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Chatgpt As Management Tools For Organization Environment Analysis: Study From Indonesian Gen Y And Z

Chatgpt Sebagai Alat Manajemen Untuk Analisis Lingkungan Organisasi: Studi Dari Generasi Y Dan Z Indonesia

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ABSTRACT
ChatGPT has become a valuable tool for individuals, offering an interactive platform to complete tasks with precision and efficiency capabilities often beyond traditional tools. As AI adoption grows rapidly, especially in Indonesia where ChatGPT ranks among the top-used platforms, there is a growing need to understand what drives its continued use, particularly among young digital natives. This study aims to explore behavioral factors habit formation and perceived information accuracy that influence users' intention to adopt ChatGPT within educational and organizational environments. Drawing on the UTAUT2 framework, this research employs a quantitative method involving 129 Indonesian respondents from Generations Y and Z. Data were collected via structured questionnaires and analyzed using SmartPLS to examine the relationships among key variables. The study contributes to AI adoption literature by contextualizing behavioral technology acceptance within the Southeast Asian user base. Its novelty lies in examining ChatGPT use not only as a technological trend, but also as a cognitive and habitual practice. Managerially, the insights benefit AI developers, educators, and institutional leaders by helping them foster sustainable usage through accurate content delivery and reinforcement of positive user habits. The findings aim to provide insight into the factors driving ChatGPT adoption and broader adoption trends in decision-making within the management field.
Keywords: *Habit, Behavioral Intentions, Information Accuracy, ChatGpt, UTAUT2.*

ABSTRAK
ChatGPT telah menjadi alat yang berharga bagi individu, menawarkan platform interaktif untuk menyelesaikan tugas dengan presisi dan efisiensi yang seringkali melebihi alat tradisional. Seiring dengan pertumbuhan adopsi AI yang pesat, terutama di Indonesia di mana ChatGPT termasuk di antara platform yang paling banyak digunakan, terdapat kebutuhan yang semakin besar untuk memahami faktor-faktor yang mendorong penggunaan berkelanjutan ChatGPT, terutama di kalangan generasi muda yang terbiasa dengan teknologi digital. Studi ini bertujuan untuk mengeksplorasi faktor-faktor perilaku, pembentukan kebiasaan, dan persepsi akurasi informasi yang memengaruhi niat pengguna untuk mengadopsi ChatGPT dalam lingkungan pendidikan dan organisasi. Menggunakan kerangka kerja UTAUT2, penelitian ini menerapkan metode kuantitatif dengan melibatkan 129 responden Indonesia dari Generasi Y dan Z. Data dikumpulkan melalui kuesioner terstruktur dan dianalisis menggunakan SmartPLS untuk mengeksplorasi hubungan antar variabel kunci. Studi ini berkontribusi pada literatur adopsi AI dengan mengkontekstualisasikan penerimaan teknologi perilaku di kalangan pengguna Asia Tenggara. Keunikan penelitian ini terletak pada pengkajian penggunaan ChatGPT tidak hanya sebagai tren teknologi, tetapi juga sebagai praktik kognitif dan kebiasaan. Secara manajerial, wawasan ini bermanfaat bagi pengembang AI, pendidik, dan pemimpin institusi dengan membantu mereka mendorong penggunaan berkelanjutan melalui penyampaian konten yang akurat dan penguatan kebiasaan pengguna yang positif. Temuan ini bertujuan untuk memberikan wawasan tentang faktor-faktor yang mendorong adopsi ChatGPT dan tren adopsi yang lebih luas dalam pengambilan keputusan di bidang manajemen.
Kata Kunci: Kebiasaan, Niat Perilaku, Akurasi Informasi, Chatgpt, UTAUT2.

1. Introduction

Over the past decade, artificial intelligence (AI) has emerged as a transformative technology, enhancing learning outcomes, optimizing training methods, and improving work efficiency. Despite its benefits, concerns remain regarding potential misuse (Yahaya et al., 2024). AI-powered instruments like ChatGPT encounter demonstrated their ability to support education by responding to queries, providing clarifications, and assisting users effectively (Pillai, 2023) (Kuhail et al., 2023). Research highlights ChatGPT's duty in improving teaching methods and automating Work Environment writing (Lund et al., 2023) (Taecharungroj, 2023). In Indonesia, ChatGPT adoption has surged, making the country the third-largest user globally by March 2024, following the United States and India.

Table 1. List of Countries using ChatGPT

Rank	Country	Proportion of ChatGPT Users
1	United State	12.22%
2	India	10.71%
3	Indonesia	9.02%

(explodingtopics, 2024)

Research by Populix (2023) reveals that 45% of Indonesian internet users leverage AI applications to enhance productivity and efficiency. Among these, ChatGPT emerges as the most preferred AI platform, with 52% of respondents favoring it. The majority of users are from Java (76%), followed by Sumatra (14%) and other islands (10%). ChatGPT adoption spans various age groups, with the largest segment being 17-25 years old (51%), followed by those aged 26-35 (33%). This growing trend underscores ChatGPT's significant role in supporting productivity and Work Environment engagement in Indonesia.

Table 2. List of the most commonly used A.I platforms

List of the most commonly used A.I platforms (April 2023)		
Rank	Ai Name	Percentage (%)
1	ChatGPT	52%
2	Copy.ai	29%
3	Luminar AI	18%

(Populix, 2023)

The rapid advancement of AI in education has the potential to revolutionize learning environments and redefine the roles of all stakeholders involved (Becker et al., 2018). However, improper application of AI in educational settings can lead to several challenges, including dehumanization of learning, privacy violations, plagiarism, bias, unemployment, and over-reliance on technology (Oxford University Press, 2024).

Plagiarism has become an increasing concern due to generative AI systems enabling Work Environment members to complete tasks without acknowledging external assistance (Becker et al., 2018). Moreover, excessive reliance on AI may obstruct the progress of essential development and independent thinking skills, as students might default to AI-generated responses instead of actively engaging in the learning process (Seldon & Abidoye, 2018). Preserving cognitive engagement remains essential in fostering analytical and problem-solving abilities.

This research applies the Unified Theory of Acceptance and Use of Technology (UTAUT) and its extended model, UTAUT 2, to examine factors influencing the approval of AI-powered tools. The UTAUT structure considers performance expectancy, effort expectancy, and social influence, while UTAUT 2 expands on these by incorporating hedonic motivation, learning value, and habit. With this foundation, the study intention to analyze the element driving the Work Environment community's intention to adopt ChatGPT, proposing the research topic: "CHATGPT AS A MANAGEMENT TOOL FOR ORGANIZATIONAL ENVIRONMENT ANALYSIS: A STUDY OF INDONESIAN GEN Y AND Z"

2. Literature Review

ChatGPT

Numerous AI chatbots exist today, but ChatGPT stands out for several key reasons. Powered by advanced large script models, including GPT-3.5 and GPT-4, ChatGPT be able to develop coherent and in relation to the context relevant responses across various domains. It excels in tasks such as essay writing, coding, translation, and personalized assistance with remarkable accuracy. ChatGPT supports a diverse array of applications, from assisting with assignments to providing personalized feedback. In programming, it aids in coding and debugging, enhancing efficiency for developers (Kim, 2023). In contrast to conventional search engines that depend on static keyword-based queries, ChatGPT offers an interactive experience, engaging users in dynamic conversations (Kim, 2023). Despite its advancements, ChatGPT still faces challenges, including information inaccuracies and ethical concerns, which impact its seamless integration across different sectors (Zhang et al., n.d.). Nevertheless, ChatGPT has significantly influenced the field of AI-powered conversation systems. Compared to its earlier versions, the latest iterations interact in a more human-like manner and demonstrate enhanced efficiency, making ChatGPT a groundbreaking tool in artificial intelligence.

UTAUT2

UTAUT 2 (Unified Theory of Acceptance and Use of Technology 2) is an extension of the original UTAUT model introduced by (Venkatesh et al., 2003) to better explain technology acceptance in consumer contexts. Developed by (Venkatesh et al., 2012), UTAUT 2 expands the original model by incorporating three additional structures Hedonic Motivation, worth, and Habit while retaining key elements such as Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions.

This model addresses limitations in earlier theories by integrating moderators like age, gender, and experience, which significantly influence behavioral intention and use behavior. Empirical studies have validated UTAUT 2 in diverse settings, such as mobile banking, e-learning, and smart home technologies (Risitano et al., 2017)

Habit

The adoption of ChatGPT and similar technologies in the work environment is influenced by habit, which is linked to psychological factors and behavior (Kim, 2023) ("The Role and Impact of Online Learning Platforms in Higher Education," 2024). Research, including cross-sectional and longitudinal studies, has examined how habit impacts technology adoption among college students, affecting both initial usage and sustained engagement with educational technologies. Understanding the formation of habit is mandatory for promoting more frequent use of these technologies, ultimately enhancing learning experiences and work environment outcomes.

Behavioral Intentions

The UTAUT2 model defines behavioral intention as an private motivation to acknowledge and use technology, influenced by factors such as intrinsic enjoyment, performance and effort expectations, social influence, facilitating conditions, and habit. Research highlights hedonic motivation and habit as key determinants in contexts like mobile banking and healthcare applications, while performance and effort expectations often have minimal impact (Safitri et al., n.d.) (Huang et al., 2024) (Dewi et al., 2024). In sectors like Islamic banking, low expectations have led to calls for extending UTAUT2 with risk and credibility perception to enhance understanding of behavioral intention (Pratiwi, 2024). Overall, UTAUT2 provides a comprehensive framework for analyzing user adoption of new technologies.

Information accuracy

Public risk perception of technology is affected by several factors according to individual characteristics which include knowledge and trust as risk perception etiologies and cost as the risk perception factor (Li & Li, 2023). Following this trend, the same determinants in these studies, including self-efficacy, suspicion, and pleasure were identified as significantly associated to use modern technology in the policymakers demographic survey operations of Ghana (Ofosu-Ampong et al., 2023). The studies listed above reveal the multiple relationships involved in the adoption and perception of information technologies.

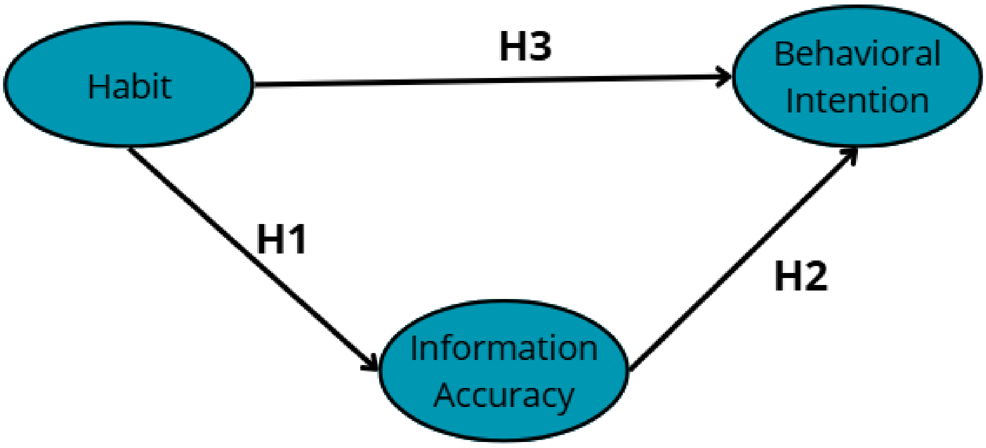

Figure 3. Research Framework
(Processed by the author)

H1. Habit positively influences the Information Accuracy.
H2. Information Accuracy positively influences the behavioral intention to use ChatGPT.
H3. Habit positively influences the behavioral intention to use ChatGPT.

Linked between Habit and Information accuracy

Habit significantly influences perceptions of information accuracy, often leading individuals to accept or share content without thorough evaluation. (Ceylan et al., 2023) highlight that social media's reward mechanisms encourage engagement-driven disinformation sharing, reducing concern for accuracy. (Rathje et al., 2022) suggest that motivation, rather than knowledge, plays a crucial role in distinguishing misinformation, with accuracy-driven individuals demonstrating improved discernment. (Sui & Zhang Citation, 2021) emphasize that beliefs of information aspect and source credibility impact credibility assessments but can be undermined by cognitive biases. (Druică et al., 2021) argue that habitual behaviors often override cognitive risk evaluations, while (Perceptions of Accuracy in Online News during the COVID-19 Pandemic, n.d.) note that young individuals tend to trust established news sources rather than critically verifying information.
H1. Habit positively influences the Information Accuracy.

Linked between Information accuracy and Behavioral Intention

The relationship between the credibility of information and behavioral intention in the UTAUT2 framework is elaborated on by many people who speak to user acceptance and the adoption of technology. Evidence exists that there are factors that largely affect behavioral

intention such as trust, perceived privacy risk, and information quality which proves that correct information increases the willingness of users to adopt and engage with technology (Palacios-Marqués et al., n.d.). The inclusion of trust in the UTAUT2 model has been shown to positively influence the willingness of users to continue using the applications, emphasizing the fundamentality of accurate information in maintaining the users (Arisona et al., n.d.). Also, studies indicate that other aspects such as the accuracy of information and the absence of risks to information are important factors determining behavioral intention and explain between 61% and 80% of the variation of behavioral intention. Therefore, accurate information is important for enhancing user trust and as a result, modifying behavioral intention in reference to the acceptance of technology.
H2. Information Accuracy positively influences the behavioral intention to use ChatGPT.

Linked between Habit and Behavioral Intention

The UTAUT2 model outlines the influence of habit and behavioral intention concerning technology adoption and defines habit as one of the key factors that influence an individual's intention toward the use of mobile payments, e-learning, fitness applications, and other technologies. It has been found that habitual behavior has a direct impact on behavioral intention and interacts with the construct's social influence and personal innovativeness, thus increasing the model's predictive power (Suo et al., 2021) (Raman & Thannimalai, n.d.). This suggests that habitual behavior should be taken into consideration because it has the potential to greatly influence user's perceptions and intentions toward the endorsement of new technologies (Widyanto et al., 2020).
H3. Habit positively influences the behavioral intention to use ChatGPT.

3. Research Method

Research Type

This study adopts a quantitative research approach, which employs scientific methods to generate numerical data and objective findings. Quantitative research agenda to validate domino effect relationships between variables through mathematical, computational, and statistical techniques. Characterized by accuracy and precision, it allows data to be categorized, ranked, and measured. Additionally, this approach facilitates result analysis by enabling data visualization through graphs and tables (Ahmad et al., 2019). This research implements a quantitative approach to define, predict, and command patterns through the structured set and analysis of numerical data. This deductive, objective, and outcome-oriented method ensures value-free results. Hypotheses are specific and testable, supported by a comprehensive literature review. With a sample of 129 respondents, findings can be generalized to broader populations. Standardized measurements and survey-based data collection enhance precision, consistency, and rigor. The systematic nature of quantitative research facilitates theory validation and contributes to evidence-based decision-making (Swanson & Holton III, n.d.).

Population

The term population in research refers to the fulfill set of individuals, objects, events, or units that share specific characteristics and are the focus of a study. It is a foundational concept in research because it defines the scope and context of the investigation, guaranteeing that the findings can be standardized to the targeted group (Shukla, 2020). This research uses a population of Peoples in Indonesia.

Sample

A sample is a representative subset of a population, enabling efficient data collection and analysis while ensuring generalizability. It reflects key population characteristics, making research more practical and cost-effective compared to studying an entire population. A well-selected sample, which is proportionate, unbiased, and diverse, enhances accuracy and reliability. Sampling methods are critical, with probability sampling ensuring objectivity and fairness by giving each unit an equal occasion of selection (Shukla, 2020).

Given the large and unknown population size, the minimum sample size was persistent using statistical techniques. A total of 129 respondents were selected based on an effect size of 0.15, α error odds of 0.05, and power of 0.95, calculated using the G-Power statistical application. Consequently, the least mandatory sample size for this study is 119 respondents (Ali Memon et al., 2020).

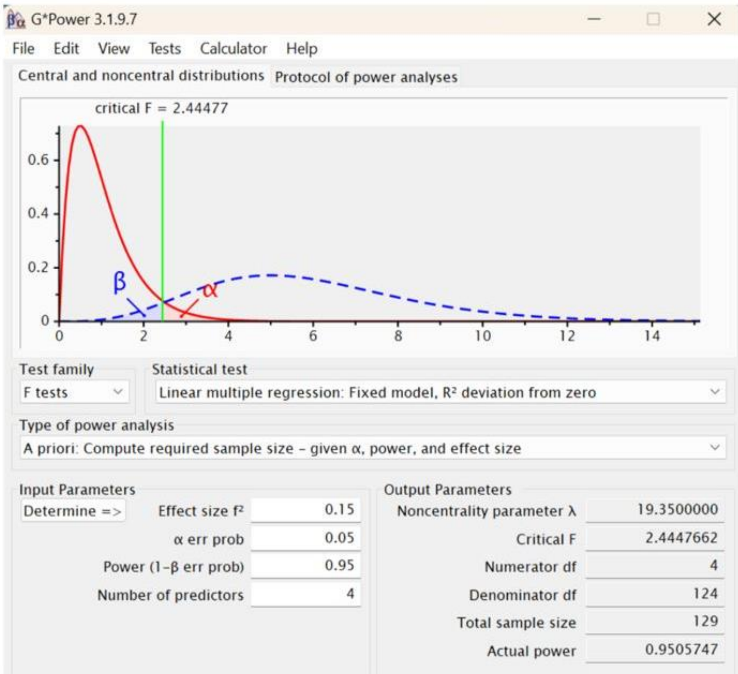

Figure 2. Power Image The analysis results from G*Power version 3.1.9.7.9 predictors.

The sample used in this study consists of at least 129 Peoples that use ChatGPT as a tool for learning in Indonesia. The sampling process was conducted using the Purposive Random Sampling technique.

This study adopts the model previously developed by (Foroughi et al., 2024), which focused on human-computer interaction in Malaysia. It aims to address research gaps, particularly by examining a different population.

Data Sources and Measurement Scales

Primary data refers to first-hand information collected directly by researchers through methods such as surveys, observations, experiments, and interviews, ensuring accuracy and relevance (Ajayi, n.d.). In this study, primary data was obtained via a structured questionnaire distributed to respondents.

Questionnaires are widely used in research due to their efficiency in collecting data from large and dispersed populations. They offer advantages such as cost-effectiveness, broad reach, anonymity, and minimized interviewer bias, leading to more reliable responses (Mazhar, 2021). This study employed a closed-ended questionnaire to ensure consistency and objectivity, enabling data analysis in Smart PLS. The questionnaire was developed based on expert-defined indicators and utilized the Likert Scale (1–5) to measure respondents' agreement levels.

The Likert scale is a widely used psychometric tool in social science and educational research to assess attitudes, opinions, and perceptions. Developed by Rensis Likert in 1932, it enables the quantification of qualitative judgments through a balanced scale ranging from "strongly disagree" to "strongly agree." Its primary advantage lies in converting subjective responses into numerical data, facilitating statistical analysis and comparison. The Likert scale is preferred for its simplicity, versatility, and ability to capture nuanced perspectives, enhancing data validity and reliability. Additionally, it supports statistical evaluations such as mean, standard deviation, and correlation. However, proper construction and interpretation are crucial to ensuring the accuracy of the measured attitudes (Joshi et al., 2015).

Tools

Partial Least Squares Structural Equation Modeling (PLS-SEM) is a statistical technique that combines factor analysis and regression to examine complex relationships between observed and latent variables. SmartPLS is a software tool designed to facilitate PLS-SEM analysis, providing a user-friendly interface for researchers to model and visualize these relationships. Researchers often choose SmartPLS for its ability to handle complex models with both reflective and formative constructs, accommodate small to medium sample sizes, and make minimal assumptions about data distribution, making it particularly useful when data do not adhere to a normal multivariate distribution(Khanthachai, 2014). The primary functions of SmartPLS include estimating path coefficients, assessing measurement models, and evaluating structural models, thereby enabling comprehensive analysis of theoretical frameworks and empirical data.

Variable

Table 3. Variable

Variable	Sources	Item
Habit	Farooq et al. (2017)	1. I often use chatbots. 2. I am used to using chatbots. 3. The use of chatbots is a habit for me.
Behavioral Intention	Venkatesh et al (2003) and Venkatesh et al (2012)	1. Assuming I had access to e-wallet, I intend to use it 2. Given that I had access to e-wallet, I predict that I would use it 3. I plan to use the e-wallet in the future 4. I recommend e-wallets to my colleagues
Information accuracy	Filieri and McLeay (2014)	1. The information I obtain from ChatGPT is correct. 2. The information I obtain from ChatGPT is accurate. 3. The information I obtain from ChatGPT is reliable.

Respondent Characteristic

Table 4. Respondent Characteristic

Gender	Qty	Percentage

Pria	54	41.86%
Wanita	75	58.14%
TOTAL	**129**	**100.00%**
Generasi	**Qty**	**Percentage**
Generasi Y (1980-1996)	33	25.58%
Generasi Z (1997-2012)	96	74.42%
TOTAL	**129**	**100.00%**
Pendidikan Saat Ini	**Qty**	**Percentage**
S1	79	61.2%
S2	29	22.5%
S3	1	0.8%
D1/D2/D3/ Pendidikan Profesi	3	2.4%
SMA dan yang setara	16	13.6%
TOTAL	**129**	**100.0%**
Domisili	**Qty**	**Percentage**
Jawa dan Bali	105	81.39%
Kalimantan dan Sulawesi	9	6.98%
Lombok dan Kepulauan NTB/NTT dan sekitarnya	2	1.55%
Papua, Kepulauan Maluku, Riau, Batam dan Kepulauan sekitarnya	2	1,56%
Sumatera	11	8.53%
TOTAL	**129**	**100.00%**

This study surveyed 129 participants, with females comprising 58.14% and males 41.86%. The majority (74.42%) were from Generation Z, while the rest (25.58%) were Generation Y. Most respondents were undergraduate students (61.2%), followed by postgraduates (22.5%), with smaller groups from doctoral, diploma, professional, and high school levels. Geographically, the largest portion resided in Java (76.74%), with fewer participants from Sumatra, Bali, Kalimantan, Sulawesi, Lombok and NTB/NTT, Papua and Maluku, and Riau and Batam. Overall, respondents were mainly young female undergraduates located in Java, favoring traditional classroom learning.

4. Result and Discussion

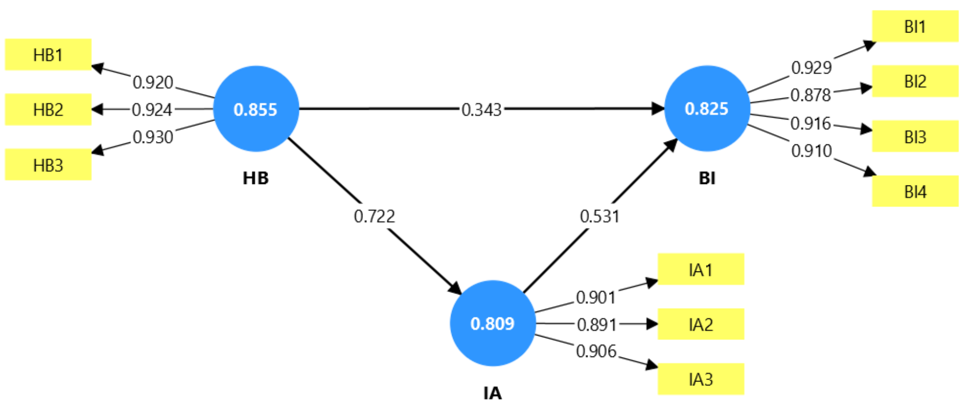

Figure 4.

Table 5. Convergent validity

Indicator	Outer loadings	AVE
Habit		

H1	0.92	0.855
H2	0.924	
H3	0.93	
Information Accuracy		
IA1	0.901	0.809
IA2	0.891	
IA3	0.906	
Behavioral Intention		
BI1	0.929	0.825
BI2	0.878	
BI3	0.916	
BI4	0.91	

Validity in research determines the extent to which a study accurately measures its intended concept, ensuring reliable and applicable conclusions. It must be assessed to confirm the credibility and generalizability of findings, preventing bias or misinterpretation. Key aspects of research validity include internal validity, which minimizes biases to establish cause-and-effect relationships, external validity, which ensures findings are applicable across different contexts, and model validity, which aligns research design with real-world applications.

In the context of Partial Least Squares Structural Equation Modeling (PLS-SEM), particularly when using the SMART PLS software, validity can be assessed through several indicators(Rasoolimanesh, n.d.-a). These include convergent validity, which is evaluated using the Average Variance Extracted (AVE) where a value above 0.5 is generally acceptable, and discriminant validity, which ensures that each construct is distinct from others, commonly assessed using the Fornell-Larcker criterion or the Heterotrait-Monotrait (HTMT) ratio(Cheung et al., 2024a) (Amora, 2021).

The results of the outer model analysis demonstrate that all indicators used to measure the constructs meet the recommended criteria for validity. For the Habit construct, the outer loading values range from 0.92 to 0.93, with an Average Variance Extracted (AVE) of 0.855, indicating a very good level of convergent validity. Similarly, the Information Accuracy construct has outer loadings between 0.891 and 0.906, with an AVE of 0.809. While most indicators show very good loading values, one indicator (IA2) is categorized as good. Nevertheless, the overall construct still demonstrates strong validity. The Behavioral Intention construct shows outer loadings between 0.878 and 0.929, and an AVE of 0.825, reflecting a very good measurement quality. These results confirm that all constructs are reliably measured, and the indicators used in the model are appropriate for further analysis.

Table 6. Discriminant validity

Validity Test Results Discriminant (Fornell Larcker)			
Construct	BI	HB	IA
BI	0.908	-	-
HB	0.726	0.925	-
IA	0.778	0.722	0.899

To assess discriminant validity, the Cross Loadings of each item must be compared to the loadings of other constructs. A higher value indicates stronger discriminant validity

(Cheung et al., 2024b). According to these criteria, the data meets the requirements for discriminant validity.

Table 7. HTMT Result

HTMT Result				
	BI	**HB**	**IA**	**Standard**
BI				<0.9
HB	0.786			<0.9
IA	0.856	0.799		<0.9

The table shows the Correlation Matrix as well as the HTMT value for the constructs investigated in this study. To make sure that the constructs in the model are different from one another, HTMT is a metric used to evaluate discriminant validity.

The table indicates that the HTMT value acceptable. Using predetermined standards for conceptually identical entities, some scholars propose a more relaxed threshold of HTMT < 0.90 (Gold et al., 2001)

Discriminant validity is confirmed because the HTMT value is below the 0.9, this suggests that there is no problem with multicollinearity across the study's constructs and that they are sufficiently different from one another. Although the HTMT value between Behavioral Intention (BI) and Individual Acceptance (IA) is 0.856 slightly approaching the commonly accepted threshold of 0.9 it is still considered acceptable due to the strong theoretical relationship between the two constructs. From a conceptual standpoint, individual acceptance is often a prerequisite for forming behavioral intention, which justifies a naturally high correlation between the two. Moreover, to address any potential concerns about discriminant validity, additional bootstrapping analysis was conducted. The results confirmed the stability of the model estimates, as all t-values for the structural paths were well above the 1.96 threshold (e.g., t = 7.329 for IA → BI), with p-values consistently below 0.001. Additionally, the original sample estimates were closely aligned with their corresponding bootstrapped means, and the confidence intervals did not cross zero, further supporting the robustness and consistency of the results. These findings provide empirical justification for retaining the constructs as theoretically and statistically distinct.

Table 8. Reliability

Reliability Test Results			
Construct	**Cronbach's Alpha**	**Composite Reliability**	**Standard**
BI	0.929	0.95	> 0.7
HB	0.915	0.947	> 0.7
IA	0.882	0.927	> 0.7

Reliability in research refers to the consistency and stability of a measurement instrument under the same conditions. A reliable instrument produces similar results across repeated measurements, enhancing the credibility of research findings by minimizing errors and random fluctuations. High reliability ensures reproducibility, allowing other researchers to achieve consistent outcomes using the same methodology

In research, reliability refers to the consistency and stability of a measurement over time(Rasoolimanesh, n.d.-b). It indicates the extent to which an instrument yields the same results under consistent conditions. Reliability is important because it ensures that the data collected are dependable and can be replicated across different studies or samples. In the context of SMART PLS-SEM (Partial Least Squares Structural Equation Modeling), reliability is typically assessed at two levels, indicator reliability and internal consistency reliability. Indicator reliability is measured through factor loadings, where values above 0.7 are considered acceptable(Hair et al., 2017). Internal consistency is commonly evaluated using Composite Reliability (CR) and Cronbach's Alpha, where values above 0.7 also indicate good reliability. To achieve reliability in SMART PLS-SEM, researchers must ensure that the indicators consistently reflect the constructs they are intended to measure, and they can confirm this using the statistical output provided by the software after running the model(Henseler et al., 2009).

Results of Inner Model Analysis

Table 8. Coefficient of Determination (R2) & Cross-Validated Redundancy Test Results (Q2)

Construct	R^2	Adjusted R^2	Q^2
BI	0.662	0.656	0.517
IA	0.521	0.517	0.514

Based on the PLS Predict results, the Q^2 predictive values for the constructs Behavioral Intention (BI) and Information Accuracy (IA) are 0.517 and 0.514, respectively. These values exceed the threshold of 0.35, indicating that the model possesses strong predictive relevance for both constructs. According to(Kante & Michel, 2023), Q^2 values greater than 0.35 suggest substantial predictive accuracy, values between 0.15 and 0.35 indicate moderate predictive relevance, and values between 0.02 and 0.15 reflect weak predictive relevance. Therefore, the obtained Q^2 values confirm that the model has a robust capability to predict outcomes related to Behavioral Intention and Information Accuracy.

This interpretation aligns with the guidelines provided by (Kante & Michel, 2023) in their comprehensive work on Partial Least Squares Structural Equation Modeling (PLS-SEM), where they emphasize the importance of Q^2 values in assessing the predictive relevance of a model. For a detailed understanding, you can refer to their publication, which is accessible at

Table 9. Effect Size Test Results (F2)

F-TEST		
Connection	f^2	Rank Influence
HB → BI	0.166	Small effect ($f^2 \geq 0.02$)
HB → IA	1.086	Big effect ($f^2 \geq 0.35$)
IA → BI	0.399	Medium effect ($f^2 \geq 0.15$)

The results of the F-test (effect size analysis) reveal that Habit (HB) has a small effect on Behavioral Intention (BI) with an f^2 value of 0.166, which exceeds the minimum threshold of 0.02(Cohen, n.d.). Meanwhile, the influence of Habit (HB) on Information Accuracy (IA) shows a large effect size, with an f^2 value of 1.086, surpassing the 0.35 cutoff for a strong effect. Furthermore, Information Accuracy (IA) has a medium effect on Behavioral Intention (BI), with an f^2 value of 0.399, which is above the 0.15 benchmark. These results indicate that while HB moderately contributes to BI, its influence on IA is substantial, and IA plays a crucial mediating role in shaping BI.

Table 10. Path Coefficients

Hypothesis	Relationship	Original Sample (β)	t-value*	p-value	Result
H1	HB → BI	0.343	4.752	<0.001	Accepted
H2	HB → IA	0.722	12.861	<0.001	Accepted
H3	IA → BI	0.531	7.329	<0.001	Accepted

The first hypothesis (H1), which proposed a relationship between Habit (HB) and Behavioral Intention (BI), is supported with a path coefficient (β) of 0.343, a t-value of 4.752, and a p-value of less than 0.001. This indicates a positive and statistically significant effect of habit on behavioral intention.

The second hypothesis (H2) suggested that Habit (HB) has an effect on Innovation Adoption (IA). This hypothesis is strongly supported with a high path coefficient (β = 0.722), a t-value of 12.861, and a p-value of less than 0.001, indicating a very significant and positive effect of habit on innovation adoption.

The third hypothesis (H3) proposed that Innovation Adoption (IA) affects Behavioral Intention (BI). This relationship is also supported, with a path coefficient of 0.531, a t-value of 7.329, and a p-value of less than 0.001, showing a positive and significant effect of innovation adoption on behavioral intention.

These results confirm the proposed relationships, suggesting that habit plays a key role in influencing both innovation adoption and behavioral intention, and that innovation adoption also significantly contributes to behavioral intention.

Habit and behavioral Intention

In the context of technology adoption, habit plays a crucial role in influencing an individual's decision to continue using a system. Habit is not merely the repetition of actions, but rather a behavioral automation mechanism formed through consistent learning and experience. In this study, habit is defined as the user's tendency to routinely use ChatGPT in various activities, both in work and learning environments. When usage behavior is repeated and results in pleasant or facilitating experiences, individuals tend to no longer consciously consider the benefits or barriers of the system. Instead, they are naturally driven to continue using the technology as it becomes part of their routine.

From a psychological perspective, habit also reduces cognitive load in the decision-making process. In other words, a person no longer needs to re-evaluate each time they want to use ChatGPT. This leads to increased efficiency, speed, and comfort in interacting with the technology. Over time, this habit strengthens behavioral intention as users develop emotional and functional attachment to ChatGPT. They feel "accustomed" and "comfortable," making the intention to switch to another technology increasingly unlikely.

The findings of this study reveal that Habit has a positive and significant influence on Behavioral Intention in the context of ChatGPT usage among users. This is evidenced by the path coefficient (β) value of 0.232, with a t-statistic of 3.521 and a p-value of 0.000, which is well below the significance threshold of 0.05. These results suggest that the more individuals become accustomed to using ChatGPT in their daily routines, the stronger their intention to continue using the tool in the future. This aligns with the theory that habit, as a learned automatic behavior, reinforces one's future behavior by reducing the cognitive effort required to make a decision. In other words, users who repeatedly engage with ChatGPT tend to develop a habitual pattern that strengthens their behavioral intention. This supports prior research within the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) framework, which consistently identifies habit as a crucial determinant of continued technology adoption. Consequently, fostering habitual use through repeated exposure and seamless user experience may be a key strategy in promoting long-term engagement with AI-based tools like ChatGPT.

For AI system developers like ChatGPT, it is important to realize that habit formation cannot happen instantly. It requires intuitive interaction design, consistent user experience, and system reliability to keep users engaged in repeated use. Additionally, reinforcing habits through features such as personalization, fast responses, and ease of access will accelerate the internalization of the technology as part of the user's daily life. Thus, habit becomes not only a predictor of behavior, but also a foundation for building a long-term relationship between users and technology.

Habit and Information Accuracy

The relationship between habit and the perception of information accuracy is an intriguing dynamic to analyze, especially in the context of using AI-based technologies such as ChatGPT. When a person becomes accustomed to consistently using a system, their perception of the output quality also tends to shift in line with that habitual pattern. In this case, users who have developed a habit of using ChatGPT are more likely to trust the information provided by the system, as they have built a high level of familiarity with its workings, language style, and the structure of its responses. This phenomenon can be explained through the process of cognitive adaptation, where consistent repeated experiences create an implicit sense of trust. Even if the system may have potential errors or biases, habitual users tend to overlook these shortcomings because they psychologically feel comfortable and secure relying on the technology. Trust in the accuracy of information is no longer built solely on an objective evaluation of content, but also on the relationship shaped through repeated usage experiences. This, of course, can be a double-edged sword, on one hand, it strengthens user loyalty to the technology, but on the other hand, it may diminish critical thinking skills in filtering information.

The results of the study indicate that Habit exerts a strong and significant positive effect on Information Accuracy in the context of ChatGPT utilization. The path coefficient (β) of 0.722, with a t-value of 12.861 and a p-value < 0.001, provides robust statistical evidence supporting this relationship. This suggests that individuals who frequently and habitually use ChatGPT are more likely to perceive the information it provides as accurate and reliable. The formation of habit enhances familiarity with the system's responses, which can lead users to trust and accept the information without rigorous evaluation. This phenomenon is consistent with previous findings by (Ceylan et al., 2023), who argue that habitual digital behavior often leads individuals to rely on system outputs automatically, sometimes bypassing critical thinking processes. Moreover, (Druică et al., 2021) emphasize that habits can override cognitive assessments, making users less skeptical of the information provided. Therefore, the strong link between Habit and Information Accuracy in this study underscores the psychological impact of repetitive usage in shaping users' perceptions of information reliability. These findings are particularly relevant for AI platforms like ChatGPT, where consistent interaction may not only foster dependency but also shape beliefs about content credibility.

In the context of technology development, this understanding is crucial. Developers need to realize that building a perception of accuracy is not only about presenting technically correct data, but also about creating a user experience that supports the formation of positive habits. For instance, by ensuring consistent response quality, transparency of information sources, and an interface that fosters active user engagement. When habits are built on a foundation of high-quality information, the perception of accuracy will develop naturally and contribute to the sustained use of the technology.

Information Accuracy and Behavioral Intention

Perception of information accuracy is one of the key determinants in shaping users' behavioral intention toward an information-based system, including in the context of ChatGPT usage. In decision-making processes, especially those involving digital information, individuals heavily rely on the belief that the information they receive is accurate, trustworthy, and relevant to their needs. When a system consistently delivers information perceived as accurate, users are more likely to build trust in the system. This trust then evolves into a sustained intention to continue using the technology.

In the context of ChatGPT, the perception of information accuracy becomes increasingly critical, as the platform is used for various purposes ranging from academic tasks and professional document writing to workplace decision-making. If the information provided is perceived as doubtful or frequently inaccurate, users' intention to rely on the platform will significantly decrease. Conversely, when users feel that the information is consistently relevant, prompt, and insightful, their intention to continue using the system strengthens and may even develop into a positive dependence on the technology.

However, this perception is highly dependent on users' subjective experiences. Two individuals receiving the same information may interpret its accuracy differently based on their expectations, objectives, and level of digital literacy. Therefore, the challenge for AI system developers lies in creating effective feedback mechanisms and personalized content delivery that align with users' characteristics. When perceptions of accuracy are managed strategically, the resulting behavioral intention becomes stronger and more stable. In the long run, this not only promotes continued use but also fosters user loyalty, ultimately contributing to the growth and sustainability of the technology in today's digital society.

The findings of this study demonstrate that Information Accuracy has a positive and significant influence on Behavioral Intention to use ChatGPT. This is supported by the path coefficient (β) of 0.531, a t-value of 7.329, and a p-value < 0.001, indicating a strong statistical relationship. Users who perceive the information provided by ChatGPT as accurate are more inclined to continue using the platform. This supports the notion that trust in information quality directly shapes technology adoption decisions. As outlined in the extended UTAUT2 framework, accurate and reliable content strengthens user confidence and reduces uncertainty, which in turn enhances behavioral intention. This is further corroborated by research from (Palacios-Marqués et al., n.d.) and (Arisona et al., n.d.), who found that credibility and trust in AI-generated information are pivotal drivers of users' willingness to adopt technology. In high-stakes environments such as education or professional settings, the accuracy of information becomes even more critical, as it directly impacts decision-making outcomes. Thus, this study reinforces the argument that maintaining and enhancing the perceived accuracy of AI systems like ChatGPT is essential for fostering long-term user engagement and acceptance.

5. Conclusion

The relationship between habitual usage and the perception of information accuracy presents a compelling narrative for understanding how modern users interact with AI-based platforms such as ChatGPT. This study affirms that when users engage consistently with a system, they tend to build a psychological familiarity that shapes their trust in the output. As habits form and deepen, users become more receptive to the information presented, often evaluating its reliability less on objective scrutiny and more on the comfort and confidence developed through repeated exposure. While this reinforces behavioral continuity and user loyalty, it also positions habit as a subtle yet powerful factor in shaping users' cognitive processing of information. When these habits are anchored in experiences of receiving helpful and relevant content, ChatGPT evolves from a mere tool into a trusted informational assistant.

This trust, in turn, becomes the cornerstone of behavioral intention. As demonstrated in the study, users who perceive ChatGPT's information as accurate are more likely to continue using the platform. This behavior reflects the broader benefit that AI systems like ChatGPT offer streamlined access to reliable, actionable, and contextually relevant information. For users in academic, professional, and organizational settings, this translates to improved efficiency, enhanced decision-making, and reduced cognitive load. Users no longer need to sift through vast sources of data manually, ChatGPT distills complex topics into digestible insights, fostering confidence and accelerating task completion.

Moreover, when the platform consistently meets expectations, users form positive digital habits that support knowledge acquisition and self-reliance. This habit-information-intention loop becomes a self-reinforcing cycle that sustains long-term engagement. However, this also presents a responsibility for developers to design systems that prioritize not just technical correctness, but user-oriented experiences ensuring transparency, personalization, and ongoing quality assurance.

In essence, ChatGPT's strength lies not only in what it provides, but in how users experience and internalize that information over time. When habit and accuracy align, the result is not only sustained usage, but also a deeper integration of AI into human decision-making, learning, and professional productivity. This is the true potential and responsibility of intelligent systems in shaping the future of work and knowledge.

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