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The Influence of Artificial Intelligence Utilization, Self-Efficacy, and Learning Innovation on University Students' Work Productivity

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Abstract

The development of digital technology has encouraged students to employ Artificial Intelligence (AI) to support their academic activities. However, differences in individuals' technological management skills, self-efficacy levels, and learning creativity lead to variations in students' academic work productivity. This study aims to analyze the influence of AI utilization, self-efficacy, and learning innovation on students' academic work productivity. The research problem focuses on the extent to which these three variables contribute, either partially or simultaneously, to enhancing students' academic work productivity in the digital era. This study employed a quantitative survey approach with a sample of 201 university students, approximately 96.5% of whom are enrolled in Islamic higher education institutions, selected through purposive sampling. Data were collected using a five-point Likert-scale questionnaire and analyzed using multiple linear regression. The findings indicate that AI utilization (sig.=0.024), self-efficacy (sig.=0.000), and learning innovation (sig.=0.000) have a significant partial influence on students' productivity, with learning innovation being the most dominant variable. Simultaneously, the three variables exert a significant influence (F=94.425; sig.=0.000) and explain 59% of the variance in work productivity (R^2=0.590). These findings provide novel empirical evidence that learning innovation exerts a more dominant influence than AI utilization alone, underscoring the importance of integrating technological adoption with self-efficacy and innovative learning practices to enhance university students' academic work productivity, particularly within Islamic higher education contexts.

Keywords*: Artificial Intelligence; Self-Efficacy; Learning Innovation; Academic Work Productivity; University Students*

Introduction

The rapid advancement of technology in recent years has transformed various aspects of social life, including the field of education. One technological development that has experienced a significant increase in usage is Artificial Intelligence (AI). According to data reported by Kompas, the percentage of AI users in Indonesia increased to 27.34% in 2025, representing a rise of 2.61% compared to the previous year, with 43.98% of users utilizing AI for educational purposes (Stephanus Aranditio, 2025). This trend indicates that AI technology has become increasingly integrated into educational activities as a learning support tool, a source of information, and a means of developing skills and creativity. Several studies have also confirmed that AI contributes positively to educational innovation and the resolution of various learning-related challenges (Ella Rosediana Putri et al., 2023). Nevertheless, the growing intensity of AI utilization in education cannot be directly interpreted as an indicator of improved educational quality, as its impact largely depends on how the technology is used by learners.

In the context of higher education, the utilization of Artificial Intelligence (AI) has become an increasingly common practice among both students and lecturers. AI is widely used to improve task completion efficiency, expand access to academic information, and support the understanding of course materials (Anjani et al., 2025). Various platforms such as ChatGPT, Grammarly, Gamma, Gemini, and Copilot are frequently employed to assist academic activities. Empirical evidence suggests that AI utilization can shorten task completion time, enhance analytical accuracy, and support the production of more systematic and higher-quality academic writing (Akhyar et al., 2023). However, existing studies have largely overlooked how AI utilization interacts with students' internal factors that influence their academic work productivity. This condition opens a critical inquiry into the extent to which AI utilization genuinely contributes to improving students' academic work productivity, rather than merely generating short-term efficiency.

Despite the numerous advantages offered by AI-based facilities, concerns regarding potential negative impacts remain, particularly the possibility of excessive dependence on such technology. One possible consequence is the reduction of individuals' ability to think critically and independently, although these two aspects represent essential characteristics of academic competence (Farida Fitriani & Baiq Desi Arfini, 2025). Since AI technology entered the context of higher education, students have tended to prefer instant results generated through AI assistance rather than attempting to think critically in advance or searching for more accurate sources such as books or academic journals. Yet, the essence of pursuing higher education is to cultivate students' intuitive sensitivity in analyzing problems, proposing solutions, and evaluating their own academic performance (Firdaus et al., 2025). The utilization of AI itself may be defined through several indicators, such as perceived usefulness/learning effectiveness, ease of use, attitudes and trust towards AI, continuance intention to use AI in the future, as well as the frequency and actual intensity of using AI in daily academic activities (Nugroho et al., 2025).

The utilization of Artificial Intelligence (AI) in education has also encouraged the emergence of a culture of independent learning among students. AI technology appears to provide convenience for students in completing academic tasks independently without heavy reliance on others. This condition can be viewed positively as it supports the development of learner autonomy. However, from another perspective, the use of AI without adequate psychological readiness may lead to dependency and weaken students' confidence in their own abilities. Therefore, self-efficacy becomes a crucial factor in determining whether AI utilization strengthens students' learning capacity or instead undermines reflective and critical thinking processes in academic activities. Self-efficacy refers to an individual's belief in their ability to achieve success, complete tasks effectively, and maintain optimism regarding expected outcomes (Gunawan et al., 2020). Individuals with high self-efficacy tend to manage academic pressure more positively, remain motivated, and interpret success as the result of personal effort (Tessa Nabila & Eka Wahyuni, 2021).

The concept of self-efficacy is also applicable in academic contexts and is commonly referred to as academic self-efficacy (Dhimas Arya Wahyukencana & Narastri Insan Utami, 2024). Several studies indicate that academic self-efficacy is associated with students' academic work productivity, as reflected in learning motivation, persistence, and the ability to complete tasks on time (Kirsti et al., 2019). Students with high academic self-efficacy are generally more motivated, less likely to give up, and more resilient when facing academic challenges (Raharjo et al., 2025). In contrast, students with low self-efficacy tend to experience decreased motivation, procrastination, self-doubt, and heightened academic anxiety that hinders their performance (Arif Miftakhul Khoirul Anam & Surawan, 2025). Previous studies have largely treated self-efficacy as an isolated individual variable, without integratively linking it to AI utilization and learning innovation in explaining students' academic work productivity. According to (Bandura, 1997), self-efficacy can be measured through four main dimensions: level (the degree of task difficulty one believes can be managed), strength (the firmness of belief in achieving success), generality (the extent to which efficacy beliefs apply across situations), and optimism (positive expectations that effort will lead to desirable outcomes).

In addition to the utilization of technology and self-efficacy, there is another factor that may influence students' work productivity, namely learning innovation. Learning innovation refers to the ability to demonstrate creativity in learning, the use of new technologies, experimentation with learning methods, collaboration and idea sharing, as well as continuous improvement in learning processes with the aim of creating a more effective, adaptive, and contextually relevant learning environment in accordance with contemporary developments. Research in higher education has demonstrated that active learning innovations combining blended learning models, project-based learning, collaborative approaches, and technology integration are able to enhance creativity, critical analytical abilities, and students' independence in seeking knowledge (Mashudi, 2021). Thus, innovation in the learning process is not merely about replacing tools or platforms, but rather a pedagogical transformation that empowers students as active agents rather than passive recipients of information.

Learning innovation in the student context has also been shown to enhance engagement, motivation, and learning productivity. For instance, the use of social media as an online learning medium has been reported to improve students' creative thinking skills such as fluency, flexibility, originality, and elaboration because students actively select and utilize digital platforms to produce their own learning content (Ahmad Zakian Nurfauzan, 2022). This indicates that learning innovation through technological integration and the application of diverse learning methods can serve as an important factor in improving the efficiency and effectiveness of students' learning processes (Amelia et al., 2025). However, previous studies on learning innovation have predominantly focused on improving the quality of learning processes, without explicitly linking learning innovation to students' academic work productivity as a tangible outcome of the learning process.

In this study, students' work productivity is defined as students' ability to complete academic tasks effectively and efficiently in terms of time and resource utilization, as reflected through the quality of learning outcomes, task completion timeliness, and consistency in daily academic activities. This productivity variable is important as it reflects the extent to which students are able to transform their potential into tangible academic outputs. Previous studies have shown that individual factors such as motivation, time management, and self-efficacy have significant effects on students' performance, which subsequently influence academic productivity or learning performance (Lasmi et al., 2024).

Based on the foregoing background, empirical studies that integratively examine the relationship between Artificial Intelligence (AI) utilization, self-efficacy, and learning innovation within a single analytical framework to explain students' academic work productivity remain limited. Most previous studies have tended to investigate these variables separately, without adequately exploring their simultaneous interaction and combined contribution in the context of higher education. As a result, current understanding of the factors that shape students' academic work productivity remains fragmented, which may lead to less effective learning practices. Therefore, this study is conducted to address this research gap. This study offers novelty by jointly examining AI utilization, self-efficacy, and learning innovation within a unified model to explain students' academic work productivity, particularly in Islamic higher education institutions. Rather than viewing AI merely as a technological tool, this study emphasizes the critical role of psychological and pedagogical factors in fostering sustainable academic productivity. Accordingly, this study aims to analyze the influence of AI utilization, self-efficacy, and learning innovation on students' academic work productivity. The hypotheses proposed in this study are as follows:

H_1 : AI utilization has a significant influence on students' work productivity.

H_2 : Self-efficacy has a significant influence on students' work productivity.

H_3 : Learning innovation has a significant influence on students' work productivity.

H_4 : AI utilization, self-efficacy, and learning innovation simultaneously have significant influence on students' work productivity.

Method

This study employed a quantitative approach using a survey method to measure the influence of the independent variables, namely the utilization of Artificial Intelligence (X1), self-efficacy (X2), and learning innovation (X3), on students' work productivity (Y). The quantitative approach was selected because this study emphasizes the empirical and measurable examination of relationships among variables through statistical analysis (Sugiyono, 2018). This research is associative-causal in nature, aiming to determine the extent to which the independent variables influence or have a causal relationship with the dependent variable. This approach enables the analysis of both partial and simultaneous influences of the independent variables within a single analytical framework, thereby providing an empirical basis for explaining how AI utilization, self-efficacy, and learning innovation collectively and individually contribute to students' work productivity. The relationships among the research variables can be illustrated as follows:

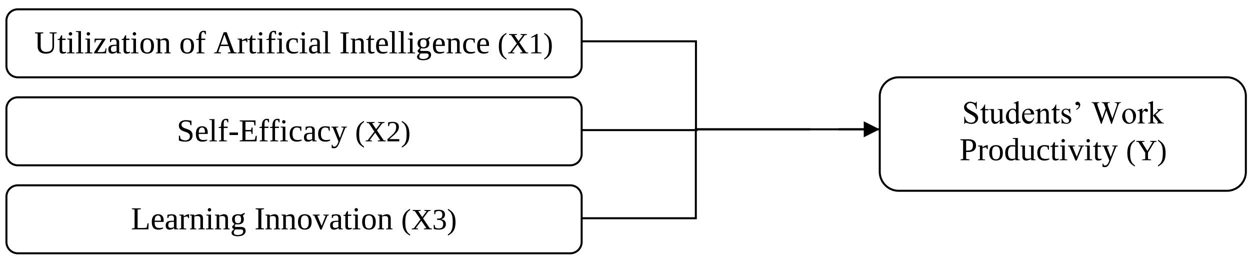


Figure 1. Relationships among Research Variables

The population of this study consists of university students who have used Artificial Intelligence (AI) based applications or platforms in their academic activities. Given the large size of the population, the sample was selected using a purposive sampling technique, namely the selection of respondents based on specific criteria relevant to the focus of the study (Sugiyono, 2018). The criteria for respondents in this study were university students who had used Artificial Intelligence (AI) based applications or platforms, such as ChatGPT, Grammarly, Quillbot, or Canva, for academic purposes. Based on these criteria, a total of 201 respondents from several higher education institutions were included in the study, as follows:

Table 1 Respondents' University Affiliation

No.	University Affiliation	Number	Percentage
1.	IAI Al-Khoziny Sidoarjo	107	53%
2.	UIN Sunan Ampel Surabaya	60	30%
3.	UIN Maulana Malik Ibrahim Malang	25	12%
4.	Universitas Terbuka Surabaya	3	1%
5.	Universitas Nahdlatul Ulama' Sidoarjo	2	1%
6.	Universitas Negeri Surabaya	4	2%
	Total	201	100%

Source: Research Data Processed (2025)

Data were collected using a questionnaire administered with a five-point Likert scale, ranging from Strongly Disagree (1), Disagree (2), Neutral (3), Agree (4), to Strongly Agree (5). The questionnaire was distributed online using Google Forms to facilitate respondents' participation. The instrument was developed based on the indicators of each research variable, comprising 10 items for each variable. Data that met validity and reliability criteria were subsequently used in the classical assumption tests (pre-analysis requirements), including normality testing, linearity testing, and heteroscedasticity testing. Thereafter, multiple linear regression analysis was conducted to examine the research hypotheses, both partially and simultaneously, using SPSS version 22.

Results

Characteristics of Respondents

During the data collection process, the researcher obtained respondent characteristics classified by gender, age range, level of study, and type of higher education institution, as follows:

a. The number of respondents by gender consisted of 86 males (43%) and 115 females (57%).
b. The respondents' age distribution was as follows: 18–21 years, 96 respondents (48%); 22–25 years, 101 respondents (50%); and above 26 years, 4 respondents (2%).
c. In terms of level of study, 171 respondents (85%) were undergraduate (Bachelor) students, and 30 respondents (15%) were postgraduate (Master's) students.
d. Regarding the type of higher education institution, 93 respondents (46%) were from public universities, 3 (1%) from private universities, 2 (1%) from public institutes, and 103 (51%) from private institutes.

Validity Test

The collected data must be subjected to a validity test prior to further analysis to ensure that all items to be analyzed are indeed valid. If any item is found to be invalid, it will be removed from the analysis stage. The determination of item validity is based on the r-table value, which is calculated using the degrees of freedom df = N − 2. With a total of 201 respondents, the degree of freedom becomes df = 201 − 2 = 199. Thus, the r-table value for df = 199 at the significance level of 5% ($\alpha = 0.05$) is 0.138. An item is considered valid if the calculated r-value (r-count) ≥ 0.138; conversely, if the r-count < 0.138, the item is considered invalid. The following table presents the results of the item validity test for each item using SPSS version 22.

Table 2 Item Validity Test for AI Utilization (X1)

Item	r-count	r-table	Description
X1.1	0.568	0.138	Valid
X1.2	0.491	0.138	Valid
X1.3	0.137	0.138	Invalid
X1.4	0.491	0.138	Valid
X1.5	0.472	0.138	Valid
X1.6	0.478	0.138	Valid
X1.7	0.553	0.138	Valid
X1.8	0.524	0.138	Valid
X1.9	0.582	0.138	Valid
X1.10	0.598	0.138	Valid

Source: Data Processed Using SPSS 22 (2025)

Table 3 Validity Test of Self-Efficacy Items (X2)

Item	r-count	r-table	Description
X2.1	0.569	0.138	Valid
X2.2	0.572	0.138	Valid
X2.3	0.607	0.138	Valid
X2.4	0.537	0.138	Valid
X2.5	0.523	0.138	Valid
X2.6	0.571	0.138	Valid
X2.7	0.514	0.138	Valid
X2.8	0.546	0.138	Valid
X2.9	0.514	0.138	Valid
X2.10	0.362	0.138	Valid

Source: Data Processed Using SPSS 22 (2025)

Table 4 Validity Test of Learning Innovation Items (X3)

Item	r-count	r-table	Description
X3.1	0.429	0.138	Valid
X3.2	0.604	0.138	Valid
X3.3	0.437	0.138	Valid
X3.4	0.591	0.138	Valid
X3.5	0.561	0.138	Valid
X3.6	0.544	0.138	Valid
X3.7	0.534	0.138	Valid
X3.8	0.512	0.138	Valid

Item	r-count	r-table	Description
X3.9	0.643	0.138	Valid
X3.10	0.375	0.138	Valid

Source: Data Processed Using SPSS 22 (2025)

Table 5 Validity Test of Work Productivity Items (Y)

Item	r-count	r-table	Description
Y.1	0.414	0.138	Valid
Y.2	0.653	0.138	Valid
Y.3	0.464	0.138	Valid
Y.4	0.562	0.138	Valid
Y.5	0.618	0.138	Valid
Y.6	0.523	0.138	Valid
Y.7	0.113	0.138	Invalid
Y.8	0.581	0.138	Valid
Y.9	0.522	0.138	Valid
Y.10	0.597	0.138	Valid

Source: Data Processed Using SPSS 22 (2025)

Based on the results of the validity test for each research item, out of a total of 40 items, 2 items were found to be invalid as they did not fulfill the requirement of r-count ≥ 0.138, namely items X1.3 and Y.7. Therefore, these two items were excluded from the subsequent analytical procedures.

Reliability Test

After conducting the validity test on each item, the valid items were then subjected to a reliability test using the Cronbach's Alpha coefficient. The reliability test aims to ensure that the items in each variable have good internal consistency and are capable of producing stable results when the measurement is repeated. The assessment criteria of reliability are based on the Cronbach's Alpha values, with the following general provisions:

Table 6 Interpretation of Cronbach's Alpha Values

Cronbach's Alpha Values	Description
≥ 0.90s	Highly Reliable
0.70 – 0.89	Reliable
0.60 – 0.69	Acceptable Reliability
< 0.60	Not Reliable

The following are the results of the reliability test for each research variable using SPSS version 22.

Table 7 Reliability Test Results

Variabel	Cronbach's Alpha Values	Description
Utilization of AI (X1)	0.675	Acceptable Reliability
Self Efficacy (X2)	0.719	Reliable
Learning Innovation (X3)	0.704	Reliable
Students' Work Productivity (Y)	0.714	Reliable

Source: Data Processed Using SPSS 22 (2025)

From the table above, it can be seen that the reliability values of each variable meet the reliability requirements, indicated by Cronbach's Alpha values that exceed the minimum threshold (≥ 0.60). This indicates that all items in each variable have good internal consistency and are appropriate to be used in the subsequent analysis. Thus, each variable can be considered reliable to produce stable and accurate data in the following hypothesis testing procedures.

Descriptive Statistics

Descriptive statistics provide a general overview of the research data, including the mean, minimum value, maximum value, and standard deviation of each variable. This analysis helps in understanding the characteristics and distribution of the data prior to further testing.

Table 8 Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Dev.
X1 Total	201	2.00	4.56	3.6302	0.56505
X2 Total	201	2.30	4.50	3.6841	0.56218
X3 Total	201	2.00	4.60	3.6920	0.57274
Y Total	201	2.00	4.56	3.6440	0.62493

Source: Data Processed Using SPSS 22 (2025)

Classical Assumption Test (Pre-Analysis Requirements)

After all items were declared valid and reliable, the data were subjected to classical assumption testing as a prerequisite before conducting further statistical analysis. This step is necessary to ensure that the data meet the requirements of the analytical model, which include the normality test, linearity test, and heteroscedasticity test.

The normality test was conducted to determine whether the research data were normally distributed, as normal distribution is a prerequisite to ensure that estimation results and hypothesis testing can be considered valid and reliable.

Table 9 Normality Test Results

	Kolmogorov-Smirnov			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Y Total	0.107	201	0.000	0.949	201	0.000

Source: Data Processed Using SPSS 22 (2025)

The results of the normality test indicate that the residual data are not normally distributed, as shown by the Shapiro–Wilk significance value of 0.000 (< 0.05). Nevertheless, this study can still employ linear regression analysis because the number of respondents is sufficiently large (201 respondents). With large sample sizes, the data are generally considered to approximate a normal distribution; therefore, the issue of normality does not substantially affect the analysis results.

The linearity test was conducted to ensure that the relationship between the independent variables and the dependent variable is linear. This is essential because linear regression analysis can only be applied if the relationship pattern between variables forms a straight line. The requirement for linearity is that the Sig. value of the Deviation from Linearity should be greater than 0.05, meaning that the relationship between variables is linear. Conversely, if Sig. ≤ 0.05, the relationship is considered non-linear.

Table 10 Linearity Test Results of Variables X1 and Y

			Sum of Squares	df	Mean Square	F	Sig.
Y_total*X1 _total	Between Groups	(Combined)	33.107	22	1.505	5.953	.000
		Linearity	28.998	1	28.998	114.704	.000
		Deviation from Linearity	4.109	21	.196	.774	.749
	Within Groups		45.000	178	.253		
	Total		78.107	200			

Source: Data Processed Using SPSS 22 (2025)

The Deviation from Linearity value was 0.749 (> 0.05), indicating that there was no deviation from linearity. Therefore, the relationship between X1 and Y is linear.

Table 11 Linearity Test Results of Variables X2 and Y

			Sum of Squares	df	Mean Square	F	Sig.
Y_total*X2 _total	Between Groups	(Combined)	40.773	22	1.853	8.836	.000
		Linearity	35.137	1	35.137	167.530	.000
		Deviation from Linearity	5.636	21	.268	1.280	.194
	Within Groups		37.333	178	.210		
	Total		78.107	200			

Source: Data Processed Using SPSS 22 (2025)

The Deviation from Linearity value was 0.194 (> 0.05), indicating that there was no deviation from linearity. Thus, the relationship between X2 and Y is linear.

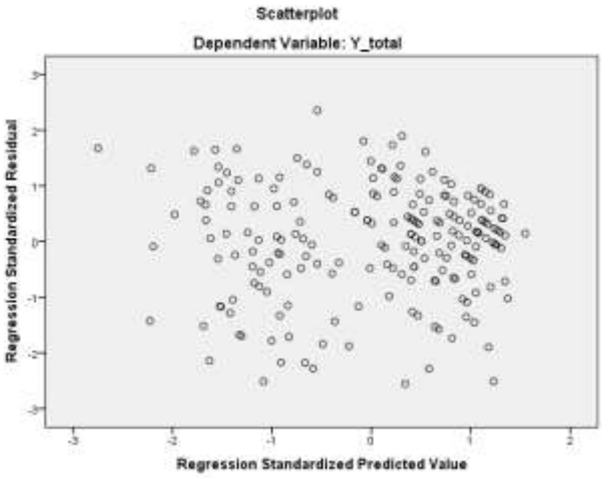
Table 12 Linearity Test Results of Variables X3 and Y

			Sum of Squares	df	Mean Square	F	Sig.
Y_total*X3 _total	Between Groups	(Combined)	44.651	23	1.941	10.271	.000
		Linearity	39.606	1	39.606	209.538	.000
		Deviation from Linearity	5.045	22	.229	1.213	.242
	Within Groups		33.456	177	.189		
	Total		78.107	200			

Source: Data Processed Using SPSS 22 (2025)

The Deviation from Linearity value was 0.242 (> 0.05), indicating that there was no deviation from linearity. Therefore, the relationship between X3 and Y is linear.

Table 13 Heteroscedasticity Test Results



Source: Data Processed Using SPSS 22 (2025)

Based on the scatterplot between the Regression Standardized Predicted Value and the Regression Standardized Residual, the points appear to be randomly dispersed above and below the horizontal axis and do not form specific patterns such as waves, funnels, or a widening–narrowing pattern. This random distribution indicates that the residual variance is constant.

Multiple Linear Regression Analysis

After conducting the classical assumption tests and confirming that all statistical prerequisites were met, the analysis proceeded to multiple linear regression as the core analytical technique of this study. The regression test was carried out through several stages, namely the t-test, F-test, and the coefficient of determination (R^2).

1. t-test

   The t-test was used to examine the partial effect of each independent variable (X1, X2, X3) on the dependent variable (Y). The criterion applied was that if Sig. < 0.05, the variable has a significant partial effect.

Table 14 t-Test Results

Model		**Unstadardized Coefficients**		**Standardized Coefficients**	**t**	**Sig.**
		B	**Std. Error**	**Beta**		
1	(Constant)	.136	.213		.637	.525
	X1_total	.163	.072	.147	2.275	.024
	X2_total	.325	.074	.292	4.376	.000
	X3_total	.466	.070	.427	6.609	.000

Source: Data Processed Using SPSS 22 (2025)

Based on the results of the multiple linear regression analysis presented in the Coefficients table, it was found that the variable X1_total has a significance value of 0.024 (< 0.05), the variable X2_total also shows a significance value of 0.000 (< 0.05), and the variable

X3_total has a significance value of 0.000 (< 0.05). Based on the Standardized Coefficients (Beta) values, the variable X3_total (learning innovation) shows the highest Beta coefficient of 0.427, compared to X2_total (self-efficacy) with a Beta value of 0.292 and X1_total (AI utilization) with a Beta value of 0.147.

2. F-Test

The F-test is a statistical procedure used to determine whether all independent variables (X1, X2, X3) jointly have a significant effect on the dependent variable (Y). Hence, this test examines the simultaneous (collective) influence rather than individual effects as in the t-test. The decision criterion is based on the significance value: if Sig. < 0.05, the model is declared significant and the independent variables jointly influence the dependent variable; conversely, if Sig. ≥ 0.05, the model is not significant and there is no simultaneous effect.

Table 15 F-Test Results

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	46.069	3	15.356	94.425	.000[b]
	Residual	32.038	197	.163		
	Total	78.107	200			

Source: Data Processed Using SPSS 22 (2025)

Based on the ANOVA results, the computed F-value was 94.425 with a significance value of 0.000.

3. Coefficient of Determination (R^2)

The coefficient of determination (R^2) is used to determine the extent to which the independent variables explain the variation in the dependent variable. The R^2 value ranges from 0 to 1, where a value closer to 1 indicates that the independent variables contribute more strongly to influencing the dependent variable, while a value closer to 0 indicates weaker contribution. In simple terms, R^2 shows the percentage of the combined effect of the independent variables on the dependent variable in the regression model. In certain research contexts, an $R^2 \geq 0.50$ is generally considered strong, whereas an $R^2 < 0.50$ is considered weak.

Table 16 Coefficient of Determination (R^2) Results

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.768[a]	.590	.584	.40327

Source: Data Processed Using SPSS 22 (2025)

The R Square value of 0.590 indicates that the three independent variables (X1_total, X2_total, and X3_total) are able to explain 59% of the variation occurring in Y_total. Meanwhile, the remaining 41% is influenced by factors outside the scope of this study.

Discussion

In general, the results of the data analysis demonstrate that each variable exhibits a particular tendency in influencing the level of students' academic work productivity. The utilization of Artificial Intelligence (AI) contributes to changes in students' learning patterns, particularly in terms of accelerating information retrieval, facilitating assignment completion, and enhancing time management efficiency. These changes require students to possess strong self-efficacy in order to optimize technology appropriately, develop confidence in meeting academic demands, and adapt to ongoing digital developments. In line with this, learning innovation becomes an essential domain that needs to be strengthened, since students' ability to adopt new strategies, experiment with learning methods, and utilize technological tools creatively will further enhance their academic work productivity. Thus, these three variables are interrelated and collectively influence the level of students' academic work productivity throughout their academic processes.

Based on the results of the t-test, variable X1 (AI utilization) shows a t-value of 2.275 with a significance level of 0.024 (< 0.05). This indicates that a higher level of artificial intelligence utilization in academic activities is associated with increased student work productivity. With the support of this technology, students are able to save time, work in a more organized manner, and produce higher-quality academic outputs within a more efficient timeframe. The use of AI in higher education can enhance learning quality and academic outcomes through easier access to information, greater efficiency in task completion, and support for independent learning (Aniella Mihaela Vieriu & Gabriel Petrea, 2025). Furthermore, AI usage among students has become deeply embedded and constitutes a significant and integral part of daily academic activities (Zoltán Rajki et al., 2025). Therefore, it can be understood that artificial intelligence has now become a fundamental necessity in students' academic lives and makes a substantial contribution to their work productivity.

However, higher education institutions need to guide the utilization of artificial intelligence in a structured manner within the learning process, rather than allowing it to function merely as a technical tool used individually by students. Universities are encouraged to integrate AI into academic activities so that its use genuinely supports the enhancement of academic work productivity. In addition, higher education institutions should provide ethical guidelines and AI literacy training for students to ensure that this technology is utilized as a means to strengthen understanding, improve work efficiency, and develop critical thinking skills, rather than serving as a substitute for the learning process itself.

The t-test results for variable X2 (self-efficacy) show a t-value of 4.376 with a significance level of 0.000 (< 0.05). These results indicate that the higher students' beliefs in their own abilities, the stronger their motivation to complete tasks in a timely manner and with higher quality. In line with previous studies, this finding also supports the view that self-efficacy is positively associated with learning engagement and academic achievement. Students with high levels of self-efficacy tend to be more active in seeking information, making efforts to understand learning materials, and demonstrating better academic outcomes (Meng & Zhang, 2023). In contrast, students with low self-efficacy are more prone to anxiety, procrastination, and giving up when facing academic difficulties (I.A. Maharani & I.G.A.V. Purnama, 2023). Other studies further indicate that self-efficacy has a significant effect on students' academic problem-solving abilities (Novita Sari & Nisa', 2024).

Therefore, higher education institutions need to pay more serious attention to strengthening students' self-efficacy, as confidence in one's own abilities has been proven to play an important role in enhancing academic productivity. Self-efficacy can be reinforced through learning processes that provide students with opportunities to complete tasks according to their capabilities and to experience success from their efforts, receive clear and constructive feedback from lecturers, and engage in a learning environment that supports self-confidence and the courage to try. These findings emphasize that psychological factors such as self-efficacy are critical determinants of student work productivity and should be understood as an integral component of technology utilization and the implementation of learning innovations.

Furthermore, based on the t-test results, variable X3 (learning innovation) obtained a t-value of 6.609 with a significance level of 0.000 (< 0.05). The use of active and innovative learning methods and practices has been shown to improve students' academic achievement (Suci Ramadhani et al., 2025). Innovation in the learning process not only enhances conceptual understanding but also facilitates the development of problem-solving skills and adaptive abilities in responding to dynamic learning situations (Mursida & Az-Zahra, 2025). These findings indicate that learning innovation plays a very important role in increasing student work productivity. From a practical perspective, higher education institutions need to encourage the implementation of innovative learning models, such as the use of varied instructional methods, the purposeful utilization of technology, and student-centered learning design, in order to increase student engagement and learning autonomy. Theoretically, learning innovation is a key factor in optimizing the use of technology and students' potential, thereby making a significant contribution to the improvement of academic work productivity.

Among the three variables, X3 (learning innovation) is statistically considered to have the most dominant influence ($\beta = 0.427$) compared to the other variables in enhancing variable Y (student work productivity). This indicates that changes in X3 have the greatest impact on changes in Y relative to the other variables in the model. These results suggest that the success of improving student work productivity is largely determined by the ability of higher education institutions to design and implement learning innovations that are adaptive to technological developments and students' needs. Learning innovation in this context is not limited to the use of digital media alone, but also includes variations in methods, strategies, and learning designs that encourage active engagement, autonomy, and creativity in completing academic tasks.

Furthermore, the dominant influence of learning innovation suggests that the utilization of artificial intelligence and students' self-efficacy will contribute more optimally when integrated into innovative and structured learning models. In other words, learning innovation functions as an enabling factor that bridges technology utilization and students' psychological factors, ultimately leading to improved academic work productivity. Therefore, higher education institutions need to position learning innovation as a strategic priority in curriculum development and pedagogical practices, so that AI technology is not used sporadically but becomes an integral part of a meaningful and productive learning process.

The F-test value of 94.425 with a significance level of 0.000 indicates that AI Utilization, Self-Efficacy, and Learning Innovation do not operate independently but function simultaneously in increasing students' academic work productivity. This finding reinforces the view that the learning process in higher education represents a combination of technological capabilities, psychological aspects, and creative learning strategies, such that academic performance cannot be attributed to a single factor. Theoretically, this result is consistent with contemporary educational concepts emphasizing adaptive learning, technology integration, and the development of autonomous learning skills. Practically, students need to familiarize themselves with technology, strengthen their confidence in learning, and be willing to try new approaches to be more productive. At the same time, universities and lecturers are expected to foster learning environments that support innovation and provide opportunities for students to develop more autonomous learning skills. Thus, it can be affirmed that the three variables have a significant simultaneous effect on students' academic work productivity.

An R^2 value of 0.590 (Adjusted R^2 = 0.584) indicates that approximately 59% of the variation in students' academic work productivity is explained by the combined effect of AI Utilization, Self-Efficacy, and Learning Innovation. This implies that the model is sufficiently strong in describing how the three variables jointly influence students' academic outcomes. This finding supports the notion that academic achievement is not determined merely by one particular aspect such as motivation or technology, but rather by a combination of personal abilities, learning strategies, and adaptation to technological tools. This result is also consistent with studies showing that self-efficacy and learning motivation jointly influence students' academic performance (Nila Zusmita Wasni et al., 2024). Similarly, research has demonstrated that the combination of self-efficacy and learning engagement significantly explains variations in academic achievement with an R^2 value of approximately 0.514 (Yuhan Zhang, 2025).

Conclusion

Based on the results of the data analysis, it can be concluded that the variables of Artificial Intelligence (AI) utilization, self-efficacy, and learning innovation have a significant effect on students' work productivity, both partially and simultaneously. This is evidenced by the significance values of the t-test, in which the significance value of variable X1 was 0.024, variable X2 was 0.000. and variable X3 was 0.000. Among the three independent variables examined, learning innovation was identified as the variable that provides the greatest contribution to the improvement of students' work productivity. Furthermore, the F-test generated an F value of 94.425 with a significance level of 0.000, indicating that the regression model employed in this study is statistically significant simultaneously. In other words, learning strategy, learning innovation, and self-efficacy, collectively exert a significant influence on students' work productivity; therefore, these three factors need to be understood as an interrelated entity influencing learning outcomes rather than being examined in isolation. The R-Square value of 0.590 indicates that learning strategy, learning innovation, and self-efficacy explain approximately 59% of the variance in students' learning outcomes. This implies that a majority of learning outcomes are influenced by these three factors, whereas the remaining 41% is affected by other variables not examined in this study. Overall, this value demonstrates that the regression model employed in the present study is sufficiently robust.

Despite the contributions of this study, several limitations should be acknowledged. This research employed a quantitative survey approach, in which the data relied on respondents' self-reported perceptions, potentially introducing subjective bias. In addition, the sample was limited to university students who had experience using Artificial Intelligence–based applications, which may restrict the generalizability of the findings to the broader student population. Furthermore, this study examined only three main variables, while other factors that may influence students' academic work productivity were not included. Therefore, future studies are recommended to expand the research model by incorporating additional variables such as learning motivation, digital literacy, or institutional support, as well as to adopt qualitative or mixed-methods approaches to obtain a more comprehensive understanding of students' academic productivity in higher education.

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