T1	0.896	0.796	0.879	0.701
	T2	0.805			
	T3	0.807			
Continuance Intention	CI1	0.910	0.893	0.893	0.824
	CI2	0.900			
	CI3	0.913			

Source: Data processed (2025)

Convergent Validity

To evaluate the quality of a measurement model, convergent validity must be demonstrated. Hair et al. (2019) recommend a loading factor exceeding 0.708, signifying that the concept represents more than 50% of the variance in its associated variables, thereby ensuring sufficient item reliability. If the Average Variance Extracted (AVE) score is 0.50 or higher, it means that the construct explains at least 50% of the variance in its observable variables. The loading factor analysis shows values between 0.805 and 0.936, whereas the AVE measurements show values between 0.701 and 0.842. These findings indicate that all indicators exceed the minimum thresholds for convergent validity. Consequently, the measurement instrument can be considered both valid and reliable, demonstrating its ability to consistently capture the intended construct across different model specifications.

Discriminant Validity

Discriminant validity was evaluated by the cross-loading technique. Hair et al. (2017) and Chin (1998) assert that an indicator must exhibit the largest loading on its designated construct relative to others to establish discriminant validity. Gefen and Straub (2005) further highlighted that consistently elevated loadings on the target construct signify strong discriminant validity. The findings in Table 3 indicate that all indicators exhibit their maximum loadings on their corresponding constructions, while demonstrating diminished loadings on alternative constructs. Therefore, discriminant validity is achieved using the cross-loading method, indicating that the indicators effectively distinguish their constructs.

Table 3. Cross-Loading

	CI	EE	PE	SAT	TRUST	TRUST x PE	TRUST x EE
CI1	0.910	0.864	0.849	0.852	0.134	-0.171	-0.217
CI2	0.900	0.873	0.846	0.847	0.169	-0.170	-0.184
CI3	0.913	0.886	0.884	0.863	0.120	-0.189	-0.196
EE1	0.879	0.912	0.850	0.852	0.167	-0.202	-0.234
EE2	0.871	0.885	0.850	0.819	0.109	-0.147	-0.155
EE3	0.866	0.907	0.855	0.868	0.130	-0.172	-0.221
EE4	0.880	0.923	0.863	0.851	0.173	-0.164	-0.190
PE1	0.857	0.842	0.919	0.835	0.210	-0.180	-0.184
PE2	0.843	0.854	0.914	0.842	0.179	-0.142	-0.097
PE3	0.863	0.863	0.887	0.859	0.092	-0.194	-0.186
PE4	0.850	0.836	0.885	0.847	0.175	-0.225	-0.233
SAT1	0.880	0.859	0.877	0.936	0.180	-0.188	-0.225

SAT2	0.882	0.869	0.853	0.909	0.090	-0.166	-0.211
SAT3	0.829	0.846	0.855	0.907	0.138	-0.183	-0.184
T1	0.167	0.166	0.192	0.160	0.896	-0.058	-0.053
T2	0.109	0.095	0.143	0.081	0.805	0.049	0.084
T3	0.096	0.121	0.107	0.109	0.807	-0.029	-0.007
TRUST x EE	0.220	-0.221	-0.194	-0.225	-0.008	0.906	1.000
TRUST x PE	-0.195	-0.189	-0.206	-0.195	-0.029	1.000	0.906

Source: Data processed (2025)

Composite Reliability

A build is deemed to have sufficient composite reliability when the composite reliability value surpasses 0.7 (Sarstedt et al., 2020). Furthermore, to bolster the trustworthiness of the findings, it is advisable for Cronbach's alpha to exceed the threshold of 0.7, acting as an extra measure of validity (Hair et al., 2021). Table 2 displays the composite reliability values for each variable: Performance Expectancy (0.923), Effort Expectancy (0.928), Satisfaction (0.907), Trust (0.879), and Continuance Intention (0.893), all beyond the 0.7 criterion. The Cronbach's alpha values for each variable range from 0.796 to 0.928, so meeting the dependability criterion. Consequently, it can be inferred that the measurement model exhibits satisfactory reliability and validity.

Inner Model Evaluation

R-Square

The R^2 value spans from 0 to 1, with values approaching 1 indicating a superior model fit and significant influence of exogenous variables on endogenous variables (Bagozzi, 2022). Hair et al. (2021) elucidate that a R^2 value of 0.75 signifies a strong influence, 0.50 denotes a moderate influence, and 0.25 suggests a weak influence. The exogenous variables affect Satisfaction, as indicated by a R^2 of 0.907 in Table 4. Nonetheless, owing to the model's complexity, the Adjusted R^2 somewhat decreases to 0.905, yet it continues to indicate a robust effect. The R^2 score for Continuance Intention is 0.946, signifying a substantial impact.

Table 4. R-square (R^2)

	R-square	R-square adjusted
CONTINUANCE INTENTION	0.946	0.946
SATISFACTION	0.907	0.905

Source: Data processed (2025)

Hypothesis Testing

Hypothesis testing is conducted to ascertain whether the independent variable significantly and positively affects the dependent variable. Researchers evaluate whether this influence is direct or indirect by analyzing the path coefficient, which is based on the t-statistic and p-value derived from the bootstrapping process. Bootstrapping assesses the statistical significance of the variables posited in the hypothesis and determines the nature of their interactions, whether positive or negative (Memon et al., 2021). Hair et al. (2019) indicate that a prevalent benchmark is a 5% significance threshold (alpha = 0.05), wherein a relationship between variables is deemed significant if the p-value is below 0.05 and the t-statistic surpasses 1.96.

Table 5.Hypothesis Testing Results

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Results
EE -> CI	0.538	0.531	0.057	9.420	0.000	Accepted
EE -> SAT	0.396	0.384	0.102	3.888	0.000	Accepted
PE -> CI	0.244	0.249	0.065	3.724	0.000	Accepted
PE -> SAT	0.567	0.578	0.094	6.049	0.000	Accepted
SAT -> CI	0.209	0.211	0.058	3.593	0.000	Accepted
TRUST x EE -> SAT	-0.120	-0.083	0.088	1.372	0.170	Not Accepted

TRUST x PE -> SAT	0.141	0.104	0.093	1.529	0.126	Not Accepted

Source: Data processed (2025)

The hypothesis testing results presented in Table 5, reveal multiple significant correlations among the investigated variables. Performance Expectancy has a substantial impact on both Continuance Intention (t = 3.724, p = 0.000) and Satisfaction (t = 6.049, p = 0.000), hence corroborating hypotheses H1 and H3. Effort Expectancy exhibits a robust and significant impact on Continuance Intention (t = 9.420, p = 0.000), so validating H2, and on Satisfaction (t = 3.888, p = 0.000), which confirms H4. Finally, satisfaction significantly affects continuation intention (t = 3.593, p = 0.000), meaning H5 is also accepted. Meanwhile, Trust as a moderating variable was found to have no role in moderating the relationship between PE and SAT (t=1.372, p=0.170), as well as in moderating between EE and SAT (t=1.529, p=0.126), so it can be said that both H8 and H9 are not accepted.

Table 6. Indirect Effect

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Results
EE -> CI	0.083	0.082	0.035	2.351	0.019	Accepted
PE -> CI	0.119	0.121	0.034	3.466	0.001	Accepted

Source: Data processed (2025)

Table 6, outlines the variable relationships tested in the two indirect hypotheses. The findings indicate that Effort Expectancy exerts a significant indirect influence on Continuance Intention via Satisfaction (t = 2.351, p = 0.019), hence corroborating this hypothesis. Performance Expectancy exhibits a substantial indirect effect on Continuance Intention (t = 3.466, p = 0.001), thus validating this hypothesis.

Discussion

This study confirms that Performance Expectancy (PE) strongly and positively impacts user satisfaction and continuance intention. When users see that a system adequately enhances their performance, it elevates their contentment and markedly amplifies their intention to persist in utilising the service. Prior research on digital platforms consistently corroborates this direct effect (Handayani et al., 2024; Alalwan et al., 2022; Raman & Aashish, 2023). Moreover, other research highlights that satisfaction often reinforces this relationship by mediating the effect of PE on continuance intention (Adetha & Aprilia, 2023; Prasetyo & Syaebani, 2024), indicating that the more users feel satisfied with the system's performance, the stronger their long-term engagement becomes.

Another important factor that strongly shapes user behaviour is Effort Expectancy (EE), which significantly and positively impacts both satisfaction and continuance intention. Users exhibit more satisfaction and motivation to persist in utilising a system when it is user-friendly and devoid of unnecessary complexity. EE affects continuance intention both directly and indirectly via satisfaction. As Hsu et al. (2014) explain, users who experience effortless interactions tend to be more satisfied, and this satisfaction further strengthens their intention to continue using the service. These findings highlight that EE plays a dual role: simplifying the user experience and enhancing satisfaction, promoting long-term usage (Raman & Aashish, 2021; Elok & Hidayati, 2021).

Satisfaction significantly affects continuance intention, indicating that ChatGPT users' continued use depends strongly on their satisfaction. This direct relationship is supported by studies such as Ashfaq et al. (2020), who said satisfaction significantly influences continuance intention in mobile apps, and Nascimento et al. (2018), who highlighted satisfaction as a critical factor for ongoing engagement with e-learning platforms. Similarly, Kim et al. (2009) demonstrated that satisfaction directly affects continuance intention, confirming its key role in sustaining user loyalty across digital services like ChatGPT.

The results showed that trust did not strengthen the link between performance expectancy (PE) or effort expectancy (EE) and satisfaction, which made the connection weaker. This research supports earlier studies (Jones et al., 2023; Heyns & Rothmann,

2021) that found trust usually works better as a factor or as something that explains how one thing leads to another rather than as a moderator. High or low trust does not always boost how much PE or EE affects satisfaction.

CONCLUSIONS AND SUGGESTIONS

Conclusion

This research indicates that performance and effort expectancy notably and positively impact users' intention to keep using ChatGPT. Satisfaction serves as a key mediator that strengthens the influence of those variables. When users perceive ChatGPT as helpful and easy to use, their satisfaction increases, contributing to their willingness to continue using it. Conversely, trust did not substantially alter the association between performance or effort expectancy and satisfaction, indicating that its influence in this context may be restricted. These findings underscore the necessity of enhancing user experience to ensure sustained utilization of AI-based solutions such as ChatGPT.

Suggestion

Based on the research, platforms must improve their user experience by enhancing several factors, such as adding useful features, improving answer accuracy, and supporting user tasks. Other important ways to add are regular user feedback and addressing issues promptly, thus creating a greater chance for users to continue using the platform in the future. Users are encouraged to actively explore the various features of ChatGPT to maximize the potential provided by the platform and assist users' needs more accurately. Providing feedback to the platform can also help with system improvements.

This study has several limitations in terms of variables and research objects. Numerous variables remain to be explored for assessing users' continuance intentions, and the research model can be further refined, as this study concentrated exclusively on Performance Expectancy and Effort Expectancy. Future studies may enhance the model by incorporating additional variables such as perceived risk, user experience, and social impact, or by integrating distinct individual characteristics, thereby yielding a more holistic understanding of the determinants of continuance intentions. Research topics can also be further developed; for example, comparing two platforms in the same sector would provide more information to determine user behaviour or use different platforms within one scope. Since this study used quantitative methods, future research can use different methods, such as qualitative or mixed approaches, to enrich insights into user motivation and satisfaction.

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