Jurnal Kependidikan:
Jurnal Hasil Penelitian dan Kajian Kepustakaan di Bidang Pendidikan, Pengajaran dan Pembelajaran
https://e-journal.undikma.ac.id/index.php/jurnalkependidikan/index

Vol. 12, No. 1 : March 2026
E-ISSN: 2442-7667
pp. 114-126
Email: jklppm@undikma.ac.id

Transforming Economics Learning in the AI Era: An Analysis of Senior High School Students' Acceptance of Artificial Intelligence through the UTAUT Framework

Dina Mahardika Sari, Riza Yonisa Kurniawan*
Faculty of Economics and Business, Universitas Negeri Surabaya, Indonesia.
***Corresponding Author. Email: rizakurniawan@unesa.ac.id**

Abstract: This study aims to analyze the factors that influence students' acceptance of AI use in Economics learning by applying the Unified Theory of Acceptance and Use of Technology (UTAUT) model. This research employed an explanatory quantitative method with Total sampling, involving 170 students from SMA Negeri 3 Nganjuk, Nganjuk Regency, as respondents. The research instrument consisted of a five-point Likert scale questionnaire measuring six main UTAUT constructs. Data were analyzed using Partial Least Squares – Structural Equation Modeling (PLS-SEM). The findings indicate that Social Influence is the most dominant variable with a significant effect on Behavioral Intention (β = 0.300; p = 0.001), while Performance Expectancy and Effort Expectancy did not show significant effects. Additionally, Facilitating Conditions and Behavioral Intention significantly affect Use Behavior. These results show that the UTAUT model is relevant for explaining AI technology acceptance in Economics learning. The study concludes that Social Influence, Facilitating Conditions, and prior Experience are the dominant determinants of AI acceptance in this context, while Performance Expectancy (β = 0.117; p = 0.204) and Effort Expectancy (β = 0.179; p = 0.053) did not reach statistical significance, findings consistent with Table 6. These results underscore the necessity for educational institutions to prioritize adequate digital infrastructure, foster supportive social environments, and provide progressive exposure to AI technologies to enhance successful implementation in Economics education.

Article History
Received: 09-01-2026
Revised: 12-02-2026
Accepted: 23-02-2026
Published: 25-03-2026

Key Words:
Artificial Intelligence, UTAUT, Economics Education, PLS-SEM, Technology Acceptance.

How to Cite: Sari, D. M., & Kurniawan, R. Y. (2026). Transforming Economics Learning in the AI Era: An Analysis of Senior High School Students' Acceptance of Artificial Intelligence through the UTAUT Framework. *Jurnal Kependidikan : Jurnal Hasil Penelitian Dan Kajian Kepustakaan Di Bidang Pendidikan, Pengajaran, Dan Pembelajaran*, *12*(1), 114-126. https://doi.org/10.33394/jk.v12i1.19636

https://doi.org/10.33394/jk.v12i1.19636

Introduction

The advancement of electronic innovation during the period of Industrial Revolution 4.0 has had a significant influence on the area of education. One of the innovations that has been widely developed is Artificial Intelligence (AI), a technology-driven intelligence system that imitates human abilities in processing data and generating recommendations (Zawacki-Richter et al., 2019; Marisa et al., 2024). In learning contexts, AI is capable of personalizing learning processes, analyzing students' learning styles, and providing automated feedback (Kim 2024; Wahdah et al., 2025; Rochmat et al., 2024).

At the senior high school (SMA) level, Economics as a subject requires understanding of abstract concepts such as supply and demand, inflation, and monetary policy. However, many students still struggle because learning is largely dominated by lecture-based approaches. AI represents a particularly appropriate solution to this pedagogical challenge because it can simulate real-time market fluctuations, visualize complex economic interactions through interactive models, and provide immediate feedback on students' understanding of abstract concepts, capabilities that are difficult to achieve through traditional textbooks and lectures alone. The integration of AI through virtual tutors, learning chatbots, and digital simulations has the potential to offer effective solutions by enabling

Jurnal Kependidikan:
Jurnal Hasil Penelitian dan Kajian Kepustakaan
di Bidang Pendidikan, Pengajaran dan Pembelajaran
https://e-journal.undikma.ac.id/index.php/jurnalkependidikan/index
Vol. 12, No. 1 : March 2026
E-ISSN: 2442-7667
pp. 114-126
Email: jklppm@undikma.ac.id

students to experiment with economic scenarios, analyze data patterns dynamically, and receive personalized guidance tailored to their learning pace and approaches (Rakuasa et al., 2024; Yahya et al., 2024). The integration of AI through virtual tutors, learning chatbots, and digital simulations has the potential to offer effective solutions (Lestariningrum et al., 2024; Tran & Le, 2025; Fitri et al., 2025).

The successful application of AI is strongly established by students' acceptance. The Unified Theory of Acceptance and Use of Technology (UTAUT) states that the adoption of technology is affected by Performance Anticipation, Effort Anticipation, Social Pressure, and Supporting Conditions, which subsequently determine Behavioral Intention and Use Behaviour (Venkatesh et al., 2023; Caffaratti et al., 2025a; Aprianti Astuti et al., 2024; Zhao et al., 2025). Numerous studies show that UTAUT is effective for measuring technology acceptance in educational settings (Abd Rahman et al., 2021; Xu et al., 2025; Acosta-Enriquez et al., 2024; Zainuddin et al., 2025).

However, research on AI acceptance in secondary education, particularly in Economics learning, remains limited. Most prior studies have focused on higher education (university) contexts or STEM-related subjects like Science, Tech, Engineering, and Mathematics. The distinctive characteristics of Economics which combine mathematical logic with social behavior analysis, policy interpretation, and real-world market reasoning, require a separate validation of the UTAUT model in this specific subject area and educational level. Therefore, this research intends to analyze the factors influencing high school students' approval of AI use. This research additionally adds to previous findings by examining the relevance of the UTAUT model within the framework of Economics subjects in Indonesia.

Research Method

This study utilized a detailed numerical approach through a survey technique to investigate the causal connections between variables in the Unified Theory of Acceptance and Use of Technology (UTAUT) model (Venkatesh et al., 2023), which consists of Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Behavioral Intention (BI), and Use Behaviour (UB) (Antoro 2024). This approach was used to explain the factors that influence students' intentions and behaviors in using Artificial Intelligence (AI) applications, specifically ChatGPT, Google Gemini, and educational management platforms with AI integration deployed by the school in Economics learning at the senior high school level.

The population of this study comprised all Grade X, XI, and XII Social Science (IPS) students at SMA Negeri 3 Nganjuk in the 2025/2026 academic year, totaling 170 students. Since the population was relatively small and manageable, the study employed total sampling, meaning all 170 individuals from the inhabitants were incorporated as respondents (Sugiyono 2020; Şanli 2022).

The research tool included a closed-ended survey employing a five-point Likert scale (Li et al., 2014) (1 = Strongly Disagree to 5 = Strongly Agree), developed based on UTAUT constructs (Venkatesh et al., 2023) and adapted from earlier research (Zhang et al., 2023; Xu et al., 2025); (Muhamed & Kamsin, 2025). The questionnaire was tested through a pilot test involving 30 students to ensure item clarity. Instrument Validity was evaluated through the Pearson Product-Moment correlation coefficient, and reliability was assessed using Cronbach's Alpha with a minimum threshold of ≥ 0.70 (Hair et al., 2021; Roslan et al., 2023).

Jurnal Kependidikan:
Jurnal Hasil Penelitian dan Kajian Kepustakaan di Bidang Pendidikan, Pengajaran dan Pembelajaran
https://e-journal.undikma.ac.id/index.php/jurnalkependidikan/index
Vol. 12, No. 1 : March 2026
E-ISSN: 2442-7667
pp. 114-126
Email: jklppm@undikma.ac.id

Information was gathered online through Google Forms over a two-week period during Economics learning activities. Additional data were obtained through documentation and observation related to AI usage in the school (Zawacki-Richter et al., 2019; Mohamed & Hassan, 2023). Information was examined utilizing SPSS and SmartPLS. The study involved descriptive statistics analysis, construct validity and reliability testing, and structural model assessment using Partial Least Squares Structural Equation Modeling (PLS-SEM) as recommended by Hair et al., (2021) and following validity–reliability guidelines (Henseler et al., 2015; Arifin et al., 2025). The relationships among variables were examined using path coefficients, t-statistics, and p-values, while the R^2 values were used to evaluate the model's predictive power. The significance level was set at $\alpha = 0.05$.

Table 1. Respondent Criteria

Criteria	Description	Number of Respondents	Percentage (%)
Gender	Male	50	29.41
	Female	120	70.59
Age	15 years old	16	9.41
	16 years old	54	31.76
	17 years old	57	33.53
	18 years old	43	25.29
Class	Class X	46	27.06
	Class XI	30	17.65
	Class XII	94	55.29
Total		**170**	**100%**

According to the demographic distribution presented in Table 1, the sample was predominantly female (70.59%, n=120), which may reflect broader enrollment patterns in the participating schools or gender differences in economics course participation. The age distribution clustered around 16-17 years old (65.29% combined), representing students in the mid-phase of secondary education, a developmentally critical period for forming attitudes toward technology adoption and learning preferences. The grade level composition was dominated by Class XII students (55.29%, n=94), suggesting that findings may be particularly relevant to understanding technology acceptance among students approaching graduation and making post-secondary transitions. This demographic profile indicates that the study's results are most applicable to late-adolescent learners, predominantly female, who are at a pivotal stage in their educational trajectory where technology integration may significantly influence their academic engagement and future learning behaviors. The high representation of senior-year students is particularly significant, as they have accumulated more experience with learning technologies and are likely more familiar with digital tools, making them valuable for assessing technology acceptance in educational contexts. Overall, the respondent profile reflects a diverse and contextually relevant sample, with the predominance of female students, mid-to-late adolescents, and senior-year students suggesting that the findings are particularly applicable to understanding how digitally literate and academically mature secondary school students perceive AI-driven learning innovations.

Results and Discussion

Outer Model

The External Framework, referred toas the model of measurement, is employed to evaluate the dependability and accuracy of the latent variables within the research framework. This evaluation ensures that the metrics employed to assess each construct are valid and trustworthy before conducting the structural model analysis. The external framework assessment includes concurrent validity, discriminant validity, and reliability assessments.

Convergent Validity

Convergent validity is evaluated based on the outer loading values and Average Variance Extracted (AVE). A sign is deemed valid if it has an outer loading value > 0.70 and AVE > 0.50 (Hair et al., 2019). Table 2 presents the results of the convergent validity test for all constructs in this study. Based on Table 2, all indicators have outer loading values above 0.70, ranging from 0.834 to 0.891. Additionally, all constructs have AVE values above 0.50, ranging from 0.721 to 0.779. These findings indicate that every indicator meets the concurrent validity criteria and can be used to assess its individual constructs effectively.

Discriminant Validity

Discriminant validity is assessed using the Fornell-Larcker criterion and cross-loading values. A construct has good discriminant validity if the square root of AVE for each construct is greater than the correlation between that construct and other constructs (Fornell & Larcker, 1981). Table 3 shows the discriminant validity test results using the Fornell-Larcker criterion. Table 3 shows that the diagonal values (square root of AVE) for all constructs are higher than the correlation values with other constructs. For example, Performance Expectancy has a square root of AVE of 0.861, which is higher than its correlation with all other constructs (ranging from 0.567 to 0.689). This pattern is consistent across all constructs, indicating that discriminant validity is satisfied.

Reliability Test

Reliability is assessed using Cronbach's Alpha and Composite Reliability (CR). A construct is considered reliable if it has Cronbach's Alpha > 0.70 and Composite Reliability > 0.70 (Hair et al., 2019). Table 2 presents the reliability test results for all constructs.

Table 2. Measurement Model Analysis

Variable	Item	Factor Loading	Cronbach's Alpha	Composite Reliability	AVE
Performance Expectancy (PE)	PE1	0.852	0.892	0.920	0.742
	PE2	0.876			
	PE3	0.863			
	PE4	0.854			
Effort Expectancy (EE)	EE1	0.891	0.908	0.930	0.768
	EE2	0.882			
	EE3	0.856			
	EE4	0.875			
Social Influence (SI)	SI1	0.834	0.876	0.911	0.721
	SI2	0.867			
	SI3	0.841			
	SI4	0.853			

Facilitating Conditions (FC)	FC1	0.845	0.885	0.917	0.735
	FC2	0.872			
	FC3	0.856			
	FC4	0.858			
Behavioral Intention (BI)	BI1	0.889	0.902	0.934	0.779
	BI2	0.881			
	BI3	0.878			
Use Behavior (UB)	UB1	0.863	0.881	0.914	0.752
	UB2	0.875			
	UB3	0.864			

Table 3. Discriminant Validity Test (Fornell-Larcker Criterion)

Construct	PE	EE	SI	FC	BI	UB
PE	**0.861**					
EE	**0.654**	**0.876**				
SI	**0.612**	**0.587**	**0.849**			
FC	**0.598**	**0.623**	**0.645**	**0.857**		
BI	**0.689**	**0.701**	**0.723**	**0.678**	**0.883**	
UB	**0.567**	**0.589**	**0.634**	**0.712**	**0.734**	**0.867**

Based on Table 2, all constructs have Cronbach's Alpha values above 0.70, ranging from 0.876 to 0.908. Similarly, all Composite Reliability values exceed 0.70, ranging from 0.911 to 0.934. These results confirm that all constructs in this study are reliable and internally consistent.

Inner Model

The Inner Model, also known as the structural model, is used to evaluate the relationships between latent variables and test the proposed hypotheses. The assessment of the inner model includes R-square (R^2), Q-square predictive relevance (Q^2), and hypothesis testing through path coefficients.

R-Square (R^2)

R-square (R^2) measures the proportion of variance in the dependent variable that can be explained by the independent variables. According to Chin (1998), R^2 values of 0.67, 0.33, and 0.19 are considered substantial, moderate, and weak, respectively. Table 5 presents the R^2 values for the endogenous constructs in this study. Table 5 shows that the R^2 value for Behavioral Intention is 0.682, indicating that 68.2% of the variance in students' intention to use AI can be explained by Performance Expectancy, Effort Expectancy, and Social Influence. This value is categorized as substantial. The R^2 value for Use Behavior is 0.594, meaning that 59.4% of the variance in actual AI usage is explained by Facilitating Conditions and Behavioral Intention, which is categorized as moderate. These results demonstrate that the model has good explanatory power.

Q^2 Predictive Relevance

To assess the predictive relevance of the model, the Q^2 value is calculated. A Q^2 greater than zero demonstrates that the model possesses sufficient predictive accuracy (Hair et al., 2019). The calculation uses the formula $Q^2 = 1 – (1 – R1^2) \times (1 – R2^2)$. Applying this to the model's R-square values results in a Q^2 of approximately 0.828, confirming that the model can reliably estimate the outcomes of observed variables:

$$Q^2 = 1 – (1 – 0.682) \times (1 – 0.594)$$
$$Q^2 = 1 – (0.318 \times 0.406)$$
$$Q^2 = 1 – 0.129108$$
$$Q^2 = 0.8709$$

This Q^2 value of 0.8709 is well above 0.35, indicating that the model has large predictive relevance (Hair et al., 2019). This confirms that the independent variables in the model are not only able to explain the variance in the dependent variables but also have strong predictive capabilities for future observations.

Hypothesis Testing

Testing hypotheses is carried out by analyzing the path coefficients (β), t-statistics, and p-values obtained through bootstrapping with 5000 subsamples (Khan et al., 2022). A hypothesis is supported if the t-statistic > 1.96 and p-value < 0.05 (at 5% significance level) . (Hair et al., 2019). Table 6 presents the results of the hypothesis testing for all proposed relationships in this study.

Table 5. R-Square Values

Construct	R-Square	Category
Behavioral Intention	0.682	Substantial
Use Behavior	0.594	Moderate

Table 6. Hypothesis Test Results

Hypothesis	Path	Original Sample (β)	P Value	F^2	Category	Description
Direct Effect						
H1	PE → BI	0.117	0.204	-	Low	Not Supported
H2	EE → BI	0.179	0.053	-	Low	Not Supported
H3	SI → BI	0.300	0.001	-	Medium	**Supported**
H4	FC → UB	0.311	0.000	-	Medium	**Supported**
H5	BI → UB	0.238	0.003	-	Medium	**Supported**
H6	AG → BI	-0.006	0.923	-	Low	Not Supported
H7	AG → UB	-0.083	0.139	-	Low	Not Supported
H8	GE → BI	0.001	0.988	-	Low	Not Supported
H9	EX → BI	0.246	0.006	-	Medium	**Supported**
H10	EX → UB	0.210	0.023	-	Medium	**Supported**
Indirect Effect (Mediation)						
H11	PE → BI → UB	0.028	0.270	-	Low	Not Supported
H12	EE → BI → UB	0.043	0.135	-	Low	Not Supported
H13	SI → BI → UB	0.071	0.019	-	Low	**Supported**
H14	AG → BI → UB	-0.001	0.924	-	Low	Not Supported
H15	GE → BI → UB	0.000	0.989	-	Low	Not Supported
H16	EX → BI → UB	0.059	0.058	-	Low	Not Supported
Moderating Effect						
H17	PE × AG → BI	-0.021	0.796	0.005	Low	Not Supported
H18	PE × GE → BI	-0.037	0.639	0.005	Low	Not Supported
H19	EE × AG → BI	0.024	0.816	0.005	Low	Not Supported
H20	EE × GE → BI	-0.030	0.748	0.005	Low	Not Supported
H21	EE × EX → BI	0.050	0.513	0.005	Low	Not Supported
H22	SI × AG → BI	-0.018	0.832	0.005	Low	Not Supported
H23	SI × AG → UB	0.017	0.813	0.005	Low	Not Supported

Jurnal Kependidikan:
Jurnal Hasil Penelitian dan Kajian Kepustakaan
di Bidang Pendidikan, Pengajaran dan Pembelajaran
https://e-journal.undikma.ac.id/index.php/jurnalkependidikan/index

Vol. 12, No. 1 : March 2026
E-ISSN: 2442-7667
pp. 114-126
Email: jklppm@undikma.ac.id

Hypothesis	Path	Original Sample (β)	P Value	F²	Category	Description
H24	SI × EX → BI	0.122	0.175	0.010	Medium	Not Supported
H25	SI × GE → BI	0.010	0.893	0.005	Low	Not Supported
H26	FC × EX → UB	0.087	0.215	0.010	Medium	Not Supported

(Note: solid lines represent significant paths; dashed lines represent non-significant paths; values shown are path coefficients β; R^2 values: BI = 0.682, UB = 0.594)

The results of the direct effect testing indicate that only some variables have significant effects in the model. First, Performance Expectancy (PE) exerts a beneficial influence on Behavioural Intention (BI), but it is not statistically significant (β = 0.117; p = 0.204), suggesting that perceived benefits are not yet strong enough to influence usage intention. Second, Effort Expectancy (EE) also shows a positive effect on BI, but it is not significant (β = 0.179; p = 0.053), indicating that sensed simplicity of use has not yet become a primary determinant in shaping intention. Third, Social Influence (SI) is proven to have a positive and significant effect on BI (β = 0.300; p = 0.001), which indicates that support and social influence from the surrounding environment are important factors in increasing the intention to use technology.

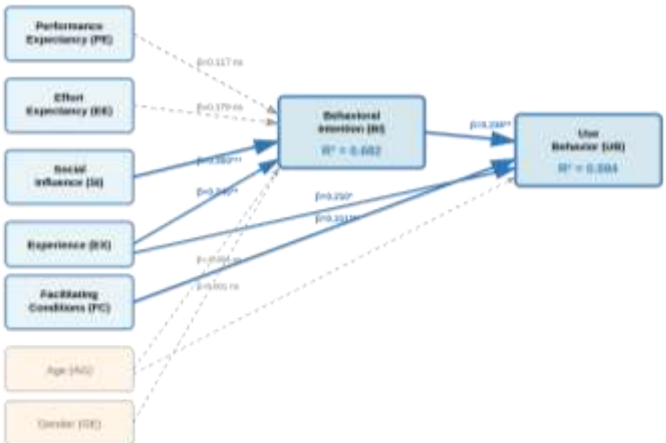

Figure 1. Structural Path Diagram

Furthermore, in the actual usage model, Facilitating Condition (FC) exhibits a favorable and substantial effect on Use Behavior (UB) (β = 0.311; p = 0.000), demonstrating that the accessibility of facilities, technical support, and infrastructure is proven to be a key factor in promoting usage behavior. Finally, Behavioural Intention (BI) also has a positive and significant effect on UB (β = 0.238; p = 0.003), showing that the higher a person's intention, the greater the likelihood they will actually use the technology.

The mediation testing results show that among the three pathways analyzed, only the relationship of Social Influence (SI) → Behavioural Intention (BI) → Use Behavior (UB) proved to be significant, with a coefficient value of O = 0.071, t = 2.361, and p = 0.019. This finding confirms that BI is able to serve as an effective mediator in transmitting the influence of SI on UB, so that social support, pressure, or encouragement not only increases interest but also drives the realization of actual usage behavior. Conversely, the other two mediation pathways, namely Performance Expectancy (PE) → BI → UB and Effort Expectancy (EE) → BI → UB, showed non-significant results with p = 0.270 and p = 0.135, respectively, indicating that although PE and EE can increase BI, these influences are not strong enough to be continued into UB through BI.

During the moderation tests, the moderating variables Gender (GE), Age (AG), and Experience (EX) did not demonstrate significant moderation effects on the primary

Vol. 12, No. 1 : March 2026
E-ISSN: 2442-7667
pp. 114-126
Email: jklppm@undikma.ac.id

relationships in the model. The moderation of GE on the links between PE, EE, and SI → BI was non-significant with p-values of 0.648, 0.755, and 0.895 each in turn, suggesting that gender differences do not influence the strength of these three constructs' relationships with BI. The moderation of AG on the connections between PE → BI, EE → BI, and SI → BI was similarly not significant ($p = 0.807$, 0.830, and 0.842), indicating that the impact of these three variables on BI remains consistent across younger and older age cohorts. Furthermore, the moderation of AG on Facilitating Conditions (FC) → UB was also not significant ($p = 0.924$). The moderation analysis of EX on the connections between EE → BI and SI → BI produced p-values of 0.521 and 0.245, whereas EX on FC → UB resulted in $p = 0.058$, which, despite nearing significance, stayed above 0.05. This suggests that the quality of user experience neither enhances nor diminishes the connections among these variables. In summary, the study results indicate that BI acts as an important mediator in the SI → UB association, whereas the moderation effects of GE, AG, and EX were not shown to influence the inter-variable relationships within the model.

The discovery that Performance Expectancy (PE) lacks a considerable impact on Behavioural Intention (BI) ($\beta = 0.117$; $p = 0.204$) differs from numerous earlier research studies. Lavidas et al., (2024) discovered that PE was a significant indicator of intentions to adopt AI among students in the humanities and social sciences, while Zhao et al., (2025) showed that recognized utility had a significant impact on students' adoption of AI tools in tertiary education. This variation might be due to the particular context of learning Economics in senior high school, where students might not have yet completely understood the practical advantages of AI for their academic achievements. Likewise, the insignificant impact of Effort Expectancy (EE) on BI ($\beta = 0.179$; $p = 0.053$) contrasts with results from Muhamed & Kamsin (2025), who indicated that the simplicity of use was a key element in educators' approval of AI technology. Nonetheless, this outcome somewhat corresponds with Caffaratti et al., (2025), who noted that the influence of effort expectancy might differ based on the technological advancement of the educational institution and previous experience with digital tools. Another reason for the lack of significance of both PE and EE resides in the Generation Z characteristics of the student participants. High school students, being digital natives accustomed to smartphones and internet access, might find AI tools like ChatGPT intuitively easy to navigate (making Effort Expectancy irrelevant in their decision-making) and may frequently employ them for enjoyment or to complete tasks, such as answering assignment inquiries, instead of actively assessing their performance advantages regarding academic enhancement (thereby diminishing the impact of Performance Expectancy). This understanding fits the hedonic motivation framework, indicating that for Generation Z learners, pleasure and ease of use might influence technology adoption more than logical assessments of performance.

The substantial positive impact of Social Influence (SI) on Intention to Act ($\beta = 0.300$; $p = 0.001$) firmly backs the conclusions of Abd Rahman et al., (2021), who showed that societal impact was essential in ESL instructors' decision to implement flipped learning. This discovery is also in agreement with Zhang et al., (2023), who found that social impact had a considerable influence on pre-service teachers' readiness to accept artificial intelligence. In the Indonesian educational setting, the significance of social impact may be notably emphasized because of the collectivist cultural values, where the views of peers and suggestions from teachers strongly impact students' choices (Aprianti Astuti et al.,, 2024). Wahdah et al., (2025) likewise discovered that societal influence played a crucial role in ChatGPT adoption by university students in Indonesia, indicating that this trend spans various educational tiers.

The notable impact of Facilitating Conditions (FC) on Use Behavior (β = 0.311; p = 0.000) is in alignment with several earlier studies. Xu et al., (2025) discovered that enabling conditions were vital elements affecting educators in primary and secondary schools' adoption of AI instruments, highlighting the significance of technical infrastructure and organizational assistance. This result is also backed by Arifin et al., (2025), who showed that sufficient technological resources and institutional backing greatly affected students' real utilization of online learning technologies. The Indonesian context, as noted by Rakuasa et al., (2024), presents distinct challenges concerning the availability of digital infrastructure, rendering facilitating conditions a more crucial aspect for effective AI implementation in educational institutions in schools. Lestariningrum et al., (2024) also underscored that access to digital resources and tech assistance significantly influences students' academic performance via technology involvement.

The substantial connection between Intentions of Behavior and Actual Usage (β = 0.238; p = 0.003) aligns with the fundamental concept of the UTAUT model (Venkatesh et al.,, 2023) and is backed by various research. Acosta-Enriquez et al., (2024) discovered that intention to behave significantly predicted the real application of AI in university settings, whereas Zainuddin et al., (2025) showcased analogous trends among polytechnic students employing AI tools for technical English. This result verifies that establishing positive intentions is an essential step for genuine technology adoption; however, the moderate effect size indicates that different contextual elements might significantly influence the conversion of intentions into actions.

The notable impacts of Experience regarding both Behavioral Intention (β = 0.246; p = 0.006) and Use Behavior (β = 0.210; p = 0.023) signify a valuable addition to the existing literature. Although Tran & Le (2025) discovered that previous technology experience affected students of information technology readiness to utilize generative AI, limited research has focused on experience as a straightforward indicator instead of a moderator in the UTAUT model. This observation indicates that students who have more experience with digital technologies cultivate more resolute intentions and are increasingly inclined to use AI tools, underscoring the necessity of advancing digital literacy across the curriculum.

The notable mediating role of Action Intent in the SI → UB pathway (β = 0.071; p = 0.019) indicates that social influence functions through the creation of intention to impact actual behavior. This discovery builds on the research of Manulat (2025), who explored essential predictors of academic achievement in adaptable learning settings with PLS-SEM, by pinpointing the process by which social elements convert into behavioral results. Nonetheless, the insignificant mediation of PE → BI → UB and EE → BI → UB indicates that in the context of Indonesian secondary education, cognitive assessments of usability and ease of use might be less advanced or applicable than social influences.

The total lack of notable moderation effects of Gender, Age, and Experience is inconsistent with several prior findings. Caffaratti et al., (2025) discovered that psychological and contextual elements, such as age and experience, influenced AI adoption trends among teenagers. Mohamed & Hassan (2023) additionally stated that demographic factors affected technology adoption in secondary education. The lack of moderation effects in this research may be ascribed to the relatively uniform characteristics of the sample, consisting entirely of students from one school, sharing comparable socioeconomic backgrounds and having little age variation (15-18 years). This suggests that in highly homogeneous educational settings, the main effects of UTAUT constructs may operate uniformly across demographic groups.

These results carry significant consequences for the application of AI in Economics education for senior high school students in Indonesia. The prominence of Social Impact

Jurnal Kependidikan:
Jurnal Hasil Penelitian dan Kajian Kepustakaan di Bidang Pendidikan, Pengajaran dan Pembelajaran
https://e-journal.undikma.ac.id/index.php/jurnalkependidikan/index
Vol. 12, No. 1 : March 2026
E-ISSN: 2442-7667
pp. 114-126
Email: jklppm@undikma.ac.id

indicates that strategies for AI adoption should focus on peer learning methods, endorsements from educators, and noticeable success cases (Marisa et al., 2024). Additionally, the essential importance of Supporting Circumstances highlights the necessity for considerable funding for digital infrastructure, technology assistance, and educator training prior to anticipating broad AI integration (Kim, 2024; Rochmat et al., 2024). Third, the comparatively minor impact of Performance Anticipation and Effort Anticipation indicates that students might require clearer demonstrations and practical experiences to understand AI's advantages and user-friendliness in Economics learning scenarios (Fitri et al., 2025).

The results of the research, when placed within the larger body of literature, suggest that the UTAUT model remains relevant for understanding AI acceptance in secondary education, though the relative importance of its constructs may vary significantly, determined by academic qualifications, cultural context, and technological maturity of the institution. Future research should explore longitudinal changes in these relationships as students gain more experience with AI tools and as digital infrastructure continues to develop in Indonesian schools.

Conclusion

This research effectively examined the elements that influence students' readiness to embrace Artificial Intelligence in Economics education at the senior high school tier through the UTAUT framework. The results indicate that Social Impact, Enabling Factors, and Knowledge are the key factors in AI acceptance, whereas Expectation of Performance and Expectation of Effort demonstrate negligible impacts. Importantly, Behavioural Intention plays a significant mediating role in the relationship between Social Influence and Behavioral Use, emphasizing the value of social and peer assistance motivation in converting intentions into real technology usage. The lack of influence of demographics on moderation factors (Gender, Age, Experience) indicates consistent trends of AI acceptance in similar educational environments. These findings highlight the importance of educational organizations to emphasize sufficient digital infrastructure, nurture supportive social settings, and offer advanced exposure to AI technologies to improve effective integration in Economics education. The research adds to the expanding scholarship on technology adoption in high school education and offers useful guidance for decision-makers and teachers aiming to implement AI tools successfully in Indonesian schools.

Recommendation

According to the results of this research, various suggestions can be offered for upcoming studies and practical applications. Future studies should focus on broadening the study parameters through the incorporation of a wider variety of participants from different schools or areas to improve the applicability of the findings. Moreover, long-term research frameworks can be utilized to track variations in students' embrace and application of Artificial Intelligence based on their familiarity and digital skills that evolve over time. Further studies may also incorporate additional variables, such as teachers’ attitudes, digital competence, or institutional policies, to enrich the explanatory power of the UTAUT model. From a practical perspective, schools and policymakers are advised to strengthen facilitating conditions by improving digital infrastructure, providing technical support, and integrating structured AI-based learning activities to ensure the effective and lasting utilization of Artificial Intelligence in Economics instruction. Additionally, to improve students' comprehension of the advantages of AI in performance, teachers should redesign Economics assessments to explicitly demonstrate how AI tools support substantive analytical tasks. For

Jurnal Kependidikan:
Jurnal Hasil Penelitian dan Kajian Kepustakaan di Bidang Pendidikan, Pengajaran dan Pembelajaran
https://e-journal.undikma.ac.id/index.php/jurnalkependidikan/index

Vol. 12, No. 1 : March 2026
E-ISSN: 2442-7667
pp. 114-126
Email: jklppm@undikma.ac.id

example, rather than allowing students to use AI merely as a chatbot to answer assignment questions, teachers can design project-based tasks that require students to use AI to analyze real market data, simulate inflation scenarios, or interpret monetary policy decisions. Such pedagogical strategies can help students recognize the genuine academic utility of AI beyond convenience, thereby strengthening the influence of Performance Expectancy in future adoption decisions.

References

Abd Rahman, S. F., Yunus, M. M., & Hashim, H. (2021). Applying UTAUT in predicting ESL lecturers' intention to use flipped learning. *Sustainability*, *13*(15), 8571. https://doi.org/10.3390/su13158571

Acosta-Enriquez, B. G., Ramos Farroñan, E. V., Villena Zapata, L. I., et al. (2024). Acceptance of Artificial Intelligence in University Contexts: A Conceptual Analysis Based on UTAUT2 Theory. *Heliyon*, *10*(19), e38315. https://doi.org/10.1016/j.heliyon.2024.e38315

Antoro, B. (2024). Analisis penerapan formula Slovin dalam penelitian ilmiah: Kelebihan, kelemahan, dan kesalahan dalam perspektif statistik. *Jurnal Multidisiplin Sosial dan Humaniora*, *1*(2), 53–63. https://doi.org/10.70585/jmsh.v1i2.38

Aprianti Astuti, Priambada, M. N., Faelasup, & Nurwati. (2024). Efektivitas penggunaan teknologi Artificial Intelligence (AI) dalam pembelajaran Pendidikan Agama Islam (PAI) di SMA. *Jurnal Arjuna: Publikasi Ilmu Pendidikan, Bahasa dan Matematika*, *2*(4), 150–60. https://doi.org/10.61132/arjuna.v2i4.1099

Arifin, M., Annizar, A. M., Khusnuridlo, M., Soebahar, A. H., & Yudiawan, A. (2025). Acceptance and use of technology in online learning in higher education: A student perspective. *Journal of Education and E-Learning Research*, *12*(1), 104–14. https://doi.org/10.20448/jeelr.v12i1.6449

Caffaratti, L. B., Longobardi, C., Badenes-Ribera, L., & Marengo, D. (2025). AI adoption among adolescents in education: Extending the UTAUT2 with psychological and contextual factors. *Frontiers in Artificial Intelligence*, *8*, 1614993. https://doi.org/10.3389/frai.2025.1614993

Fitri, K. R., Praherdhiono, H., Kurniawan, C., & Aulia, F. (2025). *Pemanfaatan Artificial Intelligence (AI) ChatGPT dalam pembelajaran siswa sekolah menengah keatas untuk meningkatkan kreativitas siswa* (Vol. 9).

Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). *Mediation analysis*. https://doi.org/10.1007/978-3-030-80519-7_7

Hair, J. F., Howard, M. C., & Nitzl, C. (2020). Assessing measurement model quality in PLS-SEM using confirmatory composite analysis. *Journal of Business Research*, *109*, 101–10. https://doi.org/10.1016/j.jbusres.2019.11.069

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. https://doi.org/10.1108/EBR-11-2018-0203

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–35. https://doi.org/10.1007/s11747-014-0403-8

Khan, M. T., Idrees, M. D., Rauf, M., Sami, A., Ansari, A., & Jamil, A. (2022). Green supply chain management practices' impact on operational performance with the mediation of technological innovation. *Sustainability*, *14*(6), 3362. https://doi.org/10.3390/su14063362

Kim, T. K. (2024). Integrating learning analytics, AI, and STEM education. *International Journal of Research in STEM Education*, *6*(2), 61–72. https://doi.org/10.33830/ijrse.v6i2.1745

Lavidas, K., Voulgari, I., Papadakis, S., et al. (2024). Determinants of humanities and social sciences students' intentions to use artificial intelligence applications for academic purposes. *Information*, *15*(6), 314. https://doi.org/10.3390/info15060314

Lestariningrum, A., Ausat, A. M. A., Wanof, M. I., Pramono, S. A., & Syamsuri, S. (2024). The impact of AI use in learning and digital material accessibility on students' academic achievement through technology engagement as a mediating variable: The perspective of Theory of Planned Behaviour and UTAUT Theory. *Jurnal Kependidikan: Jurnal Hasil Penelitian dan Kajian Kepustakaan di Bidang Pendidikan, Pengajaran dan Pembelajaran*, *10*(4), 1317. https://doi.org/10.33394/jk.v10i4.12896

Li, G., Lai, R., Duan, G., et al. (2014). Isolation and identification of symbiotic bacteria from the skin, mouth, and rectum of wild and captive tree shrews. *Dong wu xue yan jiu = Zoological research*, *35*(6), 492–99. https://doi.org/10.13918/j.issn.2095-8137.2014.6.492

Malhotra, N. K., & Dash, S. (2011). *Marketing research: An applied orientation*. Pearson.

Manulat, J. B. (2025). Key predictors of academic success in flexible learning environments: A PLS-SEM analysis. *Frontiers in Education*, *10*, 1633040. https://doi.org/10.3389/feduc.2025.1633040

Marisa, Putri, D. A. P., Mujiono, & Jameel, A. H. (2024). Integration of Artificial Intelligence in E-learning: Distance Education Students' Responses. *Jurnal Edutech Undiksha*, *12*(1), 186–97. https://doi.org/10.23887/jeu.v12i1.62023

Mohamed, M. J., & Hassan, S. A. (2023). Studying the factors that influence the adoption of educational technology in Mogadishu secondary schools using UTAUT model. *International Journal of Information and Education Technology*, *13*(7), 1070–77. https://doi.org/10.18178/ijiet.2023.13.7.1906

Muhamed, S., & Kamsin, I. F. (2025). Teacher's acceptance and intention to use artificial intelligence technology in teaching and learning based on the UTAUT model. *International Journal of Information and Education Technology*, *15*(7), 1428–35. https://doi.org/10.18178/ijiet.2025.15.7.2344

Rakuasa, H., Faris, D. A., & Hidayatullah, M. (2024). Transforming education in the age of artificial intelligence: Challenges and opportunities in Indonesia, a literature review. *Journal Education Innovation*, *2*(1), 180–86.

Rochmat, C. S., Riza, R., & Murni, S. A. (2024). Artificial Intelligence in education: Opportunities and challenges in improving learning efficiency in the Society 5.0 era. *Progresiva: Jurnal Pemikiran dan Pendidikan Islam*, *13*(01), 91–100. https://doi.org/10.22219/progresiva.v13i01.30007

Roslan, R., Ayub, A. F. M., et al. (2023). Predictive model for factors influencing students' continuance usage intention on a gamified formative assessment application. *Journal of Technical Education and Training*, *15*(3). https://doi.org/10.30880/jtet.2023.15.03.002

Şanli, S. (2022). Sampling methods and appropriate sample size determination: A concise overview. *Pamukkale University Journal of Social Sciences Institute*. https://doi.org/10.30794/pausbed.1117138

Sugiyono. (2020). *Metodologi penelitian kuantitatif, kualitatif dan R & D*. Alfabeta.

Tran, N.-M., & Le, V.-T. (2025). Factors affecting information technology students'

Vol. 12, No. 1 : March 2026
E-ISSN: 2442-7667
pp. 114-126
Email: jklppm@undikma.ac.id

willingness to use generative artificial intelligence in learning: A UTAUT-based study. *Journal of Technical Education Science*. https://doi.org/10.54644/jte.2025.1738

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, *27*(3), 425–78. https://doi.org/10.2307/30036540

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)*, *7*(2), 312–27. https://doi.org/10.23917/ijolae.v7i2.9743

Xu, H., Hussain, Y. B., Li, X., & Wang, L. (2025). Study on factors influencing primary and secondary school teachers' acceptance of AI tools based on the UTAUT model: A case study of Tianchang City, Anhui Province. *Journal of Education and Educational Research*, *12*(3), 106–10. https://doi.org/10.54097/6kmfe396

Zainuddin, K., Mat Daud, K. A., & Hussein, N. A. (2025). PLS-SEM analysis of antecedents influencing polytechnic students' acceptance and use of Artificial Intelligence (AI) tools for technical English. *International Journal of Modern Languages and Applied Linguistics*, *9*(4). https://doi.org/10.24191/ijmal.v9i4.6802

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education – where are the educators? *International Journal of Educational Technology in Higher Education*, *16*(1). https://doi.org/10.1186/s41239-019-0171-0

Zhang, C., Schießl, J., Plößl, L., Hofmann, F., & Gläser-Zikuda, M. (2023). Acceptance of artificial intelligence among pre-service teachers: A multigroup analysis. *International Journal of Educational Technology in Higher Education*, *20*(1). https://doi.org/10.1186/s41239-023-00420-7

Zhao, Z., An, Q., & Liu, J. (2025). Exploring AI tool adoption in higher education: Evidence from a PLS-SEM model integrating multimodal literacy, self-efficacy, and university support. *Frontiers in Psychology*, *16*, 1619391. https://doi.org/10.3389/fpsyg.2025.1619391