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KEY DRIVERS OF CHATGPT ADOPTION: MANAGERIAL PERSPECTIVE FROM INDONESIAN COMMUNITIES

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A R T I C L E I N F O

Keyword: *ChatGPT, Behavioral Intention, UTAUT, Gen Z, Gen Y*

Kata Kunci: ChatGPT, Niat Perilaku, UTAUT, Gen Z, Gen Y

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Abstract. The swift progression of AI technology and the growing utilization of ChatGPT in Indonesia highlight the necessity of comprehending its integration within many circles. This study aims to examine the factors influencing the intention to use ChatGPT technology, focusing on three key components of the Unified Theory of Acceptance and Use of Technology (UTAUT), such as Performance Expectancy, Effort Expectancy, and Social Influence. Utilizing a quantitative research approach, data were gathered by purposive sampling through an online survey targeting Gen Y and Z in Indonesia. The sample size was established utilizing the G*Power tool to guarantee a rigorous examination. Partial Least Squares (PLS) analysis was utilized to investigate the correlations between the indicated parameters and adoption intentions. The results offer significant insights into the dynamics of technology acceptability in educational and business settings, highlighting the interaction among performance expectancy, effort expectancy, and social influence. These results enhance the scientific finding in technology adoption and guide developers and policymakers in optimizing ChatGPT incorporation within academic and or business environments.

Abstrak. Pesatnya perkembangan teknologi AI dan meningkatnya penggunaan ChatGPT di Indonesia menunjukkan perlunya pemahaman tentang integrasinya dalam berbagai kalangan. Penelitian ini bertujuan untuk meneliti faktor-faktor yang memengaruhi niat untuk menggunakan teknologi ChatGPT, dengan fokus pada tiga komponen utama Unified Theory of Acceptance and Use of Technology (UTAUT), seperti Performance Expectancy, Effort Expectancy, dan Social Influence. Dengan menggunakan pendekatan penelitian kuantitatif, data dikumpulkan dengan purposive sampling melalui survei daring yang menargetkan Gen Y dan Z di Indonesia. Ukuran sampel ditetapkan dengan menggunakan perangkat G*Power untuk menjamin pemeriksaan yang ketat. Analisis Partial Least Squares (PLS) digunakan untuk menyelidiki korelasi antara parameter yang ditunjukkan dan niat adopsi. Hasilnya menawarkan wawasan yang signifikan tentang dinamika penerimaan teknologi dalam lingkungan pendidikan dan bisnis, dengan menyoroti interaksi antara ekspektasi kinerja, ekspektasi upaya, dan pengaruh sosial. Hasil ini meningkatkan temuan ilmiah dalam adopsi teknologi dan memandu pengembang dan pembuat kebijakan dalam mengoptimalkan penggabungan ChatGPT dalam lingkungan akademis dan atau bisnis.

INTRODUCTION

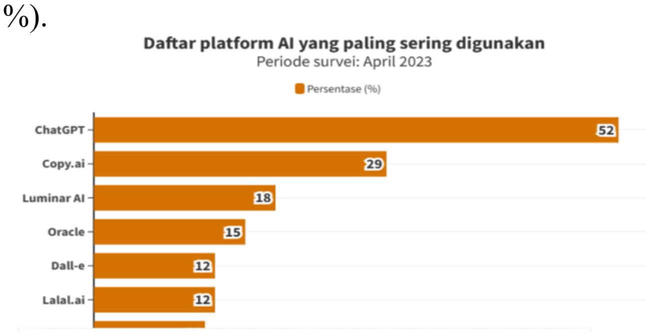
Artificial Intelligence (AI) that has developed over the past decade is a transformational technology with great potential to enhance learning outcomes and training methods, as well as boost work efficiency within organizations, although there are concerns about its misuse in its application (Yahaya et al., 2024). AI-based solutions like ChatGPT can enhance the learning experience and educational process (Kuhail et al., 2023). ChatGPT, being an AI-driven chatbot, is proficient in responding to inquiries, offering elucidations, and aiding students. (Pillai, 2023). Preliminary studies indicate that ChatGPT can improve teaching and learning methods, and serve as a prospective framework for automating essay and scientific document creation (Lund et al., 2023; Taecharungroj, 2023). ChatGPT users in Indonesia have reached millions in a short period. As of March 2024, Indonesia ranks third in ChatGPT users, after the United States and India.

Rank	Country	Proportion of ChatGPT Users
1	US	12.22%
2	India	10.71%
3	Indonesia	9.02%
4	Brazil	8.88%
5	UK	2.77%
-	Others (combined)	56.40%

Picture 1. List of ChatGPT User Countries

Source: explodingtopics, 2024

The research platform Populix reports that nearly half (45%) of internet users in Indonesia use AI applications to enhance their work effectiveness and productivity. ChatGPT has become the most favored AI platform with 52% of respondents (Populix, 2023). As preliminary study from Populix sources the majority of respondents are from Java Island (76%), followed by Sumatra Island (14%), and other islands (10%). The respondents range in age from 17 to 55 years, with a predominance of individuals aged 17 to 25 years (51%), followed by those aged 26 to 35 years (33%).



Picture 2. List of the most commonly used AI platforms

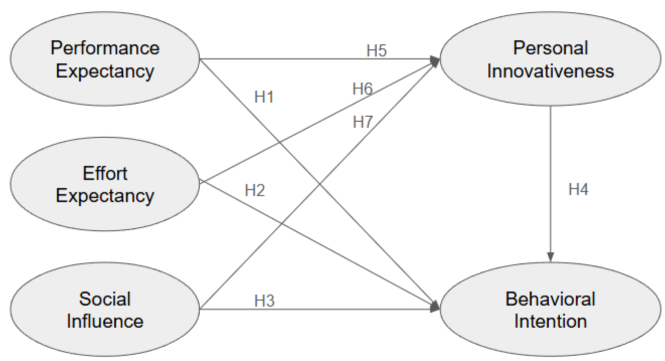
Source: Populix, 2023

The proliferation of AI in pedagogy harbors the potential to recalibrate the didactic landscape and reconfigure the functions of all constituencies engaged (Becker, 2018). The misuse of AI in education refers to the improper application or use of AI technology. Some examples of AI misuse in education include the dehumanization of learning, data privacy violations, plagiarism, bias, unemployment, and excessive reliance on technology (Oxford University Press, 2024).

Plagiarism in education is increasingly being scrutinized due to the presence of generative AI systems, which enable academic communities to use this technology to complete tasks without acknowledging its assistance (Becker, 2018). Excessive reliance on AI is also feared to reduce the ability of the academic community to think critically and independently, as they might only depend on the answers provided by AI (Seldon & Abidoye, 2018). Critical thinking skills are very important, but they may be threatened if the academic community does not actively engage in the learning process.

Different from those ethical problems in education, this research exist to examine variables related with intention to use AI for many purposes. Using the Utilize the UTAUT (Unified Theory of Acceptance and Use of Technology) to examine the determinants affecting consumers' intentions to adopt technology. The UTAUT framework encompasses performance expectancy, effort expectancy, and social influence. This research aims to evaluate the factors influencing the intents of the Gen Y and Z communities to utilize ChatGPT by proposing the research topic "Key Drivers of ChatGPT Adoption: Managerial Perspective from Indonesian Communities"

Hypothesis Development



Picture 3. Research Framework Modified UTAUT model

Source: processed by the researcher, 2024

Performance Expectancy *(PE)*

The extent of an individual's cognitive conviction that the utilization of a specified system or technological framework will amplify their vocational efficacy is denominated as performance expectancy. It is a pivotal component affecting the uptake and utilization of technology across diverse sectors. Performance expectancy directly influences user behavior and the intention to utilize technology.

Performance expectancy significantly affects behavioral intention, hence impacting user behavior (Suyanto et al., 2024). The correlation between performance expectancy and the intention to utilize ChatGPT is a vital aspect of study in technology adoption models. Performance expectancy denotes the degree to which an individual expects that utilizing a technological equipment would improve their work efficiency. This conviction is a fundamental factor influencing behavioral intention, reflecting the user's motivation to interact with the technology. The research papers analyze this connection across many contexts, highlighting its importance in the utilization of ChatGPT.

Performance expectancy is generally recognised as a crucial predictor of the behavioral intention to use ChatGPT. Research indicates that users who view ChatGPT as a means to improve efficiency and complete tasks are more inclined to intend to utilize it (Benard et al., 2024; Mehedi & Emon, 2023).

Strzelecki's study revealed that performance expectancy significantly influences behavioral intention, ranking only below habit, hence demonstrating its considerable effect on students' acceptance of ChatGPT in higher education (Strzelecki, 2024). Camilleri's research underscores that the trustworthiness and perceived interactivity of ChatGPT substantially impact performance expectancy, thus affecting behavioral intention. This indicates that users' confidence in the technology and its interactive features elevates their performance expectations (Camilleri, 2024).

H_1: PE positively influences behavioral intention to use ChatGPT.

Effort Expectancy *(EE)*

Effort expectancy, denoting the perceived simplicity of utilizing a technology, significantly influences behavioral intentions for the adoption of ChatGPT, however its effect differs across various situations. Related to Gen Y and Z characteristics, focusing on high expectancy is typically regarded as a favorable factor influencing the desire to utilize ChatGPT, indicating that users perceive the tool as user-friendly and easily integrable into their activities.

In a study of Vietnamese students, effort expectancy was shown to directly and positively influence the intention to utilize ChatGPT, indicating that students who perceive the tool as user-friendly are more inclined to use it for educational purposes (Duong et al., 2024). Business professionals in Bangladesh demonstrated that effort expectancy strongly affects adoption intention, suggesting that a reduced perception of the work required to utilize ChatGPT increases the possibility of its adoption (Mehedi & Emon, 2023). For marketing staff, effort expectancy emerged as a strong predictor of behavioral intention, following habit and performance expectancy, underscoring its relevance in the decision-making process for adopting ChatGPT (Gulati et al., 2024).

H_2: EE positively influences behavioral intention to use ChatGPT.

Social Influence (SI)

The association between social impact and the intention to utilize ChatGPT is a crucial element in diverse circumstances, as demonstrated by numerous studies. Social influence, denoting the impact of individuals or groups on a person's behavior, is important in determining the desire to utilize ChatGPT for many applications, including education, money value, and language acquisition. This impact is frequently facilitated by subjective standards and perceived social pressure, which might compel users to embrace new technologies such as ChatGPT.

Social influence profoundly affects students' propensity to utilize ChatGPT. The application of the Unified Theory of Acceptance and Use of Technology (UTAUT) model illustrates that social influence is a pivotal aspect, alongside performance expectancy and personal innovativeness (Sabeh, 2024). Subjective norms, which are a sort of social influence, favorably affect people's behavioral intentions to utilize ChatGPT. This is a component of the Theory of Planned Behaviour framework, which additionally accounts for attitudes and perceived behavioral control (Lee et al., 2024).

H_3: SI positively impacts behavioral intention to use ChatGPT.

Personal Innovativeness (PI)

Personal innovativeness is essential for technology acceptance in diverse industries such as education, hospitality, tourism and many creative job in many industries. It profoundly impacts individuals' intentions to adopt and persist in utilizing new technologies by shaping their perceptions of utility and usability.

Personal innovativeness markedly affects behavioral intention, especially with the adoption of new technologies such as ChatGPT. This relationship is demonstrated in numerous research, which indicate that personal innovativeness can improve evaluations of technology's utility and user-friendliness, thereby elevating the probability of its adoption (C.-W. Kim, 2024; H. J. Kim & Oh, 2023). Higher innovativeness reinforces these beliefs, leading to a larger inclination to adopt ChatGPT (C.-W. Kim, 2024).

Performance expectancy profoundly affects personal innovativeness regarding AI usage, as it molds users' opinions of the tool's utility and efficacy. This link is essential in ascertaining how individuals, especially students, utilize ChatGPT for many objectives (Duong et al., 2024; Kishen et al., 2024).

Effort expectancy, a crucial determinant in technology adoption, profoundly impacts individual innovativeness in utilizing AI. This relationship is especially apparent in some environments, where user-friendliness can motivate people to investigate and utilize new technologies such as ChatGPT for many objectives.

Social influence significantly impacts human innovativeness, especially regarding technology uptake. The interplay between social influence and personal innovativeness can shape individuals' perceptions and adoption of new technologies, including ChatGPT. Knowledge and perceived enjoyment may surpass social influence in influencing the adoption of AI tools such as ChatGPT (Abdalla, 2024). This underscores the necessity for a sophisticated comprehension of the interplay between social dynamics and individual characteristics in shaping technology adoption.

H_4: PI positively influences BI to use ChatGPT.

H_5: PE positively influences PI in using ChatGPT.

H_6: EE positively influences PI in using ChatGPT

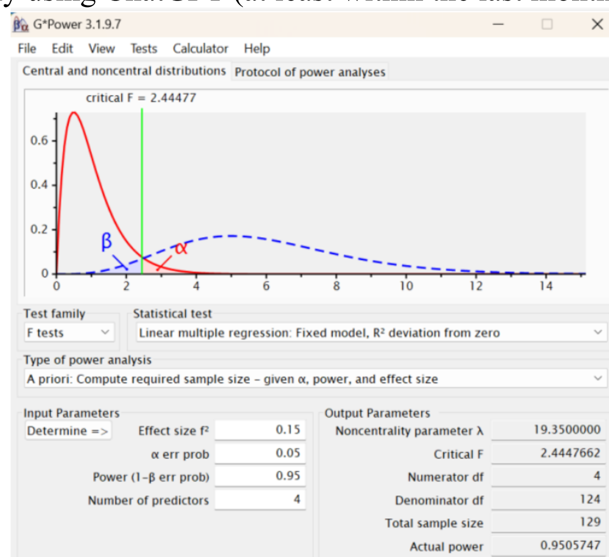
H_7: SI positively influences PI in adopting ChatGPT

Behavioral Intention (BI)

The Unified Theory of Acceptance and Use of Technology (UTAUT) model serves as a prevalent framework for comprehending behavioral intentions around technology adoption. Influenced by various factors such as performance expectancy, effort expectancy, social influence, and facilitating environments, behavioral intention serves as a key component in these models. These models have been utilized in several contexts, such as healthcare, social media, e-learning, and online gaming, to forecast and examine user intents and behaviors. The UTAUT models offer a comprehensive framework for comprehending behavioral intention; nonetheless, it is essential to account for context-specific elements and cultural nuances that may affect technology uptake. Perceived trust and conducive conditions may fluctuate in significance across various areas and user demographics, influencing the generalizability of the model's predictions (Ngusie et al., 2024).

RESEARCH METHODS

This study utilizes a survey methodology with a quantitative framework. Data was gathered via questionnaires, employing a non-probability sample strategy with a purposive sampling technique. The survey took place from September 5 to November 6, 2024. The collected data was gathered through questionnaires distributed to the respondents. This study's demographic comprises Indonesian Generation Y (1980-1996) and Generation Z (1997-2012) individuals who have used or are currently using ChatGPT (at least within the last month).



Picture 4. Result of G*Power 3.1.9.7

Source: Processed by Researcher, 2024

Researchers will take samples from Indonesian Generation Y (1980-1996) and Generation Z (1997-2012) individuals who live in Java, Bali, Kalimantan, Lombok and the NTB/NTT Islands and surrounding areas, Papua and the Maluku Islands, Riau, Batam and the surrounding Islands, Sulawesi, Sumatra. Based on the G*Power calculation version 3.1.9.7 with an effect size f2 of 0.15, an error of 0.05, a power of 0.95, and 4 predictors, a minimum of 129 samples were collected (Memon & Ting, 2020).

Adopting the model previously conducted by (Foroughi et al., 2023) with a study unit focused on human-computer interaction in Malaysia, this research aims to address the research gap, particularly in different populations.

Table 1. Variable Operational Definitions

Variable	Original Items
Performance expectancy	Utilizing ChatGPT would enable me to do things more efficiently.
Abdullah et al. (2016)	Utilizing ChatGPT would enhance my performance.
	Utilizing ChatGPT would enhance my productivity.
	Utilizing ChatGPT would augment my efficacy.
	Utilizing ChatGPT would facilitate my work.
	I consider ChatGPT to be beneficial.
Effort expectancy	Acquiring proficiency in utilizing ChatGPT is straightforward for me.
Nikolopoulou et al. (2021)	My engagement with ChatGPT is lucid and uncomplicated.
	I consider ChatGPT user-friendly.
	I find it effortless to attain proficiency in utilizing ChatGPT.
Social influence	Individuals of significance in my life believe I ought to utilize ChatGPT.
Rudhumbu, (2022)	Individuals that impact my conduct believe I ought to utilize ChatGPT.
	Individuals whose opinions I regard highly recommend that I utilize ChatGPT for my academic pursuits.
Personal innovativeness	I enjoy experimenting with new information technology.
Nikou & Economides (2017)	Upon discovering a new information technology, I would seek opportunities to play with it.
	I typically take the initiative to explore new information technology.
Behavioral Intention	I indent to utilize ChatGPT in the future.
Nikou & Economides (2017)	I plan to utilize ChatGPT in the future.
	I anticipate utilizing ChatGPT in the future.

Source: Processed Data (2024)

The data was subsequently evaluated utilizing SEM-PLS with the SmartPLS program version 3.3.3, encompassing three phases of the testing procedure including outer model, inner model, and hypothesis.

RESULTS AND DISCUSSION

Table 2. Respondent Characteristic

Gender		
Item	Qty	Percentage
Pria	54	41.86%
Wanita	75	58.14%
TOTAL	**129**	100.00%
Generasi		
Item	Qty	Percentage
Generasi Y (1980-1996)	33	25.58%
Generasi Z (1997-2012)	96	74.42%
TOTAL	**129**	100.00%
Pendidikan Saat Ini		
Item	Qty	Percentage
S1	79	61.2%
S2	29	22.5%
S3	1	0.8%
D1/D2/D3	1	0.8%
Pendidikan Profesi	2	1.6%
SMA dan yang setara	16	12.4%
SMP dan yang setara	1	0.8%
TOTAL	129	100.0%
Domisili		
Item	Qty	Percentage
Jawa	99	76.74%
Bali	6	4.65%
Kalimantan	4	3.10%
Lombok dan Kepulauan NTB/NTT dan sekitarnya	2	1.55%
Papua dan Kepulauan Maluku	1	0.78%
Riau, Batam dan Kepulauan sekitarnya	1	0.78%
Sulawesi	5	3.88%
Sumatera	11	8.53%
TOTAL	**129**	**100.00%**

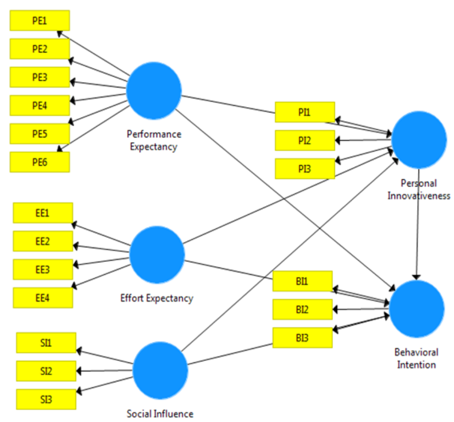
Source: data collected from respondent, 2024

The respondents in this study consist of 129 individuals, with a majority being female (58.14%) and the remaining 41.86% male. Most of the respondents belong to Generation Z (74.42%), while 25.58% are from Generation Y. In terms of education level, the majority are undergraduate students (61.2%), followed by postgraduate students (22.5%), with smaller percentages representing doctoral, diploma, professional education, and high school levels.

Geographically, most respondents are domiciled in Java (76.74%), with smaller proportions residing in Sumatra (8.53%), Bali (4.65%), Kalimantan (3.10%), Sulawesi (3.88%), and minimal representation from Lombok and NTB/NTT, Papua and Maluku, as well as Riau and Batam.

Overall, the respondents are predominantly female, from Generation Z, and pursuing undergraduate education. They primarily favor traditional in-class learning and are concentrated in Java, reflecting the characteristics of a youthful academic community within a highly populated region.

MODEL SPECIFICATION



Picture 5. Research Framework

Source: SmartPLS, 2024

From picture 5, it is concluded that the researcher intends to develop the concept through the model, in the hope of achieving several desired outcomes, including:

1) The influence of Performance Expectancy on Behavioral Intention

2) The influence of Effort Expectancy on Behavioral Intention

3) The influence of Social Influence on Behavioral Intention

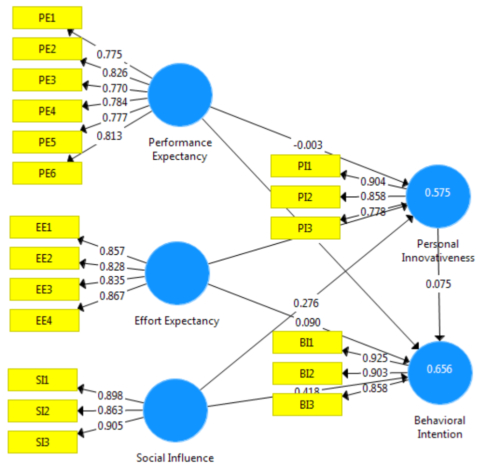
4) The influence of Personal Innovativeness on Behavioral Intention

5) The influence of Performance Expectancy on Personal Innovativeness

6) The influence of Effort Expectancy on Personal Innovativeness

7) The influence of Social Influence on Personal Innovativeness

OUTER MODEL ANALYSIS



Picture 6. Outer Model Analysis

Source: SmartPLS

1. Convergent validity

Table 3. Results of Convergent Validity Test

Indicator	Outer Loading
Performance Expectancy (X1)	
PE1	0.775
PE2	0.826
PE3	0.770
PE4	0.784
PE5	0.777
PE6	0.813
Effort Expectancy (X2)	
EE1	0.857
EE2	0.828
EE3	0.835
EE4	0.867
Social Influence (X3)	
SI1	0.898
SI2	0.863
SI3	0.905
Personal Innovativeness (Z)	
PI1	0.904

Source : Processed by the researcher, 2024

This research employed a 5-point Likert scale and was analyzed by Partial Least Squares Structural Equation Modeling (PLS-SEM). Table 3 presents the results of the exterior loading investigation. As stated by Hair et al. (2021), convergent validity is attained when each item possesses an outer loading greater than 0.70. These data indicate that all indicators accurately assess their designated constructs.

2. Discriminant validity

Table 4. Validity Test Results Discriminant (Fornell Larcker)

	Behavioral Intention	Effort Expectancy	Performance Expectancy	Personal Innovativeness	Social Influence
Behavioral Intention	0.895				
Effort Expectancy	0.655	0.847			
Performance Expectancy	0.739	0.789	0.791		
Personal Innovativeness	0.603	0.727	0.635	0.848	
Social Influence	0.749	0.612	0.712	0.616	0.889

Source: Processed by the researcher, 2024

The requirement for the discrimination validity test is to compare the Cross Loadings value with the loading value of other constructs. Higher scores indicate better validity of discrimination (Hair et al., 2014). Based on this criterion, it can be concluded that the validity of the discrimination has been met.

Table 5. HTMT Result

	Behavioral Intention	Effort Expectancy	Performance Expectancy	Personal Innovativeness
Behavioral Intention				
Effort Expectancy	0.748			
Performance Expectancy	0.832	0.897		
Personal Innovativeness	0.707	0.852	0.734	
Social Influence	0.860	0.703	0.804	0.735

Source: Processed by the researcher, 2024

Heterotrait-Monotrait Ratio (HTMT) is a measure to assess discrimination between constructs in Structural Equation Modeling (SEM) models. HTMT values lower than one indicate that the compared constructs are conceptually separate, meaning they measure different aspects of the phenomenon under study.

The HTMT values indicate sufficient discriminant validity among the constructs. Effort Expectancy on Behavioral Intention (0.748) demonstrates a negligible connection, affirming conceptual differentiation. Likewise, Performance Expectancy on Behavioral Intention (0.832) indicates adequate discriminant validity, exhibiting a moderate yet acceptable correlation. Meanwhile, Performance Expectancy in relation to Effort Expectancy (0.897) demonstrates a robust correlation, approaching the 0.90 criterion while still adhering to acceptable validity, necessitating further theoretical substantiation. Personal Innovativeness on Behavioral Intention (0.707) demonstrates strong discriminant validity with a minimal correlation, whereas Personal Innovativeness on Effort Expectancy (0.852) and Personal Innovativeness on Performance Expectancy (0.734) affirm conceptual distinction despite moderate correlations. Social Influence on Behavioral Intention (0.860) indicates a robust and acceptable association, while Social Influence on Effort Expectancy (0.703) demonstrates evident discriminant validity with negligible correlation. Furthermore, Social Influence on Performance Expectancy (0.804) and Social Influence on Personal Innovativeness (0.735) provide sufficient discriminant validity, ensuring conceptual differentiation among the constructs.

The HTMT results indicate satisfactory discriminant validity for most construct pairs, as all values are below the critical threshold of 0.90. While the pair Performance Expectancy on Effort Expectancy (0.897) approaches the upper limit, it does not breach it, implying acceptable discriminant validity. However, this pair may require further theoretical justification due to its high correlation.

3. Reliability

Table 6. Reliability Test Results

	Cronbach's Alpha	Composite Reability
Performance Expectancy	0.881	0.909
Effort Expectancy	0.869	0.910
Social Influence	0.867	0.919
Personal Innovativeness	0.805	0.885
Behavioral Intention	0.876	0.924

Source: Processed by the researcher, 2024

An indicator of a construct or variable is considered reliable if the value of Cronbach's Alpha exceeds 0.60 and the composite reliability value > 0.70 (Sarstedt et al., 2021). By considering this criterion, it can be concluded that the indicators of the construct or variable in this study are considered reliable.

C. Results of Inner Model Analysis

a. Coefficient of Determination (R2)

R2 indicates the extent to which exogenous latent variables can explain variations in endogenous latent variables. There are three criteria for interpreting the R2 value, namely 0.75 for substantial; 0.50 to medium; and 0.25 for weak (Sarstedt et al., 2021). The following are the results of the R2 test:

Table 7. Coefficient Of Determination (R2) Test Result

	R Square	R Square Adjusted
Personal Innovativeness	0.575	0.565
Behavioral Intention	0.656	0.645

Source: Processed by the researcher, 2024

Table 7 indicates that the *R2 value* for Personal Innovativeness is 0.575, placing it in the medium category. This indicates that 57.5% of the variance in Personal Innovativeness can be elucidated by this study model. The R2 for Behavioral Intention is 0.656, categorizing it as medium. This indicates that 65.6% of the variance in Behavioral Intention can be elucidated by this study model.

b. Cross-Validated Redundancy (Q2)

Q2 shows the measure for model validation that endogenous variables can be predicted. If Q2 exceeds 0, the model is said to possess predictive relevance (Sarstedt et al., 2021). Below are the Q2 test results:

Table 8. Cross-Validated Redundancy Test Results (Q2)

	Q^2
Personal Innovativeness	0.398
Behavioral Intention	0.506

Source: Processed by the researcher, 2024

In table 8, the Q2 value for each variable exceeds 0. According to these criteria, the model demonstrates predictive significance.

c. Effect Size (F2)

F2 can measure changes in R2 when exogenous constructs are included or removed from the model affecting endogenous variables. There are three criteria for interpreting the F2 value, namely 0.02 indicates a small influence; 0,15 indicates moderate influence; and 0.35 signifies a major influence (Hair et al., 2014). Here are the results of the F2 test:

Table 9. Effect Size Test Results (F2)

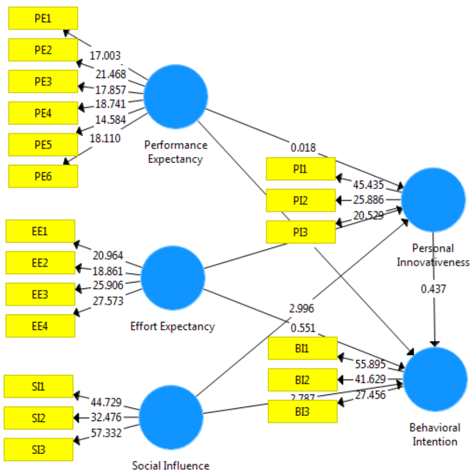
	F^2
Performance Expectancy → Behavioral Intention	0.089
Effort Expectancy →Behavioral Intention	0.007
Social Influence →Behavioral Intention	0.228
Personal Innovativeness →Behavioral Intention	0.007
Performance Expectancy →Personal Innovativeness	0.000
Effort Expectancy →Personal Innovativeness	0.275
Social Influence →Personal Innovativeness	0.087

Source: Processed by the researcher, 2024

Table 9 indicates that the F2 values of Performance Expectancy, Effort Expectancy, and Personal Innovativeness exert a minimal influence on Behavioral Intention at the structural level. *PE* and *SI* exert a minimal effect on the structural level of personal innovativeness. The effect of social influence on behavioral intention is moderate at the structural level. Simultaneously, Effort Expectancy regarding Personal Innovativeness exerts a moderate influence at the structural level.

2. Path Coefficients

In a path coefficient test, the value can range from -1 to +1. The relationship is said to be positive and the link is seen strong if the path coefficient approaches -1, but it is regarded as negative and weak if the path coefficient nears 1 (Sarstedt et al., 2021). Hypothesis testing is carried out to evaluate the relationship between research variables by examining the value of P-Values. If the P-Values value is less than 0.05, the relationship is considered significant. Below are the results of the Path Coefficients test:



Picture 7. Path Coefficients

Source: SmartPLS, 2024

Table 10. Path Coefficients Test Results

Hypothesis	Relation	Original Sample (O)	P-Values	Result
H1	Performance Expectancy -> Behavioral Intention	0.323	0.010	Accepted (Significant)
H2	Effort Expectancy -> Behavioral Intention	0.090	0.582	Rejected (Insignificant)
H3	Social Influence -> Behavioral Intention	0.418	0.006	Accepted (Significant)
H4	Personal Innovativeness -> Behavioral Intention	0.075	0.663	Rejected (Insignificant)
H5	Performance Expectancy -> Personal Innovativeness	-0.003	0.986	Rejected (Insignificant)
H6	Effort Expectancy -> Personal Innovativeness	0.560	0	Accepted Significant)
H7	Social Influence -> Personal Innovativeness	0.276	0.003	Accepted Significant)

Source: Processed by the researcher, 2024

From the results of the hypothesis test, the following interpretation can be given:

1. H1 = Effect of (X1) on (Y)

   Performance Expectancy had a significant positive effect on Behavioral Intention of 0.323 (P-Values = 0.010), so this hypothesis was accepted.

2. H2 = Effect of (X2) on (Y)

   Effort Expectancy had a positive and insignificant effect on Behavioral Intention of 0.090 (P-Values = 0.582), so this hypothesis was rejected.

3. H3 = Effect of (X3) on (Y)

   Social Influence had a significant positive effect on Behavioral Intention of 0.418 (P-Values = 0.006), so this hypothesis was accepted.

4. H4 = Effect of (Z) on (Y)

   Personal Innovativeness had a positive and insignificant effect on Behavioral Intention of 0.075 (P-Values = 0.663), so this hypothesis was rejected.

5. H5 = Effect of (X1) on (Z)

   Performance Expectancy had a negative and insignificant effect on Personal Innovativeness of -0.003 (P-Values = 0.986), so this hypothesis was rejected.

6. H6 = Effect of (X2) on (Z)

   Effort Expectancy had a significant positive effect on Personal Innovativeness of 0.560 (P-Values = 0.000), so this hypothesis was accepted.

7. H7 = Effect of (X3) on (Z)

   Social Influence had a significant positive effect on Personal Innovativeness by 0.276 (P-Values = 0.003), so this hypothesis was accepted.

Performance Expectancy and *Behavioral Intention*

The research indicates that performance expectancy significantly influences behavioral intention ($\beta = 0.323$, $p = 0.010$), implying that users regard ChatGPT as a valuable instrument for improving academic efficiency. This outcome corresponds with earlier studies, like (Benard et al., 2024; Strzelecki, 2024) which indicated that students' utilization of ChatGPT is significantly associated with their belief in its capacity to enhance learning productivity. From a managerial standpoint, education institutions can utilize these insights by incorporating ChatGPT into curriculum initiatives, highlighting its function in automated feedback, information retrieval, and individualized learning. The adoption model can be enhanced by mitigating trust-related issues and refining user experience to guarantee ongoing engagement.

Generations Y and Z regard performance expectancy as a crucial determinant of AI adoption, albeit with differing motivations. Generation Y, having undergone the digital transformation, assesses artificial intelligence according to its capacity to augment productivity and streamline operations. Simultaneously, Generation Z, as digital natives, anticipates the seamless integration of AI into their rapid, multitasking settings. Both generations saw AI as an instrument for achieving objectives efficiently, rather than as a substitute for human labor. While Generation Y employs AI with a goal-oriented mindset, Generation Z integrates it as an inherent aspect of their digital practices, emphasizing convenience and flexibility.

Effort Expectancy and Behavioral Intention

Surprisingly, effort expectancy did not significantly influence behavioral intention ($\beta = 0.090$, $p = 0.582$). This finding contradicts the research conducted by (Duong et al., 2024; Mehedi & Emon, 2023) which demonstrated that ease of use is essential for technological adoption. One possible explanation is that academic users are adept with digital technologies, causing usability difficulties to be overshadowed by factors like performance expectancy and peer influence. This indicates that technology developers and education policymakers should prioritize marketing and training initiatives that highlight the concrete advantages of ChatGPT, rather than only stressing its user-friendliness. Future research should investigate the significance of perceived usability across various user categories, including older teachers and non-tech-savvy students.

It could be that Gen Y and Z are actually aware that the existence of AI is only a support. In terms of technology adaptability, these two generations can be said to be the tech savvy generation who are familiar with technological advances and are familiar with all available AI tools to help them in their daily work. The existence of other factors also triggers this relationship so that it seems insignificant. Within the realm of e-learning, effort expectancy was determined to lack a direct and significant correlation with behavioral intention. Conversely, elements such as performance expectancy and hedonic motivation exerted a greater influence on students' satisfaction and intentions (He & Li, 2023).

Social Intention and Behavioral Intention

The social influence had a robust and significant impact on behavioural intention (0.418, p = 0.006), underscoring the role of peer and societal expectations in technology adoption. This result aligns with prior research (Lee et al., 2024; Sabeh, 2024) that emphasizes the importance of subjective norms and social pressures in shaping user behaviour. Within academic settings, the recommendations and endorsements of peers, instructors, and mentors can significantly sway individuals' decisions to adopt tools like ChatGPT.

Managers and educators must grasp social influence on technology uptake. AI adoption tactics in the corporate environment can encourage collaboration and knowledge-sharing to encourage employees to use AI tools like ChatGPT. Business leaders and digital transformation teams can promote AI by providing structured AI training to staff to use AI-powered automation solutions, Internal knowledge-sharing forums where staff discuss AI best practices and innovations encourage peer-to-peer learning. Aligning AI deployment with organizational goals and teaching people how AI can boost productivity and decision-making rather than replace them. Higher education institutions can harness social influence by integrating AI tools into classrooms, normalizing AI-assisted learning, and encouraging faculty to advocate for ethical AI adoption. This can boost student adoption of AI-powered academic tools.

Personal Innovativeness and Behavioral Intention

Personal innovativeness, while positively linked to behavioral goal, yielded insignificant effects ($\beta = 0.075$, $p = 0.663$). This suggests that a person's willingness to try new technologies does not guarantee their intention to use ChatGPT for academic or professional objectives. This contradicts other research that link personal innovation to technology adoption. Humans may be passionate about experimenting with AI, but their usage decisions are based on pragmatic factors like perceived benefits, usability, and societal impact.

Businesses should not assume tech-savvy employees will use AI. Businesses must demonstrate AI's time savings, efficiency gains, and decision-making improvements. AI adoption strategies must include training programs with use cases to ensure staff see real benefits beyond curiosity-driven research.

Academic institutions should encourage students to use AI in important applications including research support, project development, and automated feedback. Collective AI exploration, such as group-oriented AI efforts, develops genuine acceptance of experimentation.

Within the framework of integrating AI into special education, personal innovativeness was not identified as a key determinant influencing behavioral intention. Conversely, social impact assumed a more pivotal role, suggesting that in certain educational contexts, external social influences may surpass individual characteristics such as innovativeness (Han & Kang, 2012).

Performance Expectancy and Personal Innovativeness

Contrary to expectations, performance expectancy did not significantly impact personal innovativeness ($\beta = -0.003$, $p = 0.986$). This shows that an individual's desire to try new technology is not based on their idea that it would improve performance. This contradicts earlier studies linking performance expectancy to technology exploration. Users may choose familiarity above prospective benefits, thus even if they realize AI's worth, they may be hesitant to try unusual tools until social influence or organizational incentives urge them to.

Businesses could encourage AI adoption through organized onboarding and innovation-driven efforts to encourage employee experimentation. Educational institutions should give students hands-on AI tool experience to boost confidence and inspire them to use AI in problem-solving and research.

This insignificant relationship analysis is also caused by Personal Innovativeness is usually driven by intrinsic factors in a person. Humans are motivated to be innovative due to various factors, the fulfillment of social status or self-expression. In this study, it is possible that this relationship is influenced by the existence of other variables (effort expectancy and social influence) that have a strong influence on personal innovativeness.

Conversely, certain research indicate that personal innovativeness may exist independently of performance expectancy, as individuals could innovate driven by inner motivations or external pressures rather than perceived performance results (Sair & Danish, 2018).

Effort Expectancy and Personal Innovativeness

Personal innovativeness was considerably influenced by effort expectancy ($\beta = 0.560$, $p = 0.000$). This shows that user-friendly AI tools encourage experimentation and innovation. This supports previous research showing ease of use strongly predicts technology experimentation. Easy-to-use ChatGPT users are more willing to try new apps, tweak outputs, and use AI in their workflows.

AI-powered tool developers should prioritize user experience design to minimize entry barriers and increase exploration and adoption. For educational institutions, AI technologies should be gradually integrated into coursework to ensure students are comfortable with technology before asking them to utilize it creatively.

Social Influence and Personal Innovativeness

Personal innovativeness was favorably and significantly influenced by social influence ($\beta = 0.276$, $p = 0.003$). This shows that people are more inclined to use AI if their peers, colleagues, or significant persons do. This supports the assumption that social approbation motivates consumers to try new technology. As AI becomes mainstream, people are more likely to experiment and innovate.

To promote AI adoption in enterprises, establish peer-driven knowledge-sharing forums for employees to share best practices. Use company influencers or technology evangelists to demonstrate successful AI use cases and encourage AI-driven workflows. Educational institutions should develop collaborative learning spaces where students and teachers cooperate on AI-assisted projects to legitimize AI exploration. Use academic endorsements and business partnerships to boost credibility and engage students with AI-driven technologies.

CONCLUSION

This study investigates the factors affecting ChatGPT adoption in Indonesian communities, namely performance expectancy, effort expectancy, social influence, and personal innovativeness, utilizing the UTAUT framework. Performance expectancy and social influence are the principal determinants of behavioral intention, while effort expectancy and personal innovativeness act as indirect determinants.

These findings clarify how individual viewpoints and external factors drive technology adoption in many domains. Performance Expectancy, Effort Expectancy, Social Influence, and Personal Innovativeness considerably impact customers' adoption of AI technology, notwithstanding their comprehension of its potential benefits. This study suggests that personal innovativeness alone is not a robust predictor of behavioral intention, indicating that organizations and institutions should prioritize realistic implementation strategies, systematic AI integration, and social influence to promote adoption.

Business executives, policymakers, and educators can leverage the findings to incorporate AI-driven technologies such as ChatGPT into their operations. Designed for Higher Education Institutions: Universities want to establish organized AI literacy programs to assist students and staff in utilizing AI tools. To enhance personalized learning and content development, Learning Management Systems and course materials must incorporate artificial intelligence. Leaders ought to promote the safe utilization of AI while tackling issues of integrity and plagiarism. Targeted at Businesses and Entrepreneurs: Organizations can enhance productivity through ChatGPT for digital marketing, automated content generation, and business document creation. AI adoption programs must emphasize user-friendliness and prompt business advantages to assist employees in understanding how AI may enhance operational efficiency and decision-making processes. Organizations can facilitate peer-driven AI adoption by utilizing internal advocates or influencers to showcase successful applications.

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APPENDIX

Outer Loadings

	Behavioral Intention	Effort Expectancy	Performance Expectancy	Personal Innovativeness	Social Influence
BI1	0,926				
BI2	0,903				
BI3	0,856				
EE1		0,884			
EE2		0,807			
EE3		0,820			
EE4		0,855			
PE1			0,807		
PE2			0,867		
PE3			0,809		
PE4			0,838		
PE5			0,841		
PE6			0,888		
PI1				0,904	
PI2				0,858	
PI3				0,778	
SI1					0,898
SI2					0,863
SI3					0,905

Quality Criteria

R Square

	R Square	R Square Adjusted
Behavioral Intention	0,659	0,648
Personal Innovativeness	0,588	0,578

f Square

	Behavioral Intention	Effort Expectancy	Performance Expectancy	Personal Innovativeness	Social Influence
Behavioral Intention					
Effort Expectancy	0,004			0,289	
Performance Expectancy	0,083			0,003	
Personal Innovativeness	0,006				
Social Influence	0,166			0,074	

Construct Reliability and Validity

	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
Behavioral Intention	0,876	0,879	0,924	0,802
Effort Expectancy	0,863	0,866	0,907	0,709
Performance Expectancy	0,918	0,920	0,936	0,709
Personal Innovativeness	0,805	0,832	0,885	0,720
Social Influence	0,867	0,868	0,919	0,790

Construct Reliability and Validity

	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
Behavioral Intention	0,876	0,879	0,924	0,802
Effort Expectancy	0,863	0,866	0,907	0,709
Performance Expectancy	0,918	0,920	0,936	0,709
Personal Innovativeness	0,805	0,832	0,885	0,720
Social Influence	0,867	0,868	0,919	0,790

Discriminant Validity

Fornell-Larcker Criterion

	Behavioral Intention	Effort Expectancy	Performance Expectancy	Personal Innovativeness	Social Influence
Behavioral Intention	0,895				
Effort Expectancy	0,678	0,842			
Performance Expectancy	0,765	0,839	0,842		
Personal Innovativeness	0,603	0,743	0,662	0,848	
Social Influence	0,749	0,638	0,759	0,616	0,889

Heterotrait-Monotrait Ratio (HTMT)

	Behavioral Intention	Effort Expectancy	Performance Expectancy	Personal Innovativeness	Social Influence
Behavioral Intention					
Effort Expectancy	0,779				
Performance Expectancy	0,850	0,940			
Personal Innovativeness	0,707	0,876	0,757		
Social Influence	0,860	0,736	0,850	0,735	