The Use of Unified Theory of Acceptance and Use of Technology to Analyze Students' Behavioral Interests in Utilizing Gemini AI

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***Abstract*—The field of education in Indonesia is currently undergoing a significant transformation due to the rapid advancement of technology. One notable product of this technological progress is the integration of artificial intelligence, particularly in the form of chatbots like Google Gemini, which offers instant responses, professional advice, and free access. This study aims to identify the various aspects that influence behavioral interest in using Gemini AI through the application of the Unified Theory of Acceptance and Use of Technology (UTAUT) model. The study employed purposive sampling to select 240 student users of Gemini AI from the Economics Education program at Universities in East Java, Indonesia. SmartPLS version 4 was used as the statistical analysis technique to analyze the data collected. The results of this study showed that Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions do not significantly affect Behavioral Intention or Use Behavior in adopting Gemini AI, while Behavioral Intention has a significant positive effect on Use Behavior. Additionally, Gender moderates the effect of Social Influence on Behavioral Intention, and Experience moderates the effect of Facilitating Conditions on Use Behavior.**

***Keywords*—artificial intelligence, behavioral intention, Gemini Artificial Intelligence (AI), students, Unified Theory of Acceptance and Use of Technology (UTAUT)**

I. Introduction

There is transformation big in field education in Indonesia today this as consequence from pressure progress technology. Information from the Inspectorate General of the Ministry of Education, Culture, Research, and Technology show that effort transformative, such as implementation technology, is matter fundamental. For ensure every individual can access quality education [1–3] . In this modern era technology moment this, mastery and ability use technology, especially intelligence Artificial Intelligence (AI) is urgent matters. With AI capabilities for make the work that was originally limited done by humans just for example data processing and determination decisions, artificial intelligence now play a role central in various aspect life, including education [4–9].

One of product from the development of AI is the presence of chatbots as computer programs that can interact with its users through conversation text and voice [10–13]. One of chatbot form that provides response instant and professional input as well available for free is Google Gemini [14–16]. This develop in a way rapid especially in scope education as well as lectures, Gemini AI a lot used student. For increase experience Education [14–17]. Students can using Gemini AI to strengthening and deepening learn, finish question, or even as Friend virtual discussion practical [18–20].

Quality reception users on intelligence artificial generative can evaluated using the "Unified Theory of Acceptance and Use of Technology", a theory that is commonly used this is called Unified Theory of Acceptance and Use of Technology (UTAUT) is an approach theory that explains reception technology and its use [21–23]. This model explain behavioral intention and use behavior triggered a number of variable external, namely performance expectancy, effort expectancy, social influence, and facilitating conditions [24–26].

This study own equality through studies conducted by Obenza with title "Analyzing Attitude and Behavior Student Towards AI Using the Acceptance and Use Theory Model Technology Expanded Integrated", namely determination size minimum sample applied as well as utilize the Smart PLS program as tool for analysis [27]. The difference lies in research This there is addition variable AI awareness and AI trust.

This study own difference through study conducted by Shete, Koshti, and Pujari with title "Analysis Application of UTAUT Model in the Use of Intelligent Chatbots Made In Measuring Student Self-Efficacy & Academic Achievement Accounting" is on variables bound to be contained in the research this is what research is about This use efficacy self and achievement academic. Differences furthermore there is an object used in the research This using generative chatbots in a way general and not focused on products certain [28–31]. Moreover, implications of this study lie in its potential to strengthen the integration of Gemini AI into Indonesia's educational ecosystem. The findings can serve as a reference for AI service providers like Google Gemini to enhance user-centric features, particularly in adaptive and collaborative learning contexts. Furthermore, this research holds significant impact compared to prior studies by expanding the UTAUT model through the inclusion of AI awareness and AI trust variables, which remain underexplored in higher education settings. This allows for a more holistic analysis of users' psychological factors beyond mere technical aspects. The novelty of this research lies in its integrative approach, combining technology acceptance theory (UTAUT) with the unique dynamics of generative AI, as well as its focus on chatbot AI usage in dynamic and interactive learning environments. This study also pioneers the exploration of

Gemini AI as a specific case, unlike previous research that generalized chatbot analysis. Thus, this work not only enriches academic literature on educational technology adoption but also provides practical recommendations for user-centric AI development in Indonesia.

Based on this background, this study aims to fill the existing gap by analyzing whether Performance Expectancy, Effort Expectancy, and Social Influence are positively and significantly related to Behavioral Intention in the use of Gemini AI. In addition, this study also aims to determine how Facilitating Conditions and Behavioral Intentions affect Usage Behavior. Furthermore, this study tests the role of moderation variables to understand whether the relationship between PE, EE, and SI on BI and FC on UB is influenced by age. This study also analyzes whether gender moderates the relationship between PE, EE, and SI on BI. In addition, this study examines whether experience moderates the relationship between EE and SI on BI, and FC on UB. Thus, this study is expected to provide deeper insight into the factors that influence the adoption of Gemini AI and how moderating factors play a role in shaping the intensity and behavior of using this technology. Provider service Gemini AI can utilise study This as guide use increase quality service they. While, this research limitations is constrained by its reliance on self-reported data from a specific demographic (e.g., Indonesian students), which may limit the generalizability of findings to broader populations. Additionally, the cross-sectional design restricts the ability to infer long-term causal relationships between variables like AI trust and behavioral intention. More from that, it is expected that findings study This will beneficial for future researchersFor use it as reference or material comparison moment they do similar research.

II. Review Literature

A. Gemini AI

One of product from the development of AI is the presence of chatbots as computer programs that can interact with its users through conversation text and voice. Chatbots can repay message or questions asked by its users for 24 hours and not bound time, with condition connected internet network [32, 33] sugu. One of chatbot form that provides response instant and professional input as well available for free is Google Gemini [14, 15, 34]. Gemini is a applications that can also accessed via the website, in it there is conversation menu options text, conversation voice, besides that users can also send photo and Gemini will do in accordance directions given [14, 15]. Gemini AI a lot used student for increase experience Education. Students can using Gemini AI to strengthening and deepening learn, finish question, or even as Friend virtual discussion practical [14]. Gemini AI was introduced in December 2023 is a artificial intelligence service Google product designed by Google Deepmind. Service This it is said more proceed from similar platforms other [35].

Gemini AI enhances educational effectiveness through its advanced, user-centric features tailored to diverse learning needs [36, 37]. Its multimodal analysis capability allows students to engage with content in versatile formats: for instance, a biology student can upload a microscope image of a cell structure, and Gemini AI can label components, explain their functions, and even compare them to analogous structures in other organisms [38–41]. This interactivity bridges theoretical knowledge and practical application, fostering deeper comprehension [42–44]. Additionally, its real-time problem-solving feature supports adaptive learning—when a mathematics student struggles with calculus, Gemini AI can generate step-by-step solutions, offer alternative methods, and provide practice questions aligned with the student's proficiency level [14, 45, 46]. For language learners, voice interaction and translation tools enable immersive practice, such as simulating conversational scenarios in a target language or translating academic papers while preserving technical terminology [14, 16].

Moreover, Gemini AI's 24/7 accessibility ensures uninterrupted learning opportunities, critical for students managing irregular schedules or collaborative projects across time zones [19, 47, 48]. Its integration with cloud-based platforms like Google Workspace allows seamless synchronization of notes, deadlines, and resources, streamlining academic workflows [49]. Crucially, Gemini AI's adaptive feedback system—which identifies knowledge gaps and curates personalized learning pathways—aligns with principles of self-regulated learning, empowering students to take ownership of their educational journeys [50, 51]. By combining these features, Gemini AI transcends traditional tutoring tools, positioning itself as a dynamic partner in fostering critical thinking, creativity, and lifelong learning skills [52].

B. UTAUT

Unified Theory of Acceptance and Use of Technology or commonly known as this is called UTAUT is a approach theory that explains reception technology and its uses. UTAUT was popularized by Venkatesh with blend the eight central models about reception technology, the most effective characteristics Then combined become one idea theory [53–57]. Eight theory the namely "Theory of Reasoned Action (TRA), Technology Acceptance Model (TAM), Motivational Model (MM), Theory of Planned Behavior (TPB), A Model Combining the Technology Acceptance Model and the Theory of Planned Behavior (C-TAM-TPB), The Model of The PC Utilization (MPCU), The Innovation Diffusion Theory (IDT) and Social Cognitive Theory (SCT)". The purpose of merger this is for overcome lack in previous models, apart from that Because construct certain in one model has similarity with construct others. With this UTAUT model, we can concluded that behavior as well as view user technology influence on behavior they in accept use technology.

This model explain behavioral intention (Y1) and use behavior (Y2) are triggered a number of variable external, namely performance expectancy (X1), effort expectancy (X2), social influence (X3), and facilitating conditions (X4). Behavioral intention explained as size from intention individual for do a action, use behavior refers to the extent to which or how much intense user technology utilise system information. Additionally, UTAUT incorporates moderating variables—age, gender, and experience—which influence the strength of relationships between independent variables and dependent variables. These moderators help refine the model by demonstrating how different demographic and experiential factors shape technology adoption behavior.

Understanding of performance expectancy is how many big belief somebody that use system will support they accept benefits on assignment certain. Effort expectancy refers to how much level convenience in utilization system. Social influence is how much big user feel the people around him has convince him for adopt A technology new. Facilitating conditions are level somebody think that facilities and infrastructure technology as well as available organizations moment This can facilitate utilization technology [9].

The UTAUT (Unified Theory of Acceptance and Use of Technology) model explains the adoption of Gemini AI in education through four key factors: *performance expectancy* (students' belief that Gemini AI enhances learning efficiency, such as solving complex tasks or deepening understanding of academic concepts), *effort expectancy* (the ease of using Gemini AI's intuitive interface and multimodal features), *social influence* (encouragement from academic peers to adopt the technology), and *facilitating conditions* (infrastructure support like internet access and integration with learning platforms). These variables shape *behavioral intention* (willingness to use) and *use behavior* (frequency of utilizing features like image analysis or discussion simulations), reflecting how students integrate Gemini AI into their learning routines. Moreover, age, gender, and experience moderate these relationships, influencing how different groups of students interact with and adopt the AI technology.

UTAUT is relevant because it combines psychological, social, and technical analyses to understand the adoption of generative AI like Gemini AI [57–60]. The model not only reveals reasons for adoption such as trust in the AI's functional advantages, but also helps identify practical barriers (e.g., lack of digital literacy) [31, 61] and design strategies to enhance learning experiences. With its holistic approach [62–64], UTAUT serves as an ideal theoretical foundation for exploring AI's role in modern education, particularly in fostering adaptive, collaborative, and sustainable learning practices [65]. Below This is framework applied conceptual:

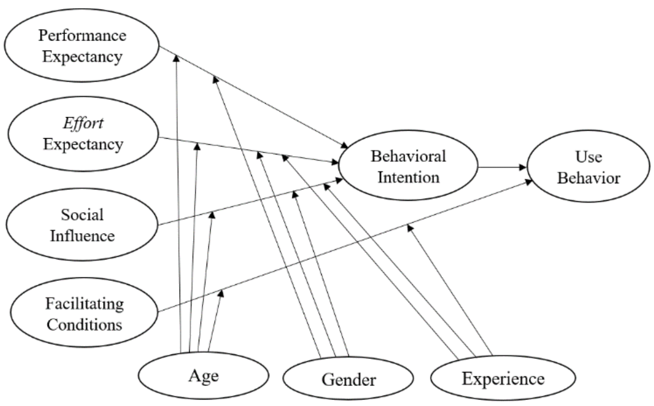

Fig. 1. Framework conceptual.

The hypothesis flow contained in studies this depicted through framework conceptual in Fig. 1. Here is a number of Hypothesis proposed:

H_1: Performance Expectancy provides connection positive as well as significant with Behavioral Intention.

H_2: Effort Expectancy provides connection positive as well as significant with Behavioral Intention.

H_3: Social Influence provides connection positive as well as significant with Behavioral Intention.

H_4: Facilitating Conditions provide connection positive as well as significant with Use Behavior.

H_5: Behavioral Intention provides connection positive as well as significant with Use Behavior.

H_6: Age moderates the relationship between Performance Expectancy and Behavioral Intention positively and significantly.

H_7: Age moderates the relationship between Effort Expectancy and Behavioral Intention positively and significantly.

H_8: Age moderates the relationship between Social Influence and Behavioral Intention positively and significantly.

H_9: Age moderates the relationship between Facilitating Conditions and Use Behavior positively and significantly.

H_{10}: Gender moderates the relationship between Performance Expectancy and Behavioral Intention positively and significantly.

H_{11}: Gender moderates the relationship between Effort Expectancy and Behavioral Intention positively and significantly.

H_{12}: Gender moderates the relationship between Social Influence and Behavioral Intention positively and significantly.

H_{13}: Experience moderates the relationship between between Effort Expectancy and Behavioral Intention positively and significantly.

H_{14}: Experience moderates the relationship between between Social Influence and Behavioral Intention positively and significantly.

H_{15}: Experience moderates the relationship between between Facilitating Conditions and Use Behavior positively and significantly.

III. MATERIALS AND METHODS

Study quantitative applied in studies this, research quantitative is studies with data in form numbers, next reviewed with statistical formula then interpreted for test hypothesis [66]. Study quantitative nature descriptive as focused study in trial hypothesis use evaluation numerical and statistical data analysis on the factors studied, which allows variable research, suitability with formulation, and measurement correlation between variable identified. This study carried out in East Java Province, Indonesia from November 20, 2024 to by January 4, 2025, with a duration of around seven weeks.

In this study, the population determined was students of the Economic Education study program, Surabaya State University, Malang State University, Jember State University, Kanjuruhan Malang PGRI University, and Madiun PGRI University, who had utilized Gemini AI. According to Hair *et al*. population is field generalization in the form of part with quantity as well as characteristic specifically determined by the researcher, then after that concluded [66]. Limitations time, energy and finances can obstruct researcher for learn a large population, so that it is determined samples. Samples include elements from quantity as well as characteristics of population. In this study, the population determined was students of the Economic Education program, Surabaya State University, Malang State University, Jember State University, Kanjuruhan Malang PGRI University, and Madiun PGRI University who had utilized Gemini AI, with amount population no known. Because amount population no known, then withdrawal sample refers to the method multiplication from a minimum of 5-10 times the amount indicators proposed by Hair *et al*. [66]. This method generally used in PLS-SEM for determine size minimal sample. Hair, JF Jr. to put forward that size sample of 100–200 respondents is ideal range. Since the number of statements in this research questionnaire is 24 statements, the sample calculation based on Hair *et al*. is; minimum: 5 × 24 = 120 respondents, maximum: 10 × 24 = 240 respondents. Thus, the sample size in this study of 240 respondents meets the criteria suggested by Hair *et al.* [66], this number can represent the population of students registered in the Economic Education study program, at Surabaya State University, Malang State University, Jember State University, Kanjuruhan Malang PGRI University, and Madiun PGRI University who have used Gemini AI.

Purposive sampling was chosen in the study this as method taking sample. Hair *et al*. say on method This chosen based on condition certain [66]. This method apply criteria certain or no anyone can be made sample in research and for ensure that respondent own relevant experience with the topic being researched. The following this is condition respondents in the study this, namely a) Is registered students in the Economic Education study program, Surabaya State University, Malang State University, Jember State University, Kanjuruhan Malang PGRI University, and Madiun PGRI University; b) Respondents already once using Gemini AI.

This research utilizing Google Forms as technique collection data, questionnaire shared online via Instagram and WhatsApp media and shared offline via classes, questionnaires that have been collected utilized as primary data. Next namely the main data analyzed using Partial Least Square (PLS) version 4, which consists of from *inner model* as well as *outer model.* The validity and reliability of the model are evaluated through evaluation of measurement models with objective ensure sufficient data strong for carry on to stage next [67, 68]. Evaluation of the structural model applied for measure and explain correlation between variable, prefixed with use R-Square (R^2) value for show to what extent the variables free can explain variance in variable tied, then to be continued with use predictive relevance value (Q^2) for evaluate the ability of the model to predict [69, 70]. The value of the t- statistic (result analysis) and t-table value (value reference) then compared to for do testing hypothesis. Hypothesis accepted if t- statistic exceeds t-table.

IV. Results and Discussion

Results and discussion section this will answer and discuss research questions, namely whether Performance Expectancy, Effort Expectancy, and Social Influence have a positive and significant relationship to Behavioral Intention in using Gemini AI. how Facilitating Conditions and Behavioral Intentions affect Usage Behavior. whether the relationship between PE, EE, and SI on BI and FC on UB is influenced by age. whether gender moderates the relationship between PE, EE, and SI on BI. whether experience moderates the relationship between EE and SI on BI, and FC on UB.. Based on technique analysis the statistics used, namely using Partial Least Square (PLS) version 4, there are two stages namely testing the inner model and outer model.

A. Outer Model Analysis Results

First, the outer model is tested use PLS-SEM analysis using the Smart-PLS program. This model analysis done with checking internal consistency reliability, reliability indicators through the indicator's outer loadings, convergent validity through AVE statistics, and discriminant validity through cross loadings.

1) Internal consistency reliability and convergent validity using AVE statistics

In this study, the evaluation of several good models was conducted using three main metrics: composite reliability, Cronbach's alpha, and Average Variance Extracted (AVE). The reliability of a construct was tested using two methods: composite reliability and Cronbach's alpha. Cronbach's alpha is a coefficient that measures the reliability of a measurement scale. In contrast, composite reliability assesses the extent to which the quality of the model is calculated based on known indicators. Composite reliability is recommended because it tends to produce higher values than Cronbach's alpha. A variable is considered reliable if the Cronbach's alpha and composite reliability values are more than 0.70. However, if the Cronbach's alpha value is slightly below 0.70, the variable can still be considered reliable. To measure convergent validity, AVE is used as an indicator that shows the extent to which indicators in a construct are related to each other. The requirement that must be met is AVE > 0.50, which means that the construct can explain more than 50% of the variance of each indicator. Conversely, if AVE < 0.50, then the variable has more error than the variance it explains.

Table 1. Construct reliability and validity

	CA	CR (rho_a)	CR (rho_c)	AVE
BI	0.718	0.734	0.841	0.640
EE	0.723	0.760	0.841	0.639
FC	0.836	0.836	0.890	0.670
PE	0.751	0.754	0.843	0.573
SI	0.826	0.863	0.877	0.641
UB	0.766	0.772	0.865	0.682

Looking at the results of Table 1, it can be said that this construct has fairly strong reliability because all constructs obtain CA and CR values > 0.70. It can also be concluded that the outer model assessment has good convergent validity because the average value of the variance extracted from the sixth construct is > 0.5.

2) Reliability indicator

Testing this through outer loadings, used for see whether every indicator own contribution or strong connection with latent construct (a concept that is not observed) which is being measured. Outer loadings indicate how much big weight or contribution of each indicator to the construct it represents. Construct considered valid and correlated with tested variables if loading factor > 0.70. The test results through Smart PLS 4.0 can be seen in Fig. 2

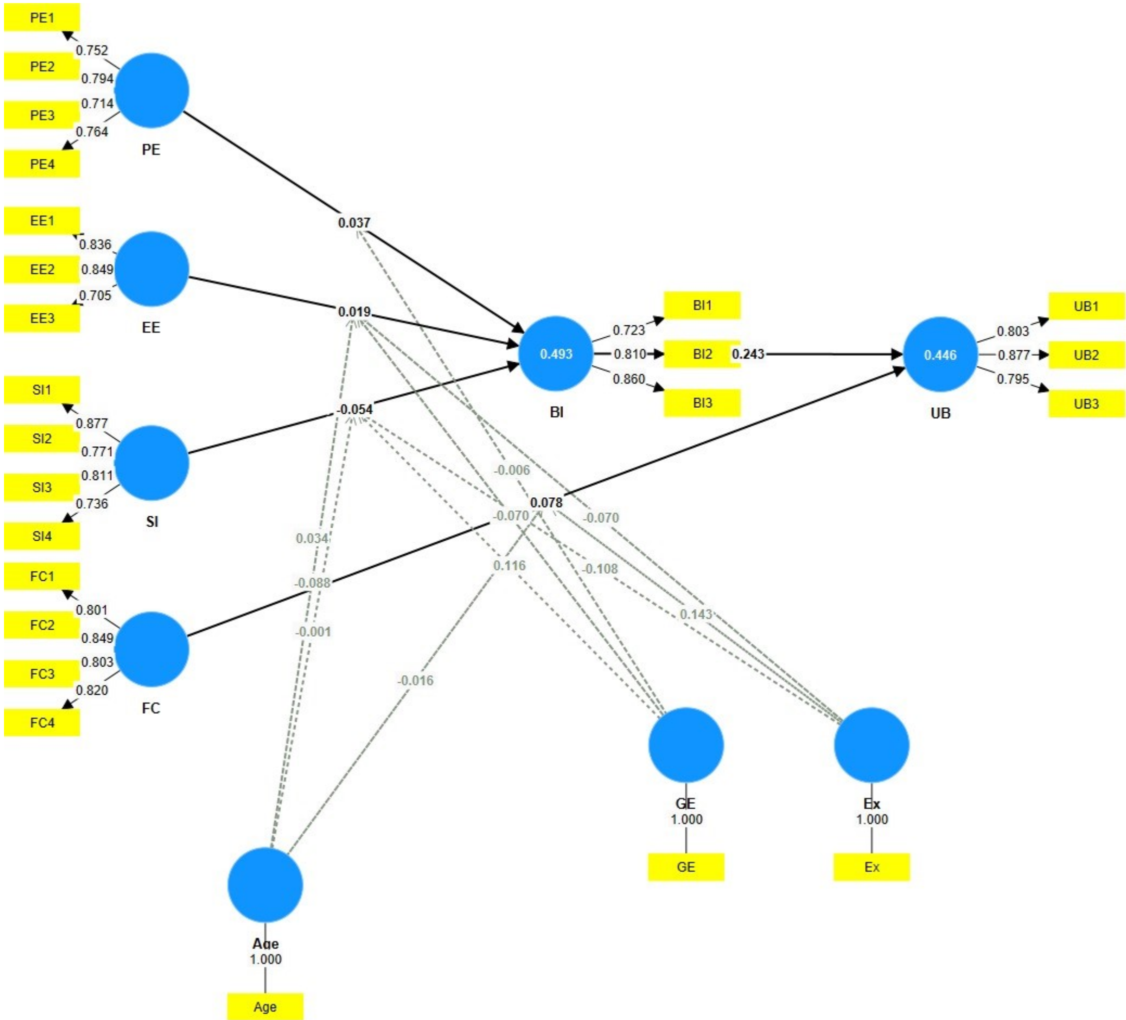

Fig. 2. Results of structural model analysis

Based on Table S1, it can be seen that the value of all statement items is > 0.07. So all statement items are stated to have a strong contribution or relationship with the latent construct being measured.

3) Discriminant validity

Implemented with objective know in a construct will has a high loading factor on the construct origin and low on other constructs. If the value indicator exceeds 0.70 or the intended loading construct value exceed other construct loading values, then construct the considered valid.

For every variable in study all of these indicator achieve discriminant validity, as shown by the cross loading and discriminant validity values in Table S2. This means that the loading factor on the indicator the more big than construct other.

B. Inner Model Analysis Results

1) R-Square (R2)

Predictive power of structural models determined by the R-Square value (R^2) for each variable. The R-Square criteria at 0.25 is a weak model, a moderate model at 0.50, and a strong model at 0.75 are used for see potential prediction.

Table 2. R-Square

	R-square	R-square adjusted
BI	0.493	0.475
UB	0.446	0.437

Table 2 shows that variable behavioral intention (Y1) gets the R-Square value (R^2) is 0.493, which means the variables performance expectancy (X1), effort expectancy (X2), and social influence (X3) can be influences 49.3% of variables behavioral intention (Y1). However, the components outside study This own impact of 50.7%. The use behavior variable (Y2) then get R-Square value (R^2) 0.446, meaning behavioral intention (Y1) and facilitating conditions (X4) influence 44.6% of the use behavior variable (Y2), while other variables outside study affecting the remaining 55.4%.

2) Predictive relevance (Q^2)

A test called predictive relevance looks at Q^2 value for show how much both blindfolding processes produce mark observation. Scale Q^2 value that can be accepted are 0.02 (small), 0.15 (medium), and 0.35 (large) in Hair *et al*. [66]. Relevance predictive indicated by the value $Q^2 > 0$.

Q^2 value = $1 – (1 – R1^2) \times (1- R2^2)$

Q^2 value = $1 – (1 – 0.493) \times (1 – 0.446)$

Q^2 value = 0.7186

Information:

Q^2 = Predictive Relevance value

$R1^2$ = R-Square value of the variable Behavioral Intention

$R2^2$ = R-Square value of Use Behavior variable

With referring to the calculation formula previously, obtained Q^2 value which is 0.7186, because its value more big from zero, can it is said the model's predictions considered has relevant.

C. Testing Hypothesis

Compare t-table and t-statistic values is method testing hypothesis is done. If the t-statistic value, as determined by the t-table, is greater than from 1,960, the result is considered significant. The results of the hypothesis testing can be seen in Table 3.

Table 3. Test results hypothesis

Path Coefficients					
Hypothesis	Variables	Original sample (O)	T statistics (|O/STDEV|)	P values	Information
H1	PE ≥ BI	0.037	0.699	0.484	Rejected
H2	EE ≥ BI	0.019	0.397	0.691	Rejected
H3	SI ≥ BI	−0.054	1.280	0.200	Rejected
H4	FC ≥ UB	0.078	1.205	0.228	Rejected
H5	BI ≥ UB	0.243	3.911	0.000	Accepted
H6	Age × PE ≥ BI	0.034	0.495	0.621	Rejected
H7	Age × EE ≥ BI	−0.088	1.618	0.106	Rejected
H8	Age × SI ≥ BI	−0.001	0.019	0.985	Rejected
H9	Age × FC ≥ UB	−0.016	0.464	0.643	Rejected
H10	GE × PE ≥ BI	−0.006	0.128	0.898	Rejected
H11	GE × EE ≥ BI	−0.070	1.468	0.142	Rejected
H12	GE × SI ≥ BI	0.116	2.882	0.004	Accepted
H13	Ex × EE ≥ BI	−0.070	1.571	0.116	Rejected
H14	Ex × SI ≥ BI	−0.108	2.770	0.006	Rejected
H15	Ex × FC ≥ UB	0.143	2.803	0.005	Accepted

D. Discussion

1) Connection between performance expectancy and behavioral intention

Connection between PE and BI in studies This get original sample (O) 0.037 which shows existence positive relationship, meaning relationship between performance expectancy and behavioral intention of 3.7%. The t- statistic value in the test hypothesis this obtained the result is 0.699 which means more small from t-table (1.960). While for probability significant results obtained is worth 0.484 so more big from level error (0.05). According to findings testing hypothesis 1 can known variable performance expectancy provides connection positive to behavioral intention but no significant, so that hypothesis 1 is rejected. This is show that other factors outside technology considered be the main motivator respondent for using Gemini AI, not the benefits, practicality, and convenience that Gemini AI offers. Findings in study this support findings previously by Crawford *et al*. [71], in research get findings performance expectations considered relate no significant on variables user behavioral intention ChatGBT. However findings not the same with study study previously like Pereira *et al*. [72] and Kanbach *et al*. [73] who got performance expectancy conclusion provides influence significant on behavioral intention.

The findings of this study indicate that Performance Expectancy (PE) has a positive but insignificant relationship with *behavioral intention* (BI) to adopt Gemini AI, with a path coefficient (O) of 0.037 (3.7%), a *t-statistic* of 0.699 (< 1.960), and a *p-value* of 0.484 (> 0.05). This suggests that while respondents perceive Gemini AI as beneficial for improving learning efficiency (e.g., completing tasks faster or deepening conceptual understanding), this factor is not the primary driver of their adoption intention. The lack of significance may stem from users perceiving Gemini AI's functional benefits—such as data analysis or concept explanations—as comparable to conventional tools (e.g., search engines or calculator apps), failing to create strong *added value*. Additionally, user characteristics (e.g., students prioritizing non-technical factors like convenience or social pressure) may explain this outcome. These findings align with Pavan *et al*. [13], who found that *performance expectancy* did not significantly influence behavioral intention to use ChatGPT, as users prioritized factors like response speed or versatility over pure performance benefits.

Conflict with Prior Studies and Contextual Factors: This result contrasts with studies like Pande *et al*. [16] and Lee *et al*. [17], which concluded that PE significantly influenced BI in AI adoption contexts. This discrepancy can be attributed to contextual differences. For example, Pande *et al*. [16] focused on business professionals prioritizing time efficiency and data accuracy, while this study targets students who may prioritize *effort expectancy* (ease of use) or *facilitating conditions* (infrastructure support). Furthermore, the research object matters: AI tools for finance versus generative AI for education. Gemini AI, as a learning tool, may be perceived as a *supplementary resource* rather than a replacement for instructors or traditional methods, diluting its perceived performance necessity. Cultural factors also play a role: in Indonesia's academic environment, pressures to adhere to norms (e.g., avoiding over-reliance on AI) may reduce the perceived urgency of Gemini AI's performance benefits.

Theoretical and Practical Implications: These findings enrich UTAUT literature by demonstrating that PE is not always a dominant predictor in generative educational technology adoption, particularly in regions with emerging AI adoption like Indonesia. Practically, Gemini AI developers should emphasize non-performance aspects such as content personalization, integration with local learning platforms (e.g., campus LMS), or collaborative features—to enhance appeal. For educational institutions like UNESA, UM, UNEJ, UNIKAMA, UNIPMA, this study suggests the need for awareness campaigns highlighting not only Gemini AI's functional strengths but also fostering supportive ecosystems (e.g., AI literacy training) to optimize student utilization. Future research should explore mediating variables like *trust in AI* to bridge PE and BI, and compare results across cultures and educational levels.

2) Connection between effort expectancy and behavioral intention

EE against BI in studies this get original sample (O) 0.019 which shows existence positive relationship, meaning connection effort expectancy to behavioral intention of 1.9%. The t-statistic value in the test hypothesis this obtained result 0.397 so < t-table (1.960). While for probability significant results obtained is worth 0.691 so more big from level error (0.05). According to findings testing hypothesis 2 can known variable effort expectancy gives influence positive to behavioral intention but shows an insignificant relationship, so that hypothesis 2 is rejected. Findings this support study previously conducted by Melián-González *et al*. [74], the results study the say effort expectancy considered relate no significant on variables behavioral intention of chatbot users. If using a chatbot requires great effort, someone will reluctant use technology the [75]. According to a study [74], function and appearance the interface of the virtual assistant is simple, easy to search, and easy to interact with natural chat no need improvement anything for user with knowledge technical. Then findings this own difference with results findings from 7,18 who obtained conclusion effort expectancy provides influence significant on behavioral intention.

The findings of this study indicate that effort expectancy has a positive but insignificant effect on behavioral intention to use Gemini AI, with a path coefficient of 0.019 (1.9%), a t-statistic value of 0.397 (< 1.960), and a p-value of 0.691 (> 0.05). This suggests that although the ease of use of Gemini AI—such as an intuitive interface, simple navigation, and the ability to understand natural language—can enhance users' positive perceptions, this factor does not serve as a primary determinant of adoption intention. The lack of significance may be due to the characteristics of the users (students) who are already accustomed to digital technology, thus considering ease of use as a baseline expectation (minimal standard) that does not need further optimization. These findings align with studies by NI Mohd Rahim *et al*. and S. Melián-González, which state that when chatbot interfaces are designed to be simple and interactive (such as Gemini AI), the effort required for users to learn them becomes minimal, causing effort expectancy to lose its predictive power. S. Melián-González emphasized that virtual assistants with user-friendly designs do not require technical enhancements to attract users, as ease of use has become the norm. However, these results contradict studies by PN Auliya and K. Wijaya, which found that effort expectancy was significant, particularly in the context of complex technologies or populations with low digital literacy. This difference underscores that the significance of EE depends on the user context and the complexity of the technology: among groups less exposed to technology (such as the elderly or non-technical users), ease of use becomes critical, whereas for students—who are already familiar with digital platforms—factors like performance expectancy or social influence may be more dominant. Thus, these findings reinforce the argument that UTAUT needs to be contextualized according to demographic characteristics and the level of technological maturity within the target ecosystem.

3) Connection between social influence against behavioral intention

Connection between SI and BI in study This own mark original sample (O) is -0.054 which shows existence negative relationship, meaning connection social influence to behavioral intention of -5.4%. The t-statistic value in the test hypothesis this obtained the result is 1.280 which means < from the t-table (1.960). While for probability significant results obtained is worth 0.200 so that more big from level error (0.05). According to findings testing hypothesis 3 can known social influence variable relate negative to behavioral intention and shows an insignificant relationship, so hypothesis 3 is rejected. The results of this study indicate that support or recommendations from people around them—such as friends, family, or coworkers—do not significantly influence students' intention to use Gemini AI. The results of this study are in line with several previous studies that show that social influence is not always a significant factor in influencing technology adoption intentions among college students. For example, a survey by F. R. Nur, N. Hadi, and A. C. Dewi found that social influence did not significantly influence students' intention to adopt mobile banking [76]. Likewise, another study by J. F. D. S. Miranda showed that social influence did not have a significant impact on students' behavioral intentions in using digital wallets [77]. These findings indicate that college students tend to be more influenced by other factors, such as perceived benefits and ease of use of technology, compared to pressure or recommendations from their social environment.

This finding is different from several previous studies that stated that social influence plays an important role in shaping individuals' behavioral intentions in adopting technology, including a study by A. G. Pelupessy and Y. Yanuar which found that social influence has a positive impact on perceived ease and benefits in using electronic money services such as GoPay and OVO among students [78]. Likewise, A. T. Chusna and M. Sabandi research shows that social influence has a positive and significant effect on the intention to use ChatGPT in students' economics learning [79]. The difference in results is likely due to different population characteristics, students in this study may have a higher level of independence in making technology-related decisions compared to other populations.

In addition, Kishen *et al*.'s research shows that individuals' attitudes toward AI greatly influence their intention to continue using the technology, with Generation Z showing the most positive attitudes [80]. However, in the context of this study, although attitudes toward AI may be positive, social influence from the surrounding environment does not play a significant role in influencing students' intentions to adopt Gemini AI.

It is important to note that the context of technology use also plays an important role in determining the impact of social influence. For example, in populations with low technological literacy or limited exposure to digital innovation, social influence may be a dominant factor because individuals rely more on guidance from their social environment. Conversely, in groups that are already familiar with technology, such as college students or technology professionals, other factors such as performance expectations or effort expectations may have a stronger influence. Therefore, these findings underscore the need for a contextual approach when applying the UTAUT theory. Each target population and type of technology has unique dynamics that must be considered to ensure the relevance of the research results. Thus, this study not only provides insight into the relationship between social influence and behavioral intention but also highlights the importance of adapting the UTAUT theory according to the demographic characteristics and level of technological maturity in a particular ecosystem.

Therefore, the results of this study emphasize the importance of considering context and demographic characteristics in analyzing factors that influence behavioral intention toward technology adoption. Although social influence often plays a role in technology adoption in various contexts, the results of this study indicate that in the student population in this study, this factor is not a major determinant in forming intentions to use Gemini AI.

4) Connection between facilitating conditions and use behavior

The relationship between FC and UB in study this own mark original sample (O) is 0.078 which shows existence positive relationship, meaning connection facilitating conditions for use behavior of 7.8%. The t-statistic value in the test hypothesis this obtained the result is 1.205 which means more small from t-table (1.960). While for probability significant results obtained is worth 0.228 so that more big from level error (0.05). According to findings testing hypothesis 4 can known variable facilitating conditions give influence positive on use behavior and show relationship that is not significant, so that hypothesis 4 is rejected. This finding indicates that although facilitating conditions such as the availability of infrastructure, training, and technical support can increase technology use behavior, their influence is not strong enough to be a dominant factor in determining the extent to which students use technology in their learning.

This finding is in line with research conducted by [81] FC has a positive but insignificant effect on UB. The lack of significance may indicate that although facilitating conditions are theoretically important, their actual impact on usage behavior depends on other factors, such as user familiarity with the technology, the quality of supporting infrastructure, or external environmental constraints. For example, if users perceive that the tools or resources provided are inadequate or do not fit their workflow, facilitating conditions may fail to produce meaningful behavioral outcomes.

In contrast, this finding differs from research by [82] which found that Facilitating Conditions have a significant effect on Technology Use Behavior. This suggests that the availability of adequate resources and support can encourage increased technology use among users. However, in the context of this study, although there is a positive relationship, the effect of Facilitating Conditions is not strong enough to reach statistical significance.

This study shows a positive relationship between positive relationship between Facilitating Conditions (X4) and Usage Behavior (Y2) in Economic Education students at Surabaya State University, Malang State University, Jember State University, Kanjuruhan Malang PGRI University, and Madiun PGRI University. The original sample value of 0.078 indicates that an increase in Facilitating Conditions contributes 7.8% to an increase in Use Behavior. However, this relationship is not statistically significant, with a t-statistic value of 1.205 (smaller than the t-table of 1.960) and a p-value of 0.228 (greater than the significance level of 0.05). These results indicate that although respondents have a slight tendency to facilitate conditions that support technology usage behavior, this factor is not the main factor that encourages students to use technology. It could be that other factors such as ease of use, perceived benefits, previous experience, or personal motivation are more dominant than simply the availability of facilities.

5) Connection between behavioral intention towards use behavior

The relationship between BI and UB in study this own mark original sample (O) is 0.243 which shows existence positive relationship, meaning connection behavioral intention to use behavior by 24.3%. The t-statistic value in the test hypothesis this obtained the result is 3.911 which means > t-table (1.960). While for probability significant results obtained is worth 0.000 so more small from level error (0.05). According to findings testing hypothesis 5 can known variable behavioral intention give influence positive on use behavior and show significant relationship in the context of technology use by economics education students at universities in East Java, so hypothesis 5 is accepted. These results are in line with the Unified Theory of Acceptance and Use of Technology (UTAUT) which states that BI is the main predictor in determining UB. In previous studies, BI is often associated with factors such as performance expectations, effort expectations, social influence, and facilitating conditions that contribute to technology adoption. Therefore, the more positive students' perceptions of technology in supporting their academic activities, the more likely they are to use it in their daily lives.

This finding is consistent with several previous studies. For example, Venkatesh *et al*. (2012) in the UTAUT 2 model found that BI has a significant influence on UB, especially in the context of technology adoption in academic and professional environments. In the local context, research by [83] shows that the higher the behavioral intention, the greater the use behavior, the greater a person's desire to use the PeduliLindungi application, and the higher the level of actualization of the behavior of using the application.

The findings of this study reveal a positive and significant relationship between behavioral intention (BI) and use behavior (UB), with an original sample coefficient of 0.243, indicating that behavioral intention accounts for only 24.3% of the variance in use behavior. The t-statistic value of 3.911 (<1.960) and a p-value of 0.000 (>0.05). The results of this study emphasize that the higher the intention of students to use technology, the more likely they are to use it in learning. This means that individual motivation and awareness play an important role in technology adoption. Students need to actively build habits of using technology, find ways to overcome obstacles such as a lack of digital skills and see technology as a tool that can improve their learning effectiveness. In addition, intention alone is not enough without real action. The more often students use technology, the more accustomed and skilled they will be in using it.

6) Connection between performance expectancy and behavioral intention moderated by age

Connection between PE and BI moderated by age in study this own mark original sample (O) is 0.034 which shows existence positive relationship, meaning connection performance expectancy to behavioral intention moderated by age is 3.4%. The t-statistic value in the test hypothesis this obtained the result is 0.495 which means < t-table (1.960). While for probability significant results obtained is worth 0.621so more big from level error (0.05). According to findings testing hypothesis 6, it can be known that the variable performance expectancy to behavioral intention moderated by age shows a positive relationship but does not show a significant relationship. So the hypothesis 6 is rejected. This finding shows that although higher performance expectations can increase students' intentions to use technology, the effect of age is not strong enough to clarify the relationship. In other words, age differences among students do not significantly affect the relationship between performance expectations and usage intentions. This study supports previous research by [84] with the results that age does not strengthen the relationship between performance expectations and utilization intentions because age differences are not an obstacle when using SID. So this finding is different from the findings of [85] with the results that the age variable has a moderating effect that strengthens the relationship between performance expectations and the behavior of using the Undiksha E-learning system.

The results showed that Performance Expectancy (PE) has a positive relationship with Behavioral Intention (BI) when moderated by age. However, this relationship is not significant with a t-statistic value = 0.495 (<1.960) and *p*-value = 0.621 (> 0.05), indicating that although there is a positive relationship between PE and BI moderated by age, statistical insignificance indicates that age does not play an important role in strengthening or weakening the relationship between performance expectations and students' behavioral intentions in using technology. In other words, regardless of their age, college students tend to have similar intentions to use technology based on their performance expectations. This finding indicates that age does not affect the relationship between performance expectations and college students' intentions to use technology. This may be due to the homogeneity of college students' characteristics in terms of access and adaptation to technology so age is not a significant differentiating factor. Adds to the evidence that age may not be a significant moderator in the relationship between performance expectations and behavioral intentions in the context of college students. However, the differences in findings with other studies suggest the need to consider context and sample characteristics in evaluating the role of age as a moderator. Further research could explore other factors that may moderate this relationship, such as technology experience or intrinsic motivation.

7) Connection between effort expectancy and behavioral intention moderated by age

EE against BI moderated by age in studies this get original sample (O) −0.088 which shows existence negative relationship, meaning connection effort expectancy to behavioral intention moderated by age of −8.8%. The t-statistic value in the test hypothesis this obtained result 1.618 so < t-table (1.960). While for probability significant results obtained is worth 0.106 so more big from level error (0.05). According to findings testing hypothesis, it can be known that the variable effort expectancy to behavioral intention moderated by age shows a negative relationship and does not show a significant relationship. So the hypothesis is rejected. The findings in this study indicate that the effort required to understand and use a technology system does not have a strong impact on the intention to use the technology, especially when considering the age factor. Therefore, the approach to increasing technology adoption does not need to be focused solely on the ease of use aspect, but rather on the benefits obtained from using the technology.

The results showed that the original sample value (O) for the relationship between EE and BI moderated by age was −0.088. This means that when age is used as a moderator, the relationship between EE and BI actually decreased by −8.8%. Although this relationship is negative, this value is relatively small, so its impact on BI is also low. The t-statistic value obtained is 1.618, which is still smaller than the t-table (1.960), indicating that this relationship is not statistically significant. In addition, the significance probability value of 0.106 is greater than the error level of 0.05, so the hypothesis that age moderates the relationship between EE and BI cannot be accepted. This confirms that the age factor does not have a significant influence in weakening or strengthening the relationship between EE and BI. This result is in line with previous research by [84], which found that there was no moderating effect of age that strengthened the relationship between effort expectancy and behavioral intention SID. However, this is in contrast to the findings of [85], which concluded that the age variable has a moderating effect that strengthens the relationship between effort expectancy and behavioral intention of the Undiksha E-learning system.

This study shows that the effort required to use a technology does not have a strong influence on user behavioral intentions, especially when age is used as a moderating factor. Therefore, strategies to increase technology adoption should focus on other factors such as technology benefits, technical support, and user needs, rather than just focusing on ease of use. Further research can consider other factors such as attitudes towards technology and institutional support to better understand the factors that influence the intention to use technology in various sectors. In addition, further studies with broader methods and additional variables can help provide a more comprehensive understanding of this phenomenon.

8) Connection between social influence against behavioral intention moderated by age

Connection between SI and BI moderated by age in study this own mark original sample (O) is −0.001 which shows existence negative relationship, meaning connection social influence to behavioral intention moderated by age of −0.1%. The t-statistic value in the test hypothesis this obtained the result is 0.019 which means < from the t-table (1.960). While for probability significant results obtained is worth 0.985 so that more big from level error (0.05). According to findings testing hypothesis 8, it can be known that the variable social influence to behavioral intention moderated by age shows a negative relationship but does not show a significant relationship. So, the hypothesis 8 is rejected. The findings in this study indicate that although there is a negative relationship between SI and BI moderated by age, statistical insignificance indicates that age does not play a significant role in strengthening or weakening the relationship between social influence and students' behavioral intention to use technology. In other words, regardless of their age, students tend to have similar intentions in using technology based on the social influence they experience.

The results on this study indicate that the influence of Social Influence (SI) on Behavioral Intention (BI) moderated by age has a negative relationship of −0.1%, with a t-statistic value of 0.019 (smaller than the t-table of 1.960) and a significance value of 0.985 (greater than 0.05). This indicates that there is a negative relationship between SI and BI when moderated by age, and the relationship is not statistically significant. This finding indicates that age factors do not affect the relationship between social influence and students' intention to use technology. This may be due to the homogeneity of student characteristics in terms of access and adaptation to technology, so age is not a significant differentiating factor. This result is in line with previous research by [84], which found that there was no moderating effect of age that strengthened the relationship between social influence and utilization interest. However, this is in contrast to the findings of [85], which concluded that the age variable has a moderating effect that strengthens the relationship between social influence and the behavior of using the Undiksha E-learning system.

This study shows that age does not moderate the relationship between SI and BI, which can be interpreted as social influences from the surrounding environment, such as peers or lecturers, do not differ significantly between different age groups. This may be due to the homogeneity of age in the study sample or because the age factor does not play a significant role in moderating the influence of SI on BI in this context.

Overall, these findings emphasize the importance of considering the context and characteristics of the sample in assessing the influence of SI on BI and the role of age as a moderator. Further research can consider other factors such as attitudes towards technology and institutional support to better understand the factors that influence the intention to use technology in various sectors. In addition, further studies with broader methods and additional variables can help provide a more comprehensive understanding of this phenomenon.

9) Connection between facilitating conditions and use behavior moderated by age

Connection between FC and UB moderated by age in study this own mark original sample (O) is −0.016 which shows existence negative relationship, meaning connection facilitating conditions for use behavior moderated by age of −1.6%. The t-statistic value in the test hypothesis this obtained the result is 0.464 which means more small from t-table (1.960). While for probability significant results obtained is worth 0.643 so that more big from level error (0.05). According to findings testing hypothesis 9, it can be known that the variable facilitating conditions for use behavior moderated by age shows a negative relationship but does not show a significant relationship. So, the hypothesis 9 is rejected. The findings in this study indicate that the older a person is, the smaller the influence of FC on UB. This means that even though the available facilities or resources support the use of technology, the age factor does not strengthen this relationship. In fact, the older a person is, the influence of FC on technology use tends to decrease, although in a small amount (−1.6%).

The results of your study show that Facilitating Conditions (X4) and Use Behavior (Y2) moderated by age get a t-statistic value of 0.464 (smaller than the t-table of 1.960) and a p-value of 0.643 (greater than 0.05), these results indicate that this relationship is not significant. This means that the influence of FC on UB is not strong enough to be considered generally applicable in the population. This could be caused by other factors that are more dominant in determining technology use behavior than simply the availability of facilities. These results are in line with previous research by [56] in the UTAUT model showing that age can be a moderator that does not always strengthen the relationship between FC and UB, depending on the context of its use. However, this is in contrast to the findings of [84] which concluded that there was no moderating effect of the moderator variable age that strengthened the relationship between facilitating conditions and SID user behavior.

This study shows that age is not always a factor that strengthens the relationship between FC and technology use behavior. This may be due to technological independence where in an academic environment, students may be accustomed to technology, so they are not too dependent on the availability of facilities. Another factor that could be the reason is that age does not play a significant role in determining how much someone relies on FC. Older age does not always make it more difficult for someone to use technology, especially if they are already familiar with the existing system.

Overall, these findings emphasize that the relationship between facilitating conditions (FC) and use behavior (UB) moderated by age is not significant, so it is important to consider other factors in understanding Gemini AI adoption. These results indicate that simply providing supporting facilities does not necessarily increase Gemini AI use, especially for different age groups. This study also highlights the need to understand contextual factors that influence the relationship between FC and UB, such as trust in the system, as well as individual preferences in using new technology. These factors can play a greater role in determining whether someone will adopt and use technology in their daily life.

10) Connection between performance expectancy and behavioral intention moderated by gender

Connection between PE and BI moderated by gender in study this own mark original sample (O) is −0.006 which shows existence negative relationship, meaning connection performance expectancy to behavioral intention moderated by gender is −0,6%. The t-statistic value in the test hypothesis this obtained the result is 0.128 which means < t-table (1.960). While for probability significant results obtained is worth 0.898 so more big from level error (0.05). According to findings testing hypothesis, it can be known that the variable performance expectancy to behavioral intention moderated by gender shows a negative relationship and does not show a significant relationship. So, the hypothesis 10 is rejected. The findings in this study indicate that gender differences do not have a significant effect in strengthening or weakening the relationship between performance expectations and individual behavioral intentions in using Gemini AI. Other factors may play a bigger role than gender in influencing a person's intention to adopt Gemini AI, such as previous technology experience, need for technology, and support from the surrounding environment. Therefore, in encouraging the use of Gemini AI, it is more effective to focus on the real usefulness aspects of the technology rather than considering gender differences as the main factor.

This result is in line with previous research by [84] which showed that the moderating effect of gender did not strengthen the relationship between Performance Expectancy and Behavioral Intention SID. However, this is in contrast to the findings of [85] which concluded that gender diversity has a moderating effect that strengthens the relationship between performance expectations and Behavioral Intention the Undiksha E-learning system. This difference in results indicates that the moderating role of gender in the relationship between performance expectations and behavioral intentions can be influenced by the research context, sample characteristics, and other variables that may play a role.

The results of this study provide theoretical contributions to understanding the relationship between performance expectancy (PE) and behavioral intention (BI) which is moderated by gender. Although many studies in the UTAUT (Unified Theory of Acceptance and Use of Technology) model emphasize that gender can be a moderating factor that influences the relationship between PE and BI, the findings in this study indicate that the influence of gender in this context is not significant. This indicates that performance expectations towards technology have a relatively uniform impact across gender groups in this study sample, challenging the assumption that men and women consider performance benefits differently in technology decision making.

11) Connection between effort expectancy and behavioral intention moderated by gender

EE against BI moderated by gender in studies this get original sample (O) −0.070 which shows existence negative relationship, meaning connection effort expectancy to behavioral intention moderated by gender of −7.0%. The t-statistic value in the test hypothesis this obtained result 1.468 so < t-table (1.960). While for probability significant results obtained is worth 0.142 so more big from level error (0.05). According to findings testing hypothesis 11, it can be known that the variable effort expectancy to behavioral intention moderated by gender shows a negative relationship and does not show a significant relationship. So, the hypothesis 11 is rejected. The findings in this study indicate that gender differences do not play a significant role in strengthening or weakening the relationship between EE and BI. This means that both men and women do not show substantial differences in how the ease of use of technology affects their intention to use it.

This finding is in line with previous research by [84], which shows that the moderating effect of gender does not strengthen the relationship between performance expectations and the intention to use SID. However, this is in contrast to the findings of [85], which concluded that gender diversity has a moderating effect that strengthens the relationship between effort expectations and the behavior of using the Undiksha E-learning system. This difference in results may be caused by differences in the research context, sample characteristics, and the type of technology used in the study.

The findings in this study differ from the assumption in the UTAUT model that gender plays an important role in moderating the relationship between EE and BI. In some contexts, especially among students, the influence of gender on how someone assesses the ease of use of technology does not seem to be very significant. Factors that may influence it are that at present, digital literacy has increased significantly in various gender groups, especially among students. Men and women have almost the same access to technology, so they have similar understandings about the ease of use of a system. Therefore, the moderating effect of gender on the relationship between EE and BI becomes insignificant. This finding also adds to the UTAUT literature by confirming that gender may no longer be a relevant factor in moderating the relationship between EE and BI, especially in the college student population, where men and women are equally familiar with technology.

12) Connection between social influence against behavioral intention moderated by gender

Connection between SI and BI moderated by gender in study this own mark original sample (O) is 0.116 which shows existence positive relationship, meaning connection social influence to behavioral intention moderated by gender of 11.6%. The t-statistic value in the test hypothesis this obtained the result is 2.882 which means > from the t-table (1.960). While for probability significant results obtained is worth 0.004 so that more small from level error (0.05). According to findings testing hypothesis 12, it can be known that the variable social influence to behavioral intention moderated by gender shows a positive and significant relationship. So, the hypothesis is accepted. The findings in this study indicate that the influence of social influence variables on behavioral intention variables is stronger or weaker depending on gender factors. This finding supports the idea that individuals of different genders may have different sensitivities to social influence in determining their intention to use a technology or system. This finding is in line with several previous studies that found that gender plays an important role in strengthening the influence of SI on BI. Venkatesh *et al*. in the UTAUT model stated that SI has a greater influence on individuals who tend to consider social opinions more in decision making, especially in groups with different genders [56]. In addition, research from Herskovitz *et al.* [86] shows that women tend to be more influenced by social factors than men in adopting new technology, which is in line with the findings of this study. However, this is in contrast to the findings from Tresnawan, Pradnyana, and Wirawan, which concluded that no gender moderating effect strengthened the relationship between social influence on utilization interest in village information systems. The difference in results in the context of this study was due to the same support from superiors for both men and women to use the village information system [84].

These findings have important implications for developing technology adoption strategies, particularly in the context of AI applications such as Gemini AI. Organizations can leverage social influence to drive AI adoption among users who are more responsive to social factors, such as through community outreach or support from influential figures. Additionally, in academic and professional settings, policies that take gender into account can help to increase acceptance and use of AI technologies more effectively. This study also adds to the literature on the Unified Theory of Acceptance and Use of Technology (UTAUT) by showing that gender moderation can strengthen the relationship between IS and BI in an academic context. This provides new insights into how social factors operate across different groups of technology users and suggests the need for further research to understand how gender differences may influence other factors in the

UTAUT model.

13) Connection between effort expectancy and behavioral intention moderated by experience

EE against BI moderated by experience in studies this get original sample (O) −0.070 which shows existence negative relationship, meaning connection effort expectancy to behavioral intention moderated by experience of -0.70%. The t-statistic value in the test hypothesis this obtained result 1.571 so < t-table (1.960). While for probability significant results obtained is worth 0.116 so more big from level error (0.05). According to findings testing hypothesis 13, it can be known that the variable effort expectancy to behavioral intention moderated by experience shows a negative relationship and insignificant relationship. So, the hypothesis is rejected. The findings in this study indicate that increasing experience slightly decreases the relationship between perceived ease of use and behavioral intention in adopting technology. The results of this study are in line with several previous studies that show that experience does not always play a significant role in moderating the relationship between Effort Expectancy and Behavioral Intention. For example, research by Venkatesh *et al*. (2003) in the Unified Theory of Acceptance and Use of Technology (UTAUT) model. In addition, research from Dewi, Kusuma, and Rakhmadani (2023) shows that the moderator variable experience does not affect the relationship between Effort Expectancy and Behavioral Intention of Shopee e-commerce users [87]. However, this study contrasts with the findings of [84] which concluded that diversity of experience has a moderating effect that strengthens the relationship between social influence on the behavior of using the Undiksha E-learning system. In their study, they argued that individuals with more experience tend to have a better understanding of the ease of use of a system, thereby increasing their intention to adopt the technology. However, in the context of this study, the experience factor does not seem to have a significant influence, possibly because the economics students who were the respondents of the study already had relatively uniform exposure to technology, so the experience is no longer the main differentiating factor in determining the intention to use technology.

This finding enriches the UTAUT literature, especially in understanding how experience moderates the relationship between Effort Expectancy and Behavioural Intention. These results indicate that experience is not always a determining factor in influencing the intention to use technology. This finding confirms that the adoption of Gemini AI is complex and depends on various factors, so a more holistic approach is needed to understand the pattern of technology acceptance in various user groups.

14) Connection between social influence against behavioural intention moderated by experience

Connection between SI and BI moderated by experience in study this own mark original sample (O) is −0.108 which shows existence negative relationship, meaning connection social influence to behavioral intention moderated by expereince of −10.8%. The t-statistic value in the test hypothesis this obtained the result is 2.770 which means > from the t-table (1.960). While for probability significant results obtained is worth 0.006 so that more small from level error (0.05). According to findings testing hypothesis 14, it can be known that the variable social influence to behavioral intention moderated by experience shows a negative and significant relationship. So, the hypothesis 14 is rejected. The findings in this study indicate that experience significantly moderates the relationship between Social Influence (SI) and Behavioral Intention (BI) but with a negative direction of the relationship. Although significant, the negative direction of the relationship indicates that individuals with higher experience tend to be less influenced by social factors in forming their intention to use technology. The higher a person's experience in using Gemini AI, the weaker the social influence on behavioral intentions in adopting Gemini AI.

The results of this study are in line with several studies that emphasize that experience can reduce the influence of Social Influence on Behavioral Intention. For example, research by Venkatesh *et al*. (2003) in the UTAUT model shows that social influence is stronger in less experienced users because they rely more on the opinions of others in adopting technology [56]. In addition, research from Tresnawan, Pradnyana, and Wirawan (2020) shows that the moderator variable experience does not strengthen the relationship between social influence and interest in utilization because the difference in experience is not a problem or obstacle so using SID makes it more trusted in doing work [84]. However, this study contrasts with the findings of [85] which concluded that diversity of experience has a moderating effect that strengthens the relationship between social influence on the behavior of using the Undiksha E-learning system. They found that in a highly dynamic and technology-based environment, even users with high experience still consider social influence in making decisions, especially when new technology is introduced.

This finding provides an important contribution to the UTAUT literature, especially in understanding how experience plays a role in moderating the relationship between Social Influence and Behavioral Intention of Gemini AI users. These results suggest that experience can be a key factor in reducing individual dependence on social norms in Gemini AI adoption decisions. Therefore, the technology acceptance model needs to consider further experience factors to explain differences in technology adoption patterns across user groups. Gemini AI application developers also need to adjust their approach to encouraging technology adoption by considering the level of user experience. For more experienced users, strategies based on technology benefits and performance enhancement may be more effective than social-based approaches.

15) Connection between facilitating conditions and use behaviour moderated by experience

Connection between FC and UB moderated by experience in study this own mark original sample (O) is −0.143 which shows existence positive relationship, meaning connection facilitating conditions for use behavior moderated by experience of 14.3%. The t-statistic value in the test hypothesis this obtained the result is 2.803 which means more big from t-table (1.960). While for probability significant results obtained is worth 0.005 so that more small from level error (0.05). According to findings testing hypothesis 15, it can be known that the variable facilitating conditions for use behavior moderated by experience shows a positive and significant relationship. So, the hypothesis 15 is accepted. The findings in this study indicate that experience plays a crucial role in strengthening the influence of facilitating conditions on Gemini AI usage behavior, the higher a person's experience in using Gemini AI, the greater the impact of facilitating conditions on Use Behavior. This finding is in line with various studies that confirm that experience can increase the role of Facilitating Conditions in shaping Use Behavior. For example, research by Venkatesh *et al*. (2003) in the UTAUT model shows that users with higher levels of experience tend to be more able to utilize facilitating conditions, such as technical support and resource availability, in improving technology usage behavior. Another study by [85] showed that diversity of experience has a moderating effect that strengthens the relationship between facilitating conditions and usage behavior of the Undiksha E-learning system. However, this study contrasts with the findings of [84] which concluded that experience does not strengthen the relationship between facilitating conditions and usage behavior because differences in experience do not become obstacles or problems in working when facilities support the use of SID.

The results of this study contribute to the UTAUT literature, by showing that experience not only moderates the relationship between Facilitating Conditions and Use Behavior but can also strengthen the role of facilitating conditions in encouraging the use of Gemini AI. This suggests that technology adoption models should take experience factors into greater consideration to understand the dynamics of user behavior across contexts. These findings underscore the importance of providing adequate technology support for experienced users, not just novices. Educational institutions and business organizations can optimize the use of technology by ensuring that facilities and technical support remain available to users with varying levels of experience. In addition, advanced training programs can be designed to help highly experienced users use technology more effectively, thereby increasing adoption rates and the sustainability of technology use in the long term.

V. Conclusion

Based on the research results described above, it can be concluded that Performance Expectancy (PE) does not have a significant effect on Behavioral Intention (BI) in the use of Gemini AI. This means that the performance expectations of this technology are not the main factor in determining the user's intention to adopt it. Effort Expectancy (EE) also does not have a significant effect on Behavioral Intention. This shows that the ease of use of Gemini AI is not a strong enough factor to encourage users to be interested in using it. Social Influence (SI) does not have a significant effect on Behavioral Intention. This indicates that social influences, such as encouragement from others or the surrounding environment, are not strong enough to motivate someone to use Gemini AI. Facilitating Conditions (FC) does not have a significant effect on Use Behavior (UB). In other words, the availability of resources and technical support alone is not enough to ensure that someone will use Gemini AI. Behavioral Intention has a positive and significant effect on Use Behavior. This means that the greater a person's intention to use Gemini AI, the more likely they are to use it in their activities. Age does not moderate the relationship between Performance Expectancy and Behavioral Intention. This means that Gemini AI performance expectations are not influenced by age in forming Behavioral Intention. Age does not moderate the relationship between Effort Expectancy and Behavioral Intention. In other words, Gemini AI's ease of use does not have a different effect depending on the user's age. Age also does not moderate the relationship between Social Influence and Behavioral Intention. This means that social influence in encouraging the use of Gemini AI does not depend on the user's age. Age does not moderate the relationship between Facilitating Conditions and Use Behavior. This shows that the support and facilities available are not more or less effective in encouraging the use of Gemini AI based on age differences. Gender does not moderate the relationship between Performance Expectancy and Behavioral Intention. This means that Gemini AI's performance expectations do not have a different effect between men and women in determining usage intentions. Gender also does not moderate the relationship between Effort Expectancy and Behavioral Intention. This means that gender differences do not make Gemini AI's ease of use more or less influential on usage intentions. Gender moderates the relationship between Social Influence and Behavioral Intention with a significant effect. This shows that social influence on the intention to use Gemini AI is stronger in certain gender groups. Experience does not moderate the relationship between Effort Expectancy and Behavioral Intention. In other words, previous experience in using similar technology does not make Gemini AI's ease of use more or less influential on user intention. Experience also does not moderate the relationship between Social Influence and Behavioral Intention. This means that social influence in encouraging the use of Gemini AI does not depend on the level of previous user experience. Experience significantly moderates the relationship between Facilitating Conditions and Use Behavior. This means that the more experienced a person is in using technology, the greater the influence of supporting facilities in encouraging them to use Gemini AI.

While this study focuses on the use of Gemini AI among students in the Economic Education study program at universities in East Java, Indonesia. The findings offer valuable insights that can be extended to other educational contexts. Future research could explore the adoption of Gemini AI across different education levels (e.g., high school, postgraduate) and institutions, as well as compare its effectiveness with other AI tools. Such comparative studies would provide a more comprehensive understanding of how AI technologies can be integrated into diverse educational environments.

In terms of practical implications, the findings of this study can guide policymakers and educators in designing strategies to enhance the adoption of AI tools in education. For instance, universities can develop training programs to familiarize students with AI technologies, integrate AI tools into the curriculum, and provide the necessary infrastructure to support their use. Policymakers can also consider creating guidelines for the ethical and effective use of AI in education, ensuring that these technologies are accessible to all students and aligned with educational goals. By addressing these aspects, the study contributes to the broader discourse on the role of AI in education and provides actionable recommendations for stakeholders.

The recommendation that can be given based on the entire series of research activities for further researchers who will conduct the same research is to use a longitudinal design, this approach allows researchers to observe how Behavioral Intention and Use Behavior develop over time, as well as how factors such as experience, performance expectations, and supporting conditions affect the adoption of this technology in the long term. In addition, a longitudinal design can also provide further insight into changes in moderating factors, such as gender, age, and experience, and how they affect user decisions in adopting Gemini AI. Technology that continues to evolve is also an important consideration in this study because updates or changes to features can affect user preferences and expectations. Therefore, future research is expected to be able to capture the dynamics of technology adoption more accurately, resulting in a more effective strategy to increase the use of Gemini AI.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

R.Y.K.: Conceptualization, research preparation, data analysis, and writing of the manuscript. A.I.M.: Assisted with data collection and research preparation, safeguarding respondent confidentiality, and reviewing the manuscript. S.R.: Funding acquisition, Project administration, Validation. R.M.D.: Data curation, Project administration, Resources, Validation. P.U.K.: Methodology, Project administration, investigation, Software. M.Z.A.M.: Formal analysis, Resources, Validation. All authors approved the final version of the manuscript.

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