

Claude AI Adoption in High School Learning: An Extended UTAUT Model of Students' Behavioral Intention and Use Behavior

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Abstract

The integration of generative artificial intelligence (AI) into secondary education is creating new opportunities for advanced, adaptive, and student-centered learning, while its educational value depends partly on students' acceptance and actual use of the technology. Therefore, this study examines the acceptance and use of Claude AI in high school economics learning through the UTAUT model, with particular attention to its implications for AI-supported learning innovation and the design of more responsive learning environments. A quantitative survey was carried out among 139 high school students from SMAN 18 Surabaya, and the proposed research model was evaluated by applying PLS-SEM. The measurement model proved the construct validity and reliability in all constructs. The structural model showed that both Performance Expectancy and Social Influence affected Behavioral Intention, whereas Effort Expectancy did not show any statistically significant effect on it. Facilitating Conditions and Behavioral Intention had a significant impact on Use Behavior. The model accounted for 59.3% of the variance of Behavioral Intention and 41.4% of the variance of Use Behavior. Moreover, no moderating effect of age, gender, and experience with Claude AI was observed on the examined relationships in the model. The findings indicate that students' acceptance of Claude AI is primarily associated with perceived learning benefits and social influence, whereas actual use is associated with behavioral intention and facilitating conditions. These findings highlight the importance of integrating generative AI through pedagogically meaningful, student-centered, and context-sensitive learning strategies rather than treating it solely as a technological tool.

Keywords: generative artificial intelligence, advanced learning, adaptive learning, learning innovation, instructional design, technology acceptance, meaningful learning.



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1. Introduction

The transformation that has shaped the present-day world, driven largely by rapid technological progress, has positioned the capacity to comprehend and apply artificial intelligence (AI) as an increasingly vital strategic skill. AI is now capable of performing various tasks previously only capable of humans,

such as analyzing data and supporting decision-making processes with high speed and accuracy (Venkatesh et al., 2003). This development has made AI a strategic element in various areas of life, including the education sector (Shete et al., 2024).

One rapidly developing form of artificial intelligence is the chatbot, a computer system

created to enable user interaction via textual or verbal communication (Asha et al., 2023). One of the many chatbots in use is Claude AI, a chatbot capable of providing quick responses accompanied by relevant input and available for free or paid access to users (Martins, 2024). Its rapid development, particularly in educational contexts, has led to increased use of Claude AI with students to enrich the learning experience, deepen understanding of material, help solve academic problems, and support more effective and efficient task completion (Abrar et al., 2025).

In high school economics, conceptual mastery represents an essential component of advanced learning because students are expected not only to recall economic concepts but also to interpret complex relationships, evaluate alternative perspectives, and apply knowledge to authentic economic situations. Learning economics therefore requires higher-order cognitive processes, particularly comprehension, critical analysis, problem solving, and evidence-based reasoning in topics such as supply and demand, market structure, financial institutions, and fiscal and monetary policy (Fortuna et al., 2025). However, learning practices that remain predominantly lecture-based may limit students' active participation, inquiry, and opportunities to construct knowledge through meaningful interaction. A progressive learning environment requires a shift from predominantly teacher-centered knowledge transmission toward more student-centered, interactive, and technology-supported learning experiences in which students actively explore, question, interpret, and apply economic concepts (Bhat et al., 2024). The integration of Claude AI as a virtual tutor introduces an adaptive learning approach by enabling students to obtain explanations, examples, feedback, and learning support according to their individual levels of

understanding and learning needs. Its potential use as a digital simulation medium can further facilitate interactive exploration of economic concepts, allowing students to engage with learning content through more flexible and individualized learning pathways (Wu et al., 2025).

Despite the growing adoption of generative AI within educational contexts, how effectively it is implemented largely hinges on the extent to which users accept it. Without understanding the factors that influence this acceptance, AI integration in learning environments risks yielding benefits that fall short of their full potential (Tapalova & Zhiyenbayeva, 2022). Therefore, identifying the determinants of students' acceptance of generative AI is important not only for understanding technology adoption but also for informing instructional design decisions. Evidence regarding students' perceived learning benefits, social influence, behavioral intention, and facilitating conditions can provide a basis for designing AI-supported learning activities, teacher guidance, learning resources, and classroom interactions that are aligned with students' learning needs and the characteristics of the instructional context (Ke et al., 2025). To explore the utilization patterns of Claude AI in academic activities, researchers used the Unified Theory of Acceptance and Use of Technology (UTAUT) model, a technology acceptance model that has been extensively used and validated to describe the determinant factors that shape individual interest and actions in accepting a technology. Venkatesh proposed this theory by integrating eight existing technology acceptance models, where the most superior and relevant constructs from each model were then combined into one comprehensive and integrated theory (Venkatesh et al., 2003). The eight theoretical frameworks include "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 Theory of Planned Behavior (C-TAM-TPB), The Model of The PC Utilization (MPCU), The Innovation Diffusion Theory (IDT) and Social Cognitive Theory (SCT)” (Hair et al., 2019). The combination of these eight models was intended to address the limitations of each of the previous models and accommodate the similarities in constructs between them. The UTAUT model explains that behavioral intention (behavioral intention) and usage behavior (usage behavior) are influenced by four external variables: performance expectancy, effort expectancy, social influence, and facilitating conditions. In addition to these primary variables, the UTAUT model also considers moderating variables, including age, gender, and user experience. These variables influence how strong the association is between the independent and dependent variables in the model. The presence of moderating variables refines and improves the UTAUT model by illustrating how differences in demographic factors and a person's level of experience can shape and influence their behavioral patterns in adopting a technology (Aideed et al., 2025). Numerous previous studies grounded in empirical data have found that UTAUT is effective in triggering user responses to the implementation of technology in educational contexts (Acosta-Enriquez et al., 2024).

Even though a considerable number of studies have proven the predictive power of the UTAUT model in explaining technology acceptance across various educational contexts, empirical evidence regarding its

application to generative AI at the secondary school level remains limited. Most previous studies have focused on college students (Aideed et al., 2025), or on STEM-based subjects (Azzam & Tendai, 2025), therefore, the existing body of findings does not entirely reflect the specific characteristics of high school students. In fact, students at this level have varying levels of cognitive maturity, technological experience, and learning contexts. Furthermore, the application of AI-based generative tools, like Claude AI in the context of Economics learning, which combines quantitative analysis, social reasoning, and interpretation of policies and market dynamics, is still rarely studied. This situation indicates the need for further research on how high school students accept and leverage AI technology within their learning experience (Sabol et al., 2023). Therefore, this research aims to analyze the determinants that influence students' acceptance and use of Claude AI using the Unified Theory of Acceptance and Use of Technology (UTAUT) framework, while providing empirical insights into how generative AI can be incorporated into learning strategies that support students' understanding, engagement, and continued participation in economics learning (Isnaini & Muslimin, 2024). This study extends the application of the UTAUT model, previously more widely used in higher education and STEM fields, in the realm of Economics learning in high school.

This study develops a UTAUT-based research framework to explain the relationships between variables in the acceptance and use of Claude AI in economics learning. The research framework is presented in Figure 1.

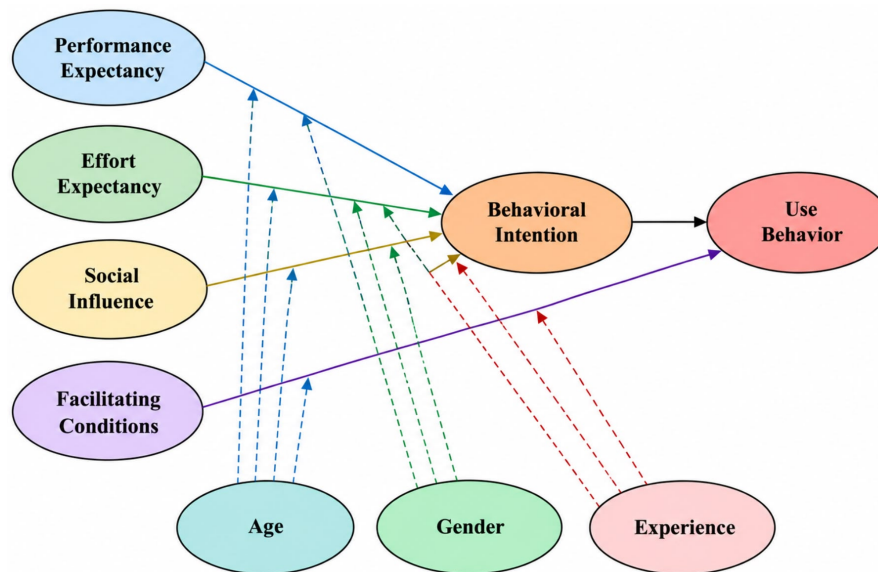


Figure 1. Research Framework

Grounded in the conceptual framework outlined above, the hypotheses proposed in and the relationships between variables this study are presented as follows.

Table 1. Research Hypothesis

Hipotesis	
H ₁	: Performance Expectancy demonstrates a significant and positive relationship with Behavioral Intention
H ₂	: Effort Expectancy demonstrates a significant and positive relationship with Behavioral Intention
H ₃	: Social Influence demonstrates a significant and positive relationship with Behavioral Intention
H ₄	: There is a positive and significant relationship between Facilitating Conditions and Behavioral Intentions
H ₅	: There is a positive and significant relationship between Behavioral Intention and Use Behavior
H ₆	: The effect of Performance Expectations on Behavioral Intentions is positively and significantly moderated by age.
H ₇	: The effect of Effort Expectancy on Behavioral Intention is positively and significantly moderated by age.
H ₈	: The effect of Social Influence on Behavioral Intention is positively and significantly moderated by age
H ₉	: The effect of Facilitating Conditions on Use Behavior is positively and significantly moderated by age
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 positively and significantly moderates the relationship between Social Influence and Behavioral Intention.
H ₁₃	: Experience significantly and positively strengthens how Effort Expectancy influence Behavioral Intention.
H ₁₄	: Experience significantly and positively strengthens how Social Influence influence Behavioral Intention.
H ₁₅	: Experience significantly and positively strengthens how Facilitating Conditions influence Use Behavior.

2. Method

This study was conducted using a quantitative, cross-sectional survey-based approach, collecting data through questionnaires distributed to participants during a single data collection period. A five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree), was used as

the research instrument, which was adapted from the Unified Theory of Acceptance and Use of Technology (UTAUT) construct developed by (Alkhwaldi, 2024), with indicators tailored to fit the context of Claude AI use in Economics learning. The indicators corresponding to each research variable are presented in Table 2.

Table 2. Variable indicators

Variable	Indicator	Question
Performance Expectancy (PE)	a. Improved Understanding	PE1: Claude can help me understand economics lessons more easily.
	b. Learning Efficiency	PE2: Claude can help me complete economics assignments more quickly and easily.
	c. Quality of Learning Outcomes	PE3: Claude can help me obtain more accurate information about economics learning resources and materials.
	d. Improved Grades	PE4: Claude helps me get better grades in economics.
Effort Expectancy (EE)	a. Ease of Use	EE1: I find Claude easy to use in learning economics. EE2: Using Claude is not difficult and doesn't require much effort to understand.
	b. Ease of Access	EE3: Learning to use Claude is easy and doesn't take a long time.
	c. Ease of Learning	EE4: Claude's interface and features are easy to understand and comfortable to use.
Social Influence (SI)	a. Peer Support	SI1: I use Claude in my economics lessons because I want to follow what my friends are doing.
	b. Teacher Support	SI2: I use Claude in my economics lessons because my teacher suggested it.
	c. Educational Institution Support	SI3: I feel compelled to use ChatGPT because many people around me use it.
Facilitating Conditions (FC)	a. Resource Availability	FC1: I have adequate equipment to use Claude (e.g., laptop/smartphone).
	b. Technical Support	FC2: I have stable internet access to use Claude.
	c. Compatibility with Technology	FC3: I can readily obtain assistance whenever I encounter difficulties using Claude.
Behavioral Intention (BI)	a. Desire to Use	BI1: I possess a strong intention to utilize Claude for my economics studies..
	b. Sustainable Willingness	BI2: I will continue to use Claude regularly to help me learn economics.
	c. Future Use Plans	BI3: I plan to use Claude more often in my economics studies.
Use Behavior (UB)	Intensity of Use	UB1: I use Claude at least a few times a week to help me learn economics.
		UB2: I use Claude to complete various assignments and various economics learning activities.

The population was 139 students of SMAN 18 Surabaya in the 2025/2026 academic year who had used Claude AI in their economics learning process. The research location was selected based on the consideration that students at the school (Rathika et al., 2024). already had experience using Claude AI as a learning medium, thus aligning with the research objectives. Sampling was conducted using the total sampling method, meaning the entire population was designated as the sample for this research (Alkhwaldi, 2024).

Data collection was conducted by distributing questionnaires directly in class and online through WhatsApp. Prior to filling out the questionnaire, participants received an explanation of the research objectives, confidentiality of identity, a informed that their involvement was of one's own free will. Furthermore, Data were processed and analyzed with the PLS-SEM (Partial Least Squares-Structural Equation Modeling) technique, supported by SmartPLS version 4 software. This study adopted PLS-SEM because of its capability to efficiently analyze causal relationships between latent constructs in complex research models and still provide strong analytical results despite using a sample sizes that are limited in scope, along with data that deviate from a normal distribution (Hair & Alamer, 2022). These characteristics make PLS-SEM suitable for testing the UTAUT model used in this study.

Two stages were involved in conducting the analysis: first, evaluating the measurement model (outer model), and second, evaluating the structural model (inner model). Validity and reliability of the constructs were assessed during the measurement model evaluation, using the outer loading value, Average Variance Extracted (AVE), Cronbach's alpha (CA), and Composite Reliability (CR) as the criteria. Meanwhile, path

coefficient testing through the bootstrapping procedure was used in the structural model evaluation to examine the relationships between constructs, while the R-Square (R^2) value served to assess the model's ability to explain and predict endogenous variables. Aside from that, the t-statistic derived from the analysis results was compared against the t-table value, which served as the reference point for hypothesis testing (Hair et al., 2021).

3. Result and Discussion

The results and discussion sections include empirical evidence about students' acceptance and usage of Claude AI within the UTAUT framework. The research is mainly centered on measurement quality of research variables, direct relations among the UTAUT variables and moderating roles of demographic and usage-related characteristics. In order to give a comprehensive interpretation of the findings, the results will be presented in three main sections: (1) measurement model and predictive capability of Claude AI acceptance, (2) determinants of behavioral intention and use of Claude AI and (3) moderating roles of age, gender and experience.

a. Measurement Model and Predictive Capability of Claude AI Acceptance

Measurement model was first assessed to ensure the validity and reliability of constructs used to study students' acceptance of Claude AI prior to structural model assessment. This step is especially critical for the current research as it uses the UTAUT framework to study relationships between latent constructs: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Behavioral Intention (BI) and Use Behavior (UB). Analysis was conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM) with the help of SmartPLS 4.0

software. The assessment took into account outer loadings, Average Variance Extracted (AVE), Cronbach's Alpha (CA) and Composite Reliability (CR) according to the criteria proposed in the research methodology (Azzam & Tendai, 2025).

The description of the characteristics of respondents can give an insight into the interpretation of the measurement findings. The study included 139 students of SMAN 18 Surabaya who had experience in using Claude

AI in their economics learning process. It can be seen from the demographics that the sample included more female students than male ones (Sharma & Singh, 2024). At the same time, most respondents were aged 16-17 years. As for experience in usage, the sample was evenly split between students who used Claude five times or less and more often.

Table 3. Participants Criteria

Criteria	Description	Number of Participants	Percentage (%)
Gender	Male	60	43,17%
	Female	79	56,83%
Age	≤ 15 years	8	5,76%
	16 years	71	51,08%
	≥ 17 years	60	43,16%
Usage Experience	≤ 5 times	79	56,83%
	≥ 5 times	60	43,17%
Total		139	100%

The distribution given in Table 3 is necessary for the interpretation of the measurement model since the participants were not completely homogenous in demographic characteristics and usage experience. Female students accounted for 56.83% (n=79) and male students made up 43.17% (n=60) of all the participants. Concerning the age, 51.08% (n=71) of participants were 16 years old and 43.16% (n=60) were aged 17 years or older, while just 5.76% (n=8) were 15 years old or younger. So, 94.24% of respondents were aged 16-17-or-older. As for usage experience distribution, 56.83% (n=79) had used Claude five times or fewer, while 43.17% (n=60) used it five times or more. All these characteristics provide enough variability for analyzing students' perception of Claude AI, while concentrated age distribution will have to be taken into

account when interpreting the moderating analysis in the next section.

In the next step, the outer model was assessed using indicator-level and construct-level criteria. As shown in the output of SmartPLS algorithm, indicators linked to the six constructs had outer loading values exceeding 0.70. It means that every measurement item contributes to its respective latent construct appropriately and has a strong link to this construct (Strzelecki, 2024). It is very important in PLS-SEM to have good outer loading, since otherwise the measurement model may have low explanatory power. In this case, consistently high loading values show that initially questionnaire items were appropriate for reflecting students' perception and behavior concerning Claude AI.

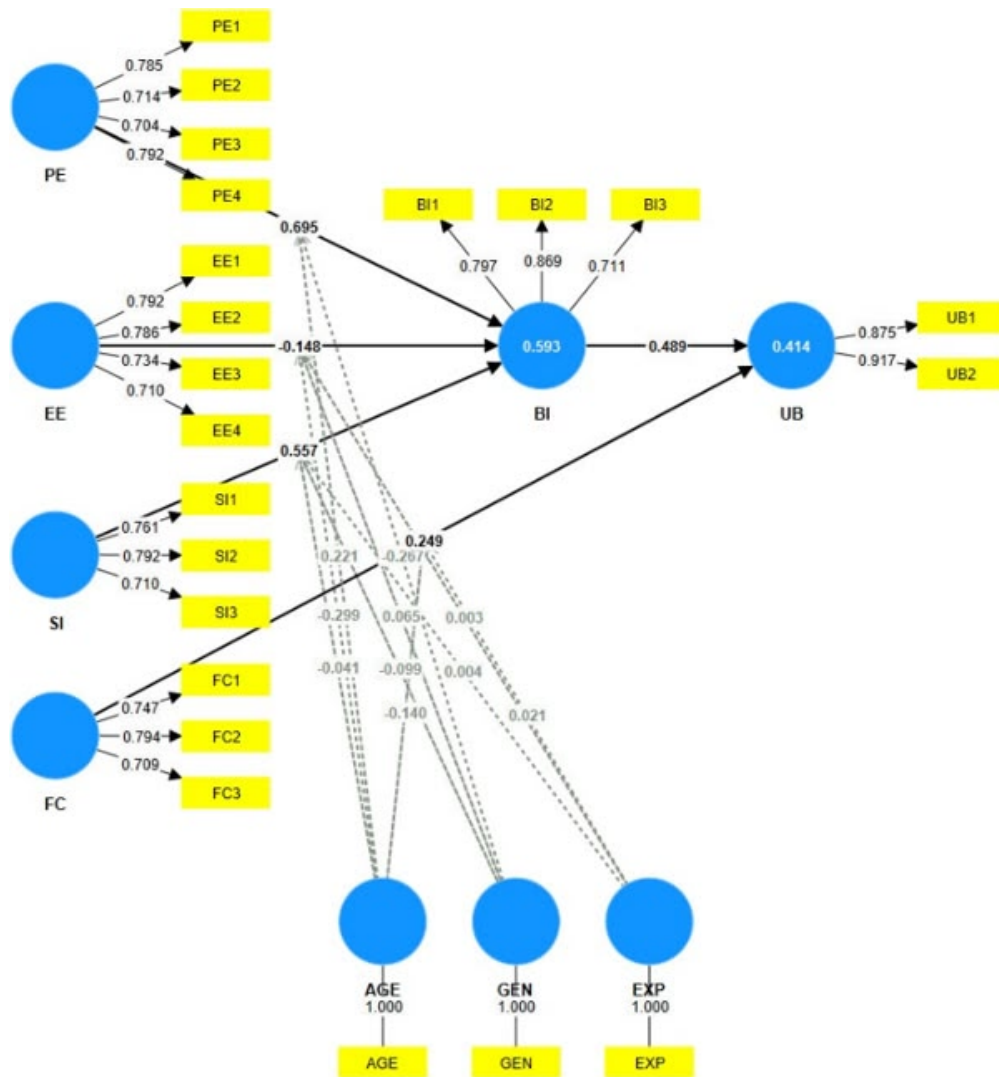


Figure 2. SmartPLS 4.0 Algorithm Results

As depicted in Figure 2, the developed measurement model in SmartPLS 4.0 shows the relationship between the latent variables and the corresponding indicators. In the presented model, it is clear that the indicators were measured properly on PE, EE, SI, FC, BI, and UB. The outcome confirms the internal consistency structure of the UTAUT-based measurement model and is a point of departure for the evaluation of construct validity and reliability (Dewanda et al., 2025). Notably, there are no problematic indicators that have to be removed, which makes it possible to conduct further analysis without narrowing the scope of each construct.

Afterwards, the construct validity was assessed with Average Variance Extracted (AVE). As shown in Table 4, AVE of all six constructs surpassed the recommended threshold of 0.50. The AVE values were varied from 0.562 for Performance Expectancy to 0.803 for Use Behavior. This suggests that each construct accounts for more than half of the total variance explained in its respective indicators (Akavova et al., 2023). Use Behavior had the largest AVE value (0.803) and, thus, can be considered as the most consistent construct in terms of shared variance among its indicators. At the same time, Performance Expectancy, despite

being the one with the smallest AVE among all the constructs, also reached the required threshold.

Table 4. Reliability and Validity Constructs

Variabel	Cronbach's Alpha	Composite Reliability	AVE
Performance Expectancy	0.740	0.837	0.562
Effort Expectancy	0.751	0.842	0.572
Social Influence	0.731	0.799	0.570
Facilitating Conditions	0.714	0.794	0.564
Behavioral Intention	0.705	0.836	0.632
Use Behavior	0.757	0.891	0.803

The findings of the reliability test make the appropriateness of the measurement model even more convincing. For Cronbach's Alpha values ranged between 0.705 and 0.757, whereas Composite Reliability values ranged from 0.794 to 0.891. All values were above the threshold of 0.70 stated in the study. Therefore, one can conclude that the indicators of all constructs exhibit sufficient internal consistency. The importance of the results is that the constructs reflect different aspects of technology acceptance including perceived usefulness (PE), perceived ease (EE), social influence (SI), feasibility (FC), behavioral intention (BI), and usage behavior

(UB) (Kurniawan et al., 2025). Hence, the consistency of the measurements may ensure the reliability of the observations for structural analysis.

Having established the adequacy of the measurement model, the predictive potential of the structural model was evaluated based on the coefficient of determination (R^2). As regards the interpretation of the obtained R^2 values, it has to be mentioned that they were analyzed in accordance with common PLS-SEM criteria where R^2 about 0.25, 0.50, and 0.75 indicate low, medium, and high explanatory power, respectively (Cabero-Almenara et al., 2024).

Table 5. R-Square Value

Variabel	Main Predictors	R-Square (R^2)	Adjusted R-Square	Explanatory Level
Behavioral Intention	PE, EE, SI	0,593	0,495	Moderate
Use Behavior	BI, FC	0,414	0,361	Weak-to-moderate

As shown in Table 5, the R^2 for Behavioral Intention (BI) was 0.593, meaning that the variables of Performance Expectancy, Effort Expectancy, and Social Influence together explain about 59.3% of the variation in the students' intention to use Claude AI. The adjusted R^2 of 0.495 is a more conservative statistic accounting for the number of predictors involved. The difference between R^2 and adjusted R^2 is that part of the explanatory power lies in the model

specification and the number of predictors used, yet the model remains explanatory (Venkatesh et al., 2012).

The R^2 value of Use Behavior (UB) was 0.414, while the adjusted R^2 was 0.361. It implies that the two predictor variables of Behavioral Intention and Facilitating Conditions jointly explain only 41.4% of the variation in students' actual usage of Claude AI, leaving 58.6% of variance due to other factors. Despite its low level relative to R^2

obtained for Behavioral Intention, it proves the fact that the set of UTAUT variables in the present model has substantial explanatory power regarding actual usage of Claude AI (Grassini et al., 2024). The difference between BI and UB reveals the fact that behavioral intention and use behavior are related but not necessarily determined by the same variables.

This result is significant from the point of theory. The model exhibits higher explanatory power with respect to students' intention to use Claude AI ($R^2 = 0.593$) than the explanatory power in relation to their

actual use behavior ($R^2 = 0.414$). From a theoretical perspective, this is very significant as behavioral intention implies the willingness or intentions of the respondents to use the technology (Harmadi et al., 2025). Meanwhile, the actual usage may depend on other contextual factors, including the presence of necessary devices, internet connection, technical support and opportunity to use Claude AI within the process of studying.

It would be appropriate to visualize the respondent characteristics that served the basis of the analysis in the following way.

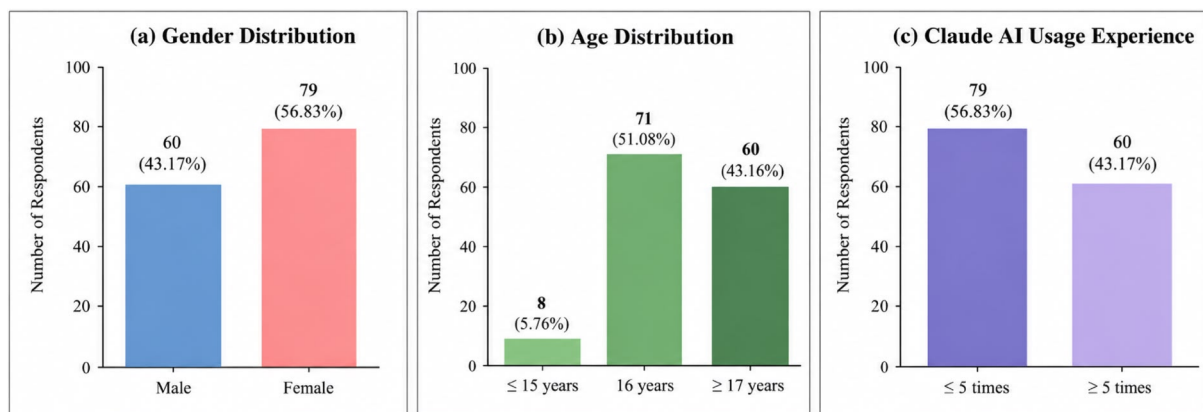


Figure 3. Distribution of Participants by Gender, Age, and Claude AI Usage Experience

Figure 3 illustrates the demographic breakdown of the 139 survey participants in terms of gender, age, and experience using Claude AI. From Figure 3, it is clear that there is a high level of clustering in the respondents aged 16-17 or older and an even distribution with regards to Claude AI usage experience. This type of distribution is helpful in putting into context future analysis because the structural relationships found in the model have to be considered and analyzed within the context of the population of this sample and not generalized automatically to include all high school students (Zhao et al., 2025).

All in all, the results show that the measurement model satisfies all criteria for validity and reliability, while the structural

model exhibits modest explanatory power when it comes to Behavioral Intention, and lower, although still substantial explanatory power in explaining Use Behavior. AVE, Cronbach's Alpha, and Composite Reliability results show that all six constructs used in the UTAUT framework are measured reliably, while the R^2 results show that the proposed predictors explain a large portion of variance related to the acceptance and use of Claude AI by the students (Baskara et al., 2023). Therefore, these results serve as a good empirical foundation for moving forward with analysis and testing the influence of Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, and Behavioral Intention on the use of Claude AI.

b. Determinants of Behavioral Intention and Actual Use of Claude AI

After the assessment of the measurement model and the predictive power of the structural model, the subsequent analysis was on the direct relationships between the UTAUT variables. The structural model was analyzed based on the path coefficient and the significance values generated through PLS-SEM analysis. In order to be considered statistically

significant, the t-value had to be above 1.96 and the p-value had to be below 0.05 (Yilmaz et al., 2024). In this case, the focus was on five direct relationships: Performance Expectancy (PE) to Behavioral Intention (BI), Effort Expectancy (EE) to BI, Social Influence (SI) to BI, Facilitating Conditions (FC) to Use Behavior (UB), and BI to UB.

Table 6. Hypothesis Test Results

Hypothesis	Variable	Original sample (β)	P values	Description
H1	PE $\rightarrow$ BI	0.695	0.001	Supported
H2	EE $\rightarrow$ BI	-0.148	0.380	Unsupported
H3	SI $\rightarrow$ BI	0.557	0.000	Supported
H4	FC $\rightarrow$ UB	0.249	0.028	Supported
H5	BI $\rightarrow$ UB	0.489	0.000	Supported
H6	AGE x PE $\rightarrow$ BI	0.221	0.275	Unsupported
H7	AGE x EE $\rightarrow$ BI	-0.299	0.158	Unsupported
H8	AGE x SI $\rightarrow$ BI	-0.041	0.764	Unsupported
H9	AGE x FC $\rightarrow$ UB	-0.140	0.203	Unsupported
H10	GEN x PE $\rightarrow$ BI	-0.267	0.116	Unsupported
H11	GEN x EE $\rightarrow$ BI	0.065	0.731	Unsupported
H12	GEN x SI $\rightarrow$ BI	-0.099	0.415	Unsupported
H13	EXP x EE $\rightarrow$ BI	0.003	0.976	Unsupported
H14	EXP x SI $\rightarrow$ BI	0.004	0.977	Unsupported
H15	EXP x FC $\rightarrow$ UB	0.021	0.867	Unsupported

However, when considering direct effects only, Performance Expectancy, Social Influence, Facilitating Conditions, and Behavioral Intention have shown statistical significance, but not Effort Expectancy. Among the statistically significant effects, Performance Expectancy was found to be the one having the highest impact on Behavioral Intention ($\beta = 0.695$, $p = 0.001$), while the second place is occupied by Social Influence ($\beta = 0.557$, $p < 0.001$). In addition, Behavioral Intention had a statistically significant positive effect on Use Behavior ($\beta = 0.489$, $p < 0.001$), while Facilitating Conditions had a statistically significant smaller effect on Use

Behavior ($\beta = 0.249$, $p = 0.028$). Thus, the acceptance and use of Claude AI appear to be closely associated with students' perceived learning benefits, social environment, and facilitating conditions (Mustafa et al., 2024). From an advanced learning perspective, this finding suggests that students' willingness to engage with generative AI is connected to whether the technology is perceived as supporting meaningful learning activities, including understanding complex concepts, completing learning tasks, accessing learning resources, and developing ideas (Mollick et al., 2024).

To illustrate statistically significant direct effects only, the following table shows path coefficients and p-values for the variables in question.

Table 7. Direct Effects of UTAUT Constructs on Behavioral Intention and Use Behavior

Hypothesis	Structural Relationship	Path Coefficient (β)	p-value	Interpretation
H1	PE $\rightarrow$ BI	0.695	0.001	Significant positive
H2	EE $\rightarrow$ BI	-0.148	0.380	Not significant
H3	SI $\rightarrow$ BI	0.557	<0.001	Significant positive
H4	FC $\rightarrow$ UB	0.249	0.028	Significant positive
H5	BI $\rightarrow$ UB	0.489	<0.001	Significant positive

Table 7 shows that Performance Expectancy exhibits the most substantial direct correlation with Behavioral Intention, having $\beta = 0.695$ and $p = 0.001$. Such a coefficient represents a fairly substantial positive connection, which implies that students that find Claude AI useful in relation to their economic learning express strong behavioral intentions to use the technology (Usman et al., 2025). The findings support the original hypothesis and help prove the statement that performance aspects play an important role in technology acceptance. At the same time, there is a substantial positive connection between Social Influence and Behavioral Intention ($\beta = 0.557$). In addition, there are positive connections between

Facilitating Conditions and Use Behavior (FCUB) and between Behavioral Intention and Use Behavior (BISB), however, they are relatively weaker than others. Finally, Effort Expectancy does not have a significant direct relationship (Du & Lv, 2024).

Firstly, the relationship between Performance Expectancy (PE) and Behavioral Intention (BI) is considered. The results show a path coefficient of $\beta = 0.695$ with $p = 0.001$, which is positive and statistically significant. Thus, it can be concluded that students' opinions about the usefulness and benefits of Claude AI are closely connected with behavioral intentions to use the technology in relation to economics learning.

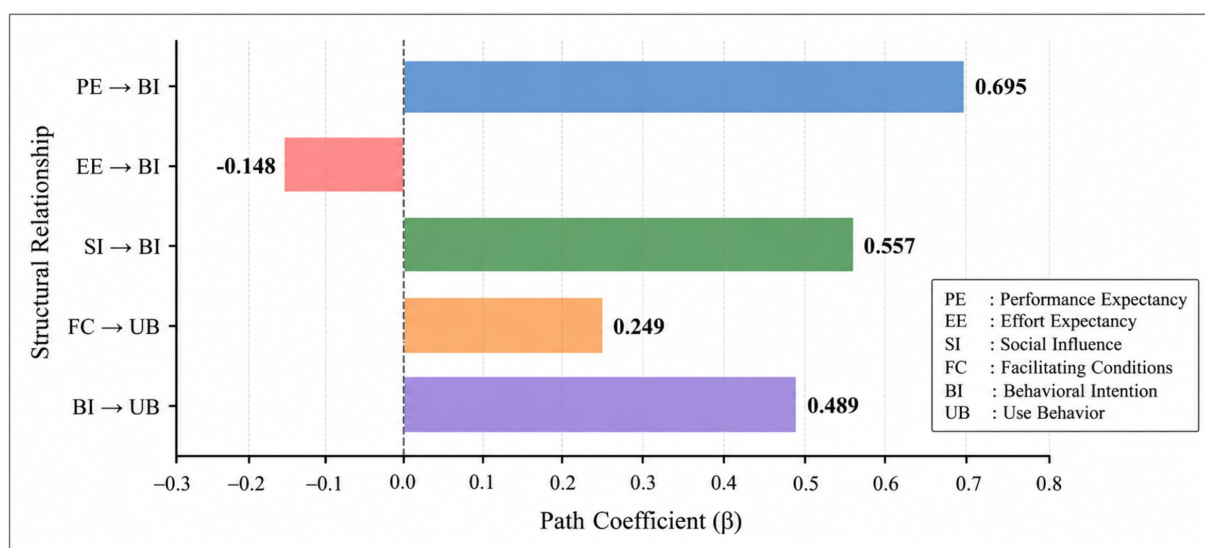


Figure 4. Direct Path Coefficients of the UTAUT Model

Figure 4 is supposed to provide visualization for the magnitude and direction of all five relationships analyzed in the structural part of the model. Such visualization underlines the fact that the coefficient for the relationship of $PE \rightarrow BI$ is the largest among direct effects, followed by $SI \rightarrow BI$ and $BI \rightarrow UB$. Moreover, $FC \rightarrow UB$ demonstrates a smaller positive coefficient, while $EE \rightarrow BI$ has a negative one. Visual representation of the coefficients allows comparing the contributions of all hypothesized relationships to the model.

The positive impact of PE on BI is in line with the results found by Grassini et al. (2024) as they revealed a significant relationship between performance expectancy and behavioral intention in regard to the use of AI chatbots. The reasoning behind this phenomenon is that the use of such AI-based chatbots can lead to perceiving productivity and learning benefits, which might motivate people to implement them in practice (Sharma & Singh, 2024). In the current study, such a connection is especially relevant due to the use of Claude AI as a learning support tool in economics classes. Students' perception of Claude AI as a source of explanations, assistance with assignments, and idea

development indicates its potential role in supporting more flexible and individualized learning processes. Rather than providing a single standardized learning pathway, generative AI may allow students to request explanations, examples, or elaborations according to their immediate learning needs (Matthes et al., 2026). This characteristic is particularly relevant to adaptive learning, although the present study measures students' acceptance and use of Claude AI rather than directly evaluating adaptive learning outcomes. Nevertheless, the result contradicts to the one reported by Kim et al. (2024) as they showed that Performance Expectancy does not have any effect on Behavioral Intention. In order to explain the discrepancies, one should take into account the differing contexts: the former study examined the work environment, while the latter considers the environment of high school students utilizing generative AI for educational purposes.

The second significant relationship is seen between Social Influence (SI) and Behavioral Intention (BI). The coefficient $\beta = 0.557$, $p < 0.001$ shows that social influence has a positive and statistically significant relationship with students' intention to use Claude AI.

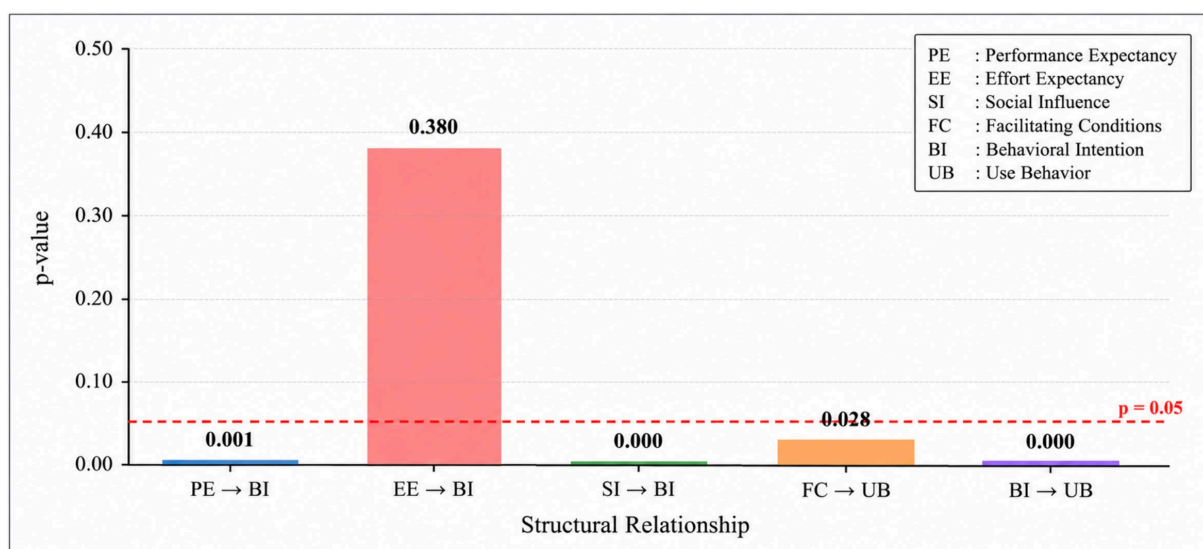


Figure 5. Statistical Significance of Direct Effects

Figure 5 presents the p-values of the five direct relationships and allows comparing them against the 0.05 significance threshold visually. Specifically, $PE \rightarrow BI$, $SI \rightarrow BI$, $FC \rightarrow UB$, and $BI \rightarrow UB$ prove to be below the statistical significance threshold, while $EE \rightarrow BI$ stays above it. Therefore, the visualization helps to confirm the information provided in Table 7 about statistically supported relationships and a non-significant relationship without solely focusing on numbers.

The significance of Social Influence in this case fits with the findings reported by [Kim et al. \(2024\)](#) and corresponds to the idea that the social environment of students can contribute to technology acceptance. Within the adolescence period and within the school-based learning process, peers' practices and teachers' advice may constitute social signals regarding which technologies are useful or acceptable for learning purposes. Nonetheless, the result contradicts the findings of [Foroughi et al. \(2025\)](#) and [Paraskevi et al. \(2023\)](#), which proved that Social Influence has no significant effect on Behavioral Intention. The reason may lie in the differences in contexts of technology use. Studies used as references in the original manuscript consider the tourism, hospitality, and customer service settings, while the present study focuses on generative AI use in the educational setting. Hence, the role of social influence may vary depending on the specific features of the population and the environment of technology adoption.

Conversely to PE and SI, Effort Expectancy (EE) had no significant influence on Behavioral Intention (BI). The relationship provided a coefficient of $\beta = -0.148$ and $p = 0.380$, which exceeds the 0.05 significance threshold. Moreover, the negative sign of the coefficient means that the observed direction of the relationship is contrary to the positive

relationship assumed in the UTAUT model. Consequently, the perceived ease of using Claude AI proves to be statistically insignificant to the intention of the students to use the technology.

This finding suggests that the willingness of the students to use Claude AI may be independent of how they perceive the system's ease of operation. One of the possible interpretations within the context of this research is that those students who already have some experience of using different technologies can see the ease of use as a basic feature of the system rather than a determining factor of behavioral intention ([Matthes et al., 2026](#)). Yet, it should be interpreted only in the context of the current study because the present analysis does not assess students' overall digital literacy. The finding is consistent with the cross-country study conducted by [Pavan Kumar et al. \(2023\)](#), which proved that Effort Expectancy had no significant association with Behavioral Intention toward generative AI use in Austria, Denmark, France, and Serbia. Nevertheless, the result contradicts the original model developed by [Hsieh & Chiu \(2020\)](#) and formulated Effort Expectancy as one of the determinants of Behavioral Intention. It seems to prove that the relevance of ease of use depends on the context of generative AI adoption.

Furthermore, the analysis shows that Facilitating Conditions (FC) significantly influenced Use Behavior (UB) with $\beta = 0.249$ and $p = 0.028$. Although the coefficient is lower than those of $PE \rightarrow BI$ and $SI \rightarrow BI$, the statistical significance means that facilitating conditions are linked to the actual use of Claude AI by the students. Within this study, FCs include having the appropriate devices, having access to the internet, and getting help in case of any difficulties during the use of Claude AI ([Nikolic et al., 2024](#)).

Consequently, facilitating conditions are not merely technical requirements but also important considerations for instructional design. Access to appropriate devices, stable internet connectivity, and available technical assistance can determine whether AI-supported learning activities can be implemented consistently within classroom and independent learning contexts.

This finding is consistent with [Cao & Peng \(2024\)](#) but contradicts [Wahdah et al \(2025\)](#), who showed that Facilitating Conditions had no significant influence on Use Behavior among employees using generative AI in a corporate setting. The reason may be connected to the specific features of the respective populations and environments. High school students may have higher variability in terms of access to the devices, internet connectivity, and technical support than adult employees in the organizational environment ([Promma et al., 2025](#)). As a consequence, facilitating conditions are observed to have a noticeable relationship with actual technology use in the context of schools.

Finally, Behavioral Intention (BI) shows the positive and statistically significant relationship with Use Behavior (UB) with $\beta = 0.489$ and $p < 0.001$. Such result means that the intention of students to use Claude AI is associated with their actual use of the technology for the economics learning purposes. It gives support to the behavioral sequence proposed in technology-acceptance models and assumes that an intention to use the technology of the person is connected to his/her actual usage behavior ([El Azhari et al., 2022](#)). Also, the finding is significant since it proves that students' acceptance of the technology is not limited to an intention but is connected to observable patterns of

technology use within the Use Behavior construct.

The significant BI $\rightarrow$ UB relationship is consistent with the findings provided by [McIntyre et al. \(2025\)](#) and [Weis et al. \(2026\)](#), which also emphasizes the role of behavioral intention in the explanation of technology adoption and use. In the context of this study, students who express stronger intention to use Claude AI are likely to report their usage of the technology ([Farooq & Mishra, 2024](#)). At the same time, the value of R^2 described in the previous section shows that Behavioral Intention and Facilitating Conditions account for 41.4% of the variance in Use Behavior, meaning that other factors also influence the actual use of the technology ([Kusumaningtyas et al., 2024](#)). Therefore, intention is an important component of usage behavior but cannot entirely determine it.

Overall, the direct-effect findings indicate that students' acceptance of Claude AI is more strongly associated with perceived learning benefits and social influence than with perceived ease of use. From a progressive learning perspective, this finding emphasizes that the educational value of generative AI is not determined solely by technological convenience but by how effectively it can be integrated into meaningful learning activities, teacher student interaction, collaborative engagement, and contextual problem solving ([Martins, 2024](#)). At the same time, the actual use of the technology is affected by behavioral intention and facilitating conditions. Such a pattern shows a difference between the factors that influence students' willingness to use Claude AI and factors connected to their actual use of the technology ([Sumandya et al., 2026](#)). Thus, the findings provide a basis for the next analysis of whether these relationships change depending

on students' age, gender, and experience of using Claude AI.

c. The Moderating Roles of Age, Gender, and Experience

Once the relationship between the UTAUT constructs was examined, the study proceeded to test whether there were any variations in the relationship among the constructs based on certain characteristics of the students. There were three characteristics

considered as the moderating variables, which included age, gender, and experience in using Claude AI (Teng et al., 2022). This moderation analysis was done to test whether there were any variations in terms of the magnitude and direction of the relationship between the key UTAUT constructs based on age, gender, and experience. The moderation was found to be significant if the p-value for each of the interaction effects was less than 0.05.

Table 8. Summary of Hypothesis Testing Results for the Structural and Moderating Relationships

Hypothesis	Relationship	β	p-value	Result
H1	PE $\rightarrow$ BI	0.695	0.001	Supported
H2	EE $\rightarrow$ BI	-0.148	0.380	Not supported
H3	SI $\rightarrow$ BI	0.557	<0.001	Supported
H4	FC $\rightarrow$ UB	0.249	0.028	Supported
H5	BI $\rightarrow$ UB	0.489	<0.001	Supported
H6-H15	Moderating relationships	-	>0.05	Not supported

Table 8 provides the general picture of the pattern of hypothesis testing and lays down the foundation for interpretation of the moderation analysis. Although there were some direct significant relationships, all hypothesis about moderation from H6 to H15 have been rejected. This is especially crucial, since the presence of significant relationships does not necessarily prove that those relations depend on demographic variables and/or previous technology use experience of the respondents (Sparkman & Witt, 2025). In this particular research, the influence of the major

constructs of the theory seems to be rather uniform across the researched groups.

The first moderating variable considered was age. There have been four interactions analyzed: age $\times$ PE $\rightarrow$ BI, age $\times$ EE $\rightarrow$ BI, age $\times$ SI $\rightarrow$ BI, and age $\times$ FC $\rightarrow$ UB. The analysis has revealed the following coefficients: $\beta = 0.221$ ($p = 0.275$) for age $\times$ PE $\rightarrow$ BI, $\beta = -0.299$ ($p = 0.158$) for age $\times$ EE $\rightarrow$ BI, $\beta = -0.041$ ($p = 0.764$) for age $\times$ SI $\rightarrow$ BI, and $\beta = -0.140$ ($p = 0.203$) for age $\times$ FC $\rightarrow$ UB. All p-values being greater than 0.05, none of those interactions have statistical significance.

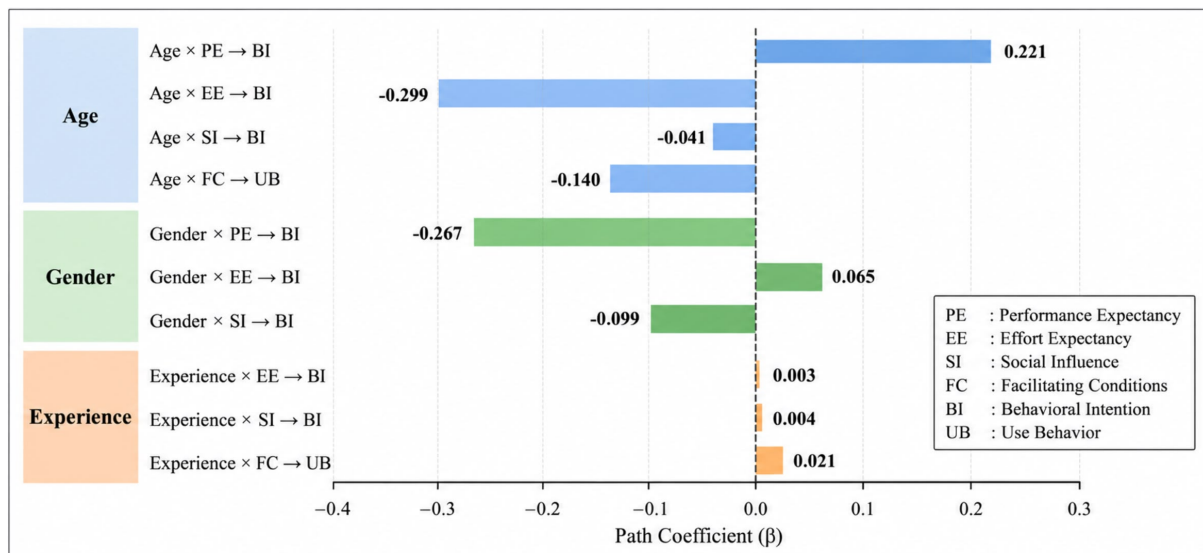


Figure 6. Moderation Path Coefficients of Age, Gender, and Experience

The Figure 6 will represent the estimated coefficients of the interaction effects for the ten moderation relationships. It is meant to prove the insignificance and relatively low values of the interaction coefficients in all examined cases (Makwana et al., 2023). Some of them are positive, whereas others are negative. However, the sign of the coefficient is not enough to state a moderation effect. Thus, the visualization of the results together with their statistical significance proves that the interaction coefficients differ in value and sign without proving that age, gender, or experience modifies the relationships between UTAUT constructs (Obenza et al., 2024).

The absence of the age moderation effect proves that the relationships between the perceptions of Claude AI and students' behavioral intentions were statistically similar for different age groups. It is especially

important because the sample used in the research included mostly adolescents (Tanmay et al., 2020). As described in the participant characteristics, the majority of participants were either 16 or 17 and older than 17. In such a way, the age distribution is relatively limited. Still, on the basis of the results obtained, one cannot claim that age is a significant moderator of the relationships under examination (Shehata et al., 2021).

The second moderator is gender. There are three interaction effects: gender × PE → BI, gender × EE → BI, and gender × SI → BI. The coefficients obtained are $\beta = -0.267$ ($p = 0.116$), $\beta = 0.065$ ($p = 0.731$), and $\beta = -0.099$ ($p = 0.415$). All p -values exceed the 0.05 level. Thus, gender does not statistically change the relationships between Performance Expectancy, Effort Expectancy, and Social Influence and Behavioral Intention.

Table 9. Moderating Effects of Age, Gender, and Experience on UTAUT Relationships

Moderator	Moderated Relationship	β	p-value	Moderation Result
Age	PE × Age → BI	0.221	0.275	Not significant
Age	EE × Age → BI	-0.299	0.158	Not significant
Age	SI × Age → BI	-0.041	0.764	Not significant
Age	FC × Age → UB	-0.140	0.203	Not significant
Gender	PE × Gender → BI	-0.267	0.116	Not significant

Moderator	Moderated Relationship	β	p-value	Moderation Result
Gender	EE $\times$ Gender $\rightarrow$ BI	0.065	0.731	Not significant
Gender	SI $\times$ Gender $\rightarrow$ BI	-0.099	0.415	Not significant
Experience	EE $\times$ Experience $\rightarrow$ BI	0.003	0.976	Not significant
Experience	SI $\times$ Experience $\rightarrow$ BI	0.004	0.977	Not significant
Experience	FC $\times$ Experience $\rightarrow$ UB	0.021	0.867	Not significant

Table 9 contains the results of the moderation analysis and demonstrates a consistent statistical pattern for all three moderators. All the p-values related to the ten interaction terms exceed the critical value of 0.05. The coefficients of age, gender, and experience interaction terms include both negative and positive values, but the variations are not statistically sufficient to draw a conclusion about systematic differences in relationships between the UTAUT constructs depending on age, gender, or level of Claude AI usage experience (Nguyen et al., 2024).

Hence, gender does not seem to play a significant role in the differentiation of the effects of major UTAUT constructs on students' Behavioral Intention. According to the original data, the p-values for all three gender interaction terms were 0.116, 0.731, and 0.415, which are above the 0.05 threshold. It means that it is impossible to say whether the positive relationship between Performance Expectancy and Behavioral

Intention or relationships between Effort Expectancy and Social Influence and Behavioral Intention can be called statistically stronger or weaker for different genders in the considered sample (Hair et al., 2024). Notably, such results do not mean that male and female students had the same experience using Claude AI, but only that the effect of gender on the relationships in question was not statistically significant.

Finally, the last moderator was experience with Claude AI. Three interaction effects were investigated: experience $\times$ EE $\rightarrow$ BI, experience $\times$ SI $\rightarrow$ BI, and experience $\times$ FC $\rightarrow$ UB. In the first case, $\beta = 0.003$ ($p = 0.976$), in the second – $\beta = 0.004$ ($p = 0.977$), in the third – $\beta = 0.021$ ($p = 0.867$). Such results are especially consistent since all three coefficients are close to zero and their p-values exceed the 0.05 threshold significantly. Thus, the experience of students with Claude AI did not have an impact on the relationships between the UTAUT constructs.

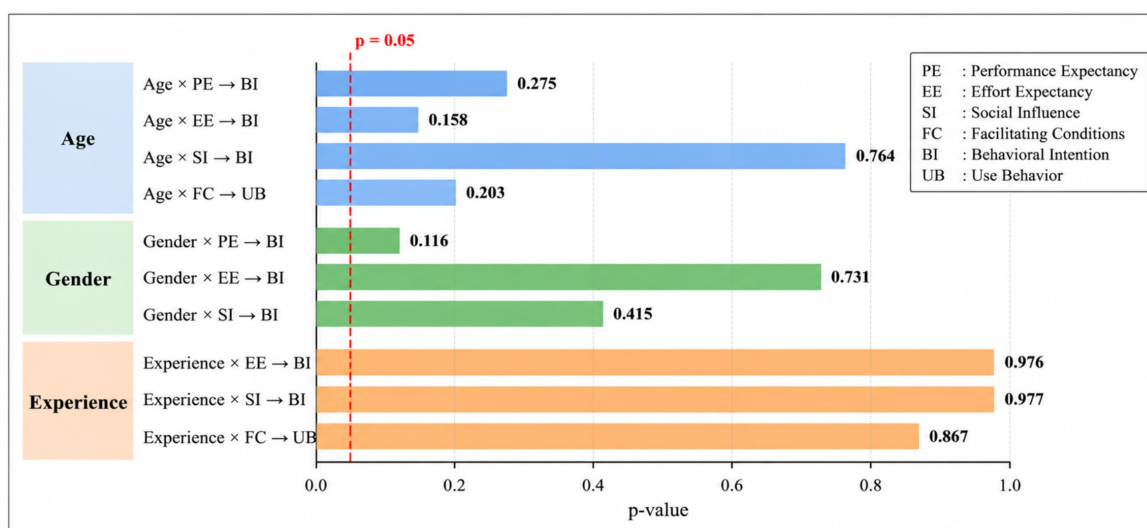


Figure 7. P-values of the Moderating Effects of Age, Gender, and Experience

Figure 7 will show p-values for all ten relationships of moderation in one graph, along with the 0.05 significance criterion line. The plot is expected to demonstrate that all pathways of moderation are located above the criterion of significance. This will serve as a confirmation of the most essential finding in this section – no matter how variable the interaction terms are in terms of direction and statistical significance, none of them presents any statistical evidence of the presence of a moderating effect (Bharathiyavaraj & Masilamani, 2024). This plot will help compare the power of statistical evidence regarding age, gender, and experience.

The lack of significance of the interaction term with respect to experience is theoretically interesting since one could expect that the students' experience of using technology can have an impact on how they perceive such components as Ease of Use, Social Influence, and Facilitating Conditions (Jen & Salam, 2025). Still, the empirical evidence does not confirm this hypothesis in this case. The p-values of 0.976, 0.977, and 0.867 indicate that the interaction effects are way above the criterion of significance. This means that the relationship with respect to Effort Expectancy, Social Influence, and Facilitating Conditions remained relatively stable in the case of Claude AI use regardless of the amount of experience.

Thus, this part of the analysis confirms the difference between direct and conditional effects in the discussed UTAUT model. The Performance Expectancy and Social Influence had a significant impact on the students' Behavioral Intention, while Facilitating Conditions and Behavioral Intention significantly influenced Use Behavior (Hair et al., 2014). In addition, there was no impact of the investigated moderators on these relationships. This means that the

most essential determinants in the suggested model function consistently without any statistically significant differences between different demographic groups or Claude AI experience levels (Kim et al., 2024). This result is crucial when interpreting the Claude AI acceptance in the discussed case, as it proves that the essential structural relationships are consistent within the sample, rather than depending on the particular age, gender, and experience group of the students.

In general, the results of the study suggest that the focus should be on the essential determinants that were found during the direct-effect analysis, which include students' perception of Claude AI's benefits, the impact of the social environment, the presence of facilitating conditions, and Behavioral Intention (Dewanda et al., 2025). At the same time, since the sample is limited only to one high school and the age distribution is rather narrow, these findings should be taken into account. Additional research with students from different schools and with varying AI use experience would be beneficial in order to determine whether these conclusions hold under different circumstances.

4. Conclusion

The purpose of the current study was to investigate the acceptance and use of Claude AI in the field of economics by 139 high school students of SMAN 18 Surabaya through the Unified Theory of Acceptance and Use of Technology (UTAUT). The results indicate that the factors of Performance Expectancy and Social Influence have a significant impact on students' Behavioral Intention, and the factor of Facilitating Conditions has a significant impact on Use Behavior. Moreover, Behavioral Intention significantly and positively affects Use Behavior, which means that the willingness of students to use

the AI is related to the application of Claude AI in the process of learning. However, Effort Expectancy does not significantly influence Behavioral Intention, which means that the ease of use is not an important element in terms of acceptance of Claude AI. The structural model has explained 59.3% of the variance in Behavioral Intention and 41.4% of the variance in Use Behavior and thus has shown a significant explanatory power. Age, gender, and experience have no significant impact on moderating the relations between the main constructs in the study, which indicates that the found relationships regarding technology acceptance are statistically similar regarding the above characteristics. Thus, in the context of the current study, the use of Claude AI in education depends on the learning benefits from it, social environment, availability of the appropriate conditions and behavior of students rather than ease of use or demographic and experience differences.

These findings provide an empirical basis for understanding generative AI as a learning innovation whose educational value depends not only on students' willingness to adopt the technology but also on how it is pedagogically integrated into the learning environment. The findings further suggest that AI-supported learning innovation should be designed around meaningful learning benefits, student needs, teacher facilitation, and adequate technological conditions so that generative AI can function as a complementary resource for advanced, adaptive, and student-centered learning. Nevertheless, since the study has been performed based on students from one high school and with the concentrated age group, the results should be considered within this framework. It is necessary to perform future research including various schools, wider group of students and additional explanatory variables to study the conditions of the varying acceptance and use of generative AI.

5. References

- Abrar, M., Aboraya, W., Khaliq, R. A., Subramanian, K. P., Husaini, Y. A., & Hussaini, M. A. (2025). AI-Powered Learning Pathways: Personalized Learning and Dynamic Assessments. *International Journal of Advanced Computer Science and Applications*, 16(1), 454–462. <https://doi.org/10.14569/IJACSA.2025.0160145>
- Acosta-Enriquez, B. G., Ramos Farroñan, E. V., Villena Zapata, L. I., Mogollon Garcia, F. S., Rabanal-León, H. C., Morales Angaspilco, J. E., & Bocanegra, J. C. S. (2024). Acceptance of artificial intelligence in university contexts: A conceptual analysis based on UTAUT2 theory. *Heliyon*, 10(19). <https://doi.org/10.1016/j.heliyon.2024.e38315>
- Aideed, H., Elbayoumi Salem, I., Magdy, A., AlAmri, T. K., Alzubaidi, A. S., & Mohamed Elbaz, A. (2025). Beyond reality: Harnessing the metaverse for transformative education through UTAUT-2 and task-technology synergy. *The International Journal of Management Education*, 23(2), 101169. <https://doi.org/https://doi.org/10.1016/j.ijme.2025.101169>
- Akavova, A., Temirkhanova, Z., & Lorsanova, Z. (2023). Adaptive learning and artificial intelligence in the educational space. *E3S Web of Conferences*, 451. <https://doi.org/10.1051/e3sconf/202345106011>
- Alkhwaldi, A. F. (2024). Understanding learners' intention toward Metaverse in higher education institutions from a developing country perspective: UTAUT and ISS integrated model. *Kybernetes*, 53(12), 6008–6035.
- Asha, V., Reddy, G. P., Nithya, B., Tungal, K., Durgaprasad, V., & Kruthik, T. N. (2023). Implication and Advantages of Machine Learning-based Chatbots in Diverse Disciplines. *2nd International Conference on Sustainable Computing*

- and Data Communication Systems, *ICSCDS 2023 - Proceedings*, 22–28. <https://doi.org/10.1109/ICSCDS56580.2023.10104649>
- Azzam, A., & Tendai, C. (2025). K-12 STEM Teachers' Experiences with Artificial Intelligence. *TEM Journal*, 14(1), 463.
- Basco, R., Hair Jr, J. F., Ringle, C. M., & Sarstedt, M. (2022). Advancing family business research through modeling nonlinear relationships: Comparing PLS-SEM and multiple regression. *Journal of Family Business Strategy*, 13(3), 100457.
- Baskara, F. R., Puri, A. D., & Wardhani, A. R. (2023). ChatGPT and the Pedagogical Challenge: Unveiling the impact on early-Career academics in Higher Education. *Indonesian Journal on Learning and Advanced Education (IJOLAE)*, 311-322.
- Bharathyvaraj, R., & Masilamani, V. (2024). Prospective Applications of Artificial Intelligence (AI) to Enhance Consistent Attention in First-Year Undergraduate Students in the Education Sector. *IET Conference Proceedings*, 2024(23), 136–140. <https://doi.org/10.1049/icp.2024.4414>
- Bhat, M. A., Tiwari, C. K., Bhaskar, P., & Khan, S. T. (2024). Examining ChatGPT adoption among educators in higher educational institutions using extended UTAUT model. *Journal of Information, Communication and Ethics in Society*, 22(3), 331–353.
- Cabero-Almenara, J., Palacios-Rodríguez, A., Loaiza-Aguirre, M. I., & Andrade-Abarca, P. S. (2024). The impact of pedagogical beliefs on the adoption of generative AI in higher education: predictive model from UTAUT2. *Frontiers in Artificial Intelligence*, 7. <https://doi.org/10.3389/frai.2024.1497705>
- Cao, Z., & Peng, L. (2024). An empirical study of factors influencing usage intention for generative artificial intelligence products: A case study of China. *Journal of Information Science*. <https://doi.org/10.1177/01655515241297329>
- Dewanda, F., Suroso, A. I., & Hasanah, N. (2025). Students' adoption of educational technology platforms for nonformal education in Indonesia. *Information Development*. <https://doi.org/10.1177/02666669241312161>
- Du, L., & Lv, B. (2024). Factors influencing students' acceptance and use generative artificial intelligence in elementary education: an expansion of the UTAUT model. *Education and Information Technologies*, 29(18), 24715–24734. <https://doi.org/10.1007/s10639-024-12835-4>
- El Azhari, K., Hilal, I., Daoudi, N., & Ajhoun, R. (2022). “AskBot”: The AI Chatbot that Enhances the Learning Process. *Lecture Notes in Networks and Systems*, 454 LNNS, 388–396. https://doi.org/10.1007/978-3-031-01942-5_39
- Farooq, S., & Mishra, P. (2024). Future trends and innovations in artificial intelligence. In *Artificial Intelligence: A Multidisciplinary Approach towards Teaching and Learning* (pp. 265–287). <https://doi.org/10.2174/9789815305180124010015>
- Foroughi, B., Iranmanesh, M., Asadi, S., Al-Emran, M., Ghobakhloo, M., & Batouei, A. (2025). *Extending UTAUT2 to explore intention to use ChatGPT for travel planning: a hybrid PLS-ANN approach. J Tour Futures*.
- Fortuna, A., Prasetya, F., Samala, A. D., Rawas, S., Criollo-C, S., Kaya, D., Raihan, M., Andriani, W., Safitri, D., & Nabawi, R. A. (2025). Artificial intelligence in personalized learning: A global systematic review of current advancements and shaping future opportunities. *Social Sciences & Humanities Open*, 12, 102114.
- Grassini, S., Aasen, M. L., & Møgelvang, A. (2024). Understanding university students' acceptance of ChatGPT: Insights from the UTAUT2 model. *Applied Artificial Intelligence*, 38(1),

- 2371168.
- Hair, J., & Alamer, A. (2022). Partial Least Squares Structural Equation Modeling (PLS-SEM) in second language and education research: Guidelines using an applied example. *Research Methods in Applied Linguistics*, 1(3), 100027.
- Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, 31(1), 2–24.
- Hair, J. F., Sarstedt, M., Hopkins, L., & Kuppelwieser, V. G. (2014). Partial least squares structural equation modeling (PLS-SEM): An emerging tool in business research. *European Business Review*, 26(2), 106–121. <https://doi.org/10.1108/EBR-10-2013-0128>
- Hair, J. F., Sarstedt, M., Ringle, C. M., Sharma, P. N., & Lienggaard, B. D. (2024). Going beyond the untold facts in PLS-SEM and moving forward. *European Journal of Marketing*, 58(13), 81–106.
- Hair Jr, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). Evaluation of reflective measurement models. In *Partial least squares structural equation modeling (PLS-SEM) using R: A workbook* (pp. 75–90). Springer.
- Harmadi, F., Maryani, I., Sukirman, S., & Montano, E. C. N. (2025). Digital transformation: Exploring the relationship between literacy, motivation, and TPACK in elementary education. *Indonesian Journal on Learning and Advanced Education (IJOLAE)*, 295–311.
- Hsieh, C.-C., & Chiu, F.-Y. (2020). *The UTAUT Model Applied to Examine the STEM in High School Robot Subject Instruction BT - Education and Technology in Sciences* (K. O. Villalba-Condori, A. Aduriz-Bravo, J. Lavonen, L.-H. Wong, & T.-H. Wang (eds.); pp. 36–46). Springer International Publishing.
- Isnaini, S., & Muslimin, A. I. (2024). The Role of AI in Enhancing Marketing Communication: Implications for Policy and Development in Indonesian Higher Education. *Studies in Media and Communication*, 12(4), 10–16. <https://doi.org/10.11114/smc.v12i4.7013>
- Jen, S. L., & Salam, A. R. (2025). Revolutionising Essay Writing Using Artificial Intelligence. *Journal of Information Systems Engineering and Management*, 10(4), 244–250. <https://doi.org/10.52783/jisem.v10i4s.495>
- Ke, Q., Gong, Y., & Ke, C. (2025). Bridging AI literacy and UTAUT constructs: structural equation modeling of AI adoption among Chinese university students. *Humanities and Social Sciences Communications*, 12(1), 1452. <https://doi.org/10.1057/s41599-025-05775-y>
- Kim, Y., Blazquez, V., & Oh, T. (2024). Determinants of Generative AI System Adoption and Usage Behavior in Korean Companies: Applying the UTAUT Model. In *Behavioral Sciences* (Vol. 14, Issue 11, p. 1035). <https://doi.org/10.3390/bs14111035>
- Kurniawan, R. Y., Mahfudhoh, A. I., Rohayati, S., Dewi, R. M., Kamalia, P. U., & Majid, M. Z. A. (2025). The Use of Unified Theory of Acceptance and Use of Technology to Analyze Students' Behavioral Interests in Utilizing Gemini AI. *International Journal of Information and Education Technology*, 15(7), 1496–1511.
- Kusumaningtyas, D. A., Manyunu, M., Kurniasari, E., Awal, A. N., Rahmaniati, R., & Febriyanti, A. (2024). Enhancing learning outcomes: A study on the development of higher order thinking skills based evaluation instruments for work and energy in high school physics. *Indonesian Journal on Learning and Advanced Education (IJOLAE)*, 14–31.
- Makwana, D., Engineer, P., Dabhi, A., & Chudasama, H. (2023). Sampling methods in research: A review.

- International Journal of Trend in Scientific Research and Development*, 7(3), 762–768.
- Martins, S. (2024). Artificial intelligence-assisted classification of library resources: The case of Claude AI. *Artificial Intelligence*, 2, 27.
- Matthes, J., Reinhardt, A., Hodzic, S., Kaňková, J., Binder, A., Bojic, L., Maindal, H. T., Paraschiv, C., & Ryom, K. (2026). Predicting the Intention to Use Generative Artificial Intelligence for Health Information: Comparative Survey Study. *J Med Internet Res*, 28, e75648. <https://doi.org/10.2196/75648>
- Mcintyre, M. M., Cui, G., & Hou, Y. (2025). Virtual avoidance: Examining STEM students' lower interest in online courses. *The Internet and Higher Education*, 65, 100995.
- Mollick, E., Mollick, L., Bach, N., Ciccarelli, L. J., Przystanski, B., & Ravipinto, D. (2024). AI agents and education: Simulated practice at scale. *ArXiv Preprint ArXiv:2407.12796*.
- Mustafa, F., Nguyen, H. T. M., & Gao, X. (Andy). (2024). The challenges and solutions of technology integration in rural schools: A systematic literature review. *International Journal of Educational Research*, 126(May), 102380. <https://doi.org/10.1016/j.ijer.2024.102380>
- Nguyen, T. T., Baker, J. R., & Le, T. Q. (2024). A Partial Least Squares Structural Equation Modeling Exploration of EFL Learners' Perceptions of What Contributes to the Readability of Model Paragraphs. *SAGE Open*, 14(2), 21582440231211800.
- Nikolic, S., Wentworth, I., Sheridan, L., Moss, S., Duursma, E., Jones, R. A., Ros, M., & Middleton, R. (2024). A systematic literature review of attitudes, intentions and behaviours of teaching academics pertaining to AI and generative AI (GenAI) in higher education: An analysis of GenAI adoption using the UTAUT framework. *Australasian Journal of Educational Technology*, 40(6), 56–75.
- Obenza, B. N., Caballo, J. H. S., Caangay, R. B. R., Makigod, T. E. C., Almocera, S. M., Bayno, J. L. M., Camposano, J. J. R., Cena, S. J. G., Garcia, J. A. K., Labajo, B. F. M., & Tua, A. G. (2024). Analyzing University Students' Attitude and Behavior Toward AI Using the Extended Unified Theory of Acceptance and Use of Technology Model. *American Journal of Applied Statistics and Economics*, 3(1), 99–108. <https://doi.org/10.54536/ajase.v3i1.2510>
- Paraskevi, G., Saprikis, V., & Avlogiaris, G. (2023). Modeling Nonusers' Behavioral Intention towards Mobile Chatbot Adoption: An Extension of the UTAUT2 Model with Mobile Service Quality Determinants. *Human Behavior and Emerging Technologies*, 2023(1), 8859989. <https://doi.org/https://doi.org/10.1155/2023/8859989>
- Pavan Kumar, P., Likhita, V., & Pranav, U. S. (2023). I-LAA: An Education Chabot. *Smart Innovation, Systems and Technologies*, 361, 325–331. https://doi.org/10.1007/978-981-99-3982-4_28
- Promma, W., Imjai, N., Usman, B., & Aujirapongpan, S. (2025). The influence of AI literacy on complex problem-solving skills through systematic thinking skills and intuition thinking skills: An empirical study in Thai gen Z accounting students. *Computers and Education: Artificial Intelligence*, 8(October 2024), 100382. <https://doi.org/10.1016/j.caeai.2025.100382>
- Rathika, P., Yamunadevi, S., Ponni, P., Parthipan, V., & Anju, P. (2024). Developing an AI-Powered Interactive Virtual Tutor for Enhanced Learning Experiences. *International Journal of Computational and Experimental Science and Engineering*, 10(4), 1594–1600. <https://doi.org/10.22399/ijcesen.782>

- Sabol, M., Hair, J., Cepeda, G., Roldán, J. L., & Chong, A. Y. L. (2023). PLS-SEM in information systems: seizing the opportunity and marching ahead full speed to adopt methodological updates. *Industrial Management & Data Systems*, 123(12), 2997–3017.
- Sharma, S., & Singh, G. (2024). Adoption of artificial intelligence in higher education: an empirical study of the UTAUT model in Indian universities. *International Journal of System Assurance Engineering and Management*, 1–27.
- Shehata, S. M., Abdeljawad, A. M., Mazouz, L. A., Aldossary, L. Y. K., Alsaeed, M. Y., & Noureldin Sayed, M. (2021). The moderating role of perceived risks in the relationship between financial knowledge and the intention to invest in the Saudi Arabian stock market. *International Journal of Financial Studies*, 9(1), 9.
- Shete, S. G., Koshti, P., & Pujari, V. I. (2024). The Impact of AI-Powered Personalization on Academic Performance in Students. *5th International Conference on Recent Trends in Computer Science and Technology, ICRTCST 2024 - Proceedings*, 295–301. <https://doi.org/10.1109/ICRTCST61793.2024.10578480>
- Sparkman, M., & Witt, A. (2025). Claude AI and literature reviews: An experiment in utility and ethical use. *Library Trends*, 73(3), 355–380.
- Strzelecki, A. (2024). Students' acceptance of ChatGPT in higher education: An extended unified theory of acceptance and use of technology. *Innovative Higher Education*, 49(2), 223–245.
- Sumandya, I. W., Widana, I. W., Mirah Dharmadewi, A. A. I., Setiawan, G. I., Habibi, A., & Hendra, R. (2026). Extending the UTAUT Model with External Variables in Inclusive Schools: An Analysis of Teacher Satisfaction and AI-STEM Use Using SEM and ANN Models. *Open Education Studies*, 8(1), 20250126.
- Tanmay, T., Bhardwaj, A., & Sharma, S. (2020). E-Health Bot to change the Face of Medicare. *Proceedings of International Conference on Research, Innovation, Knowledge Management and Technology Application for Business Sustainability, INBUSH 2020*, 49–54. <https://doi.org/10.1109/INBUSH46973.2020.9392125>
- Tapalova, O., & Zhiyenbayeva, N. (2022). Artificial intelligence in education: AIED for personalised learning pathways. *Electronic Journal of E-Learning*, 20(5), 639–653.
- Teng, Z., Cai, Y., Gao, Y., Zhang, X., & Li, X. (2022). Factors Affecting Learners' Adoption of an Educational Metaverse Platform: An Empirical Study Based on an Extended UTAUT Model. *Mobile Information Systems*, 2022. <https://doi.org/10.1155/2022/5479215>
- Usman, O., Agita, G., Murti, A. K., Aslamah, A. N., & Wibisono, I. (2025). The metaverse technology adoption process using UTAUT in digital business education. *International Journal of Innovative Research and Scientific Studies*, 8(6 SE-Articles), 2650–2658. <https://doi.org/10.53894/ijirss.v8i6.10190>
- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 425–478.
- Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. *MIS Quarterly*, 157–178.
- Wahdah, S. I., Kurniawan, R. Y., & Irawan, N. (2025). Adoption of ChatGPT in higher education: Insights from the Unified Theory of Acceptance and Use of Technology model. *Indonesian Journal on Learning and Advanced Education (IJOLAE)*, 312–327.
- Weis, L., Bele, J. L., & Erčulj, V. (2026). Acceptance and Use of Generative Artificial Intelligence in Higher Education: A UTAUT-Based Model

- Integrating Trust and Privacy. *Education Sciences*, 16(2), 173.
- Wu, X., Radloff, J. D., Yeter, I. H., Wang, L., & Chiu, T. K. F. (2025). Designing artificial intelligence chatbots for self-regulated learning from a systematic review based on Habermas's three interests. *Interactive Learning Environments*, 1–24.
- Xu, S., Chen, P., & Zhang, G. (2024). Exploring Chinese university educators' acceptance and intention to use AI tools: An application of the UTAUT2 model. *Sage Open*, 14(4), 21582440241290012.
- Yilmaz, F. G. K., Yilmaz, R., & Ceylan, M. (2024). Generative Artificial Intelligence Acceptance Scale: A Validity and Reliability Study. *International Journal of Human-Computer Interaction*, 40(24), 8703–8715.
<https://doi.org/10.1080/10447318.2023.2288730>
- Zhao, J., Wijaya, T. T., Mailizar, M., & Habibi, A. (2022). Factors influencing student satisfaction toward STEM education: Exploratory study using structural equation modeling. *Applied Sciences*, 12(19), 9717.
- Zhao, X., Liu, W., Yue, S., Chen, J., Xia, D., Bing, K., Xia, X., & Wang, K. (2025). Factors influencing medical students' adoption of AI educational agents: an extended UTAUT model. *BMC Medical Education*, 25(1), 1678.
<https://doi.org/10.1186/s12909-025-08234-z>