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Utilization of Artificial Intelligence in Management Information Systems to Increase Student Productivity in Early Semester

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Abstract

The rapid integration of Artificial Intelligence (AI) into higher education has changed how students search for information, organize academic tasks, and produce learning outputs. This study examines the utilization of AI within personal Management Information Systems and its relationship with the productivity of early-semester students. A quantitative associative design was employed using an online questionnaire completed by 102 second-semester students, most of whom were enrolled at UIN K.H. Abdurrahman Wahid Pekalongan. The independent variable measured the intensity, accessibility, and perceived efficiency of AI use, while the dependent variable represented time management, assignment quality, and speed of task completion. The research instruments met the validity and reliability requirements, and the data fulfilled the normality and linearity assumptions. ChatGPT was the most frequently used platform (83.3%), followed by Gemini AI (49%), Claude AI (20.6%), Notion AI (3.9%), and Zotero AI (3.9%). Pearson analysis produced a positive and significant correlation of 0.374, Spearman's rho reached 0.414, and Kendall's tau was 0.349, with significance values below 0.001. The coefficient of determination showed that AI utilization explained 14% of the variation in student productivity. These findings indicate that AI supports faster information retrieval, better task organization, and more efficient assignment completion, although productivity is also shaped by learning motivation, prior knowledge, self-regulation, and other factors outside the model. Responsible use, digital literacy, source verification, and institutional guidance are therefore necessary to ensure that AI strengthens productivity without reducing critical thinking, creativity, academic integrity, or independent learning.

Keywords: *Artificial Intelligence; Early Semester Students; Management Information Systems; Productivity.*

1. Introduction

The development of digital technology has brought about a fundamental transformation in the world of higher education through Artificial Intelligence (AI) innovations that are capable of delivering effective, adaptive, and personalized learning systems. In the era of Society 5.0, the integration of intelligent technology is no longer just a trend, but rather a crucial need to create an efficient learning ecosystem that suits individual needs[1]. This is supported by the fact that AI adoption among Indonesian students is very massive, as seen at Samawa University where 89.7% of students have utilized this technology in their academic activities. The use of AI in the context of personal information management systems has proven to play a positive role in helping students complete assignments more effectively, improving analytical skills, and encouraging academic innovation in the digital era [2].

John McCarthy explains that artificial intelligence is the field of study that explores how to create machines or computer programs capable of mimicking human intelligence without having to replicate the biological functioning of the brain[3]. In the field of education, artificial intelligence technology is used to tailor the learning process to the individual characteristics of each student. Through this system, data on students' abilities, learning preferences, and background experiences are analyzed to create individualized learning profiles. With the support of machine learning, this approach facilitates the development of digital content specifically designed to align with the needs and potential of each student[4].

In today"s digital era, technological advancement, including artificial intelligence, has become a key factor influencing various aspects of life, demonstrating its strategic role in supporting modrn systems, including education[5]. However, for first-semester students, the presence of AI presents significant challenges amidst the transition from high school learning patterns that demand more mature time and information management. While

AI can assist with reference searches and streamline assignments [6]. Excessive reliance without proper controls risks weakening students' critical thinking skills, creativity, and independence [7]. This phenomenon raises fundamental questions about the ideal use of AI in first-semester students' personal information management systems, the extent of its impact on their productivity, and the challenges and controls required to ensure this technology continues to function as a supporting tool without stifling critical thinking.

Although technology-assisted learning systems offer greater convenience and interaction than traditional methods, their implementation remains hampered by issues such as technological skills and ethical issues related to academic settings. Studies on the impact of artificial intelligence on student participation and achievement have emerged, but studies specifically assessing its effectiveness are still lacking. Therefore, this study aims to address this gap by assessing the current use of artificial intelligence and understanding students' perspectives to contribute to educational practices in Indonesia [8].

Based on these issues, this study aims to identify strategies for integrating AI into the academic information management of first-semester students and analyze their impact on improving efficiency and work quality. Furthermore, this study explores how to use AI appropriately to minimize the risk of dependency. Theoretically, this study is expected to enrich the literature on Management Information Systems (MIS) related to the use of intelligent technology in academic environments. Practically, the results of this study are expected to help students increase productivity wisely and provide input for educational institutions in formulating technology integration policies that maintain the integrity and quality of learning.

2. Reaserch Methods

This study employs a quantitative approach. Sugiyono explains that quantitative methods rely on numerical data analyzed statistically to test pre-established hypotheses[9]. This study also utilizes an associative method, which examines the relationship between two or more variables[10]. Data were collected via a questionnaire distributed online through social media to gain statistical insights into the impact of AI technology on student productivity.

Population and Sampel

The population in this study consists of first semester students (semester 2) who actively use AI-based tools such as ChatGPT, Gemini, or Notion AI in their academic activities. The sampling technique used is purposive sampling, where the respondent criteria are first-year college students who access social media and utilize AI as part of their personal information management system to organize assignments or learning. The sample size targeted in this study is at least 100 respondents to ensure that the processed data has an adequate level of validity in accordance with quantitative research standards.

Data collection technique

Primary data was collected through an online questionnaire (Google Forms) distributed through social media platforms such as WhatsApp, Instagram, and Telegram. Data were measured using a 1–5 Likert scale consisting of strongly disagree (STS), disagree (TS), neutral (N), agree (S), and strongly agree (SS). This research focuses on two main variables, namely the independent variable (X), which is the utilization of Artificial Intelligence in Management Information Systems, including intensity of use, ease of access, and efficiency of AI features, and the dependent variable (Y), which is early semester student productivity, including time management, quality of assignments, and speed of study completion.

Data Analysis Techniques

The collected data was processed using SPSS software through several stages of analysis. The research instrument test consists of a validity test using Pearson Product Moment to ensure that each question item is able to measure the variable correctly (r calculated > r table), and a reliability test using Cronbach's Alpha with a threshold of >0.60 to measure the consistency of respondents' answers. Furthermore, the classical assumption test includes a normality test using the Kolmogorov-Smirnov method to ensure that the residual data is normally distributed, and a linearity test to determine whether there is a linear relationship between the Artificial Intelligence (X) variable and the Productivity (Y) variable. Hypothesis testing in this study consists of Pearson Product Moment Correlation, which is used if the data is on an interval or ratio scale and is normally distributed, as well as Spearman Rank Correlation or Kendall's Tau, which are used if the data is on an ordinal scale (such as Likert) or not normally distributed. In addition, the coefficient of determination (R^2) is used to determine the percentage of influence or contribution of variable X on variable Y.

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3. Discussion Ressults

Descriptive Results

Based on the analysis of 102 respondents, consisting of second-semester students from several universities in Indonesia, 80% were from UIN KH. Abdurrahman Wahid Pekalongan, while the remaining 20% represented other institutions. The findings indicate that 83.3% of participants reported using ChatGPT, followed by 49% using Gemini AI, 20.6% Claude AI, 3.9% Notion AI, and 3.9% Zotero AI. The total percentage exceeds 100% as participants were allowed to select multiple responses.

In addition, previous research involving 70 students using ChatGPT demonstrates a predominantly positive perception of its role in academic activities. In terms of information-seeking behavior, 31.4% of participants strongly agreed and 60% agreed that ChatGPT serves as a primary source for obtaining academic information. Regarding response quality, 50% strongly agreed and 41.4% agreed that ChatGPT provides helpful and reliable answers to academic inquiries.

Furthermore, with respect to comprehension, 30% strongly agreed and 58.6% agreed that the responses generated are easy to understand and facilitate the learning process. In terms of usability, 45.7% strongly agreed and 34.3% agreed that the platform is user-friendly and easy to interact with. Concerning accuracy and relevance, 35.7% strongly agreed and 41.4% agreed that the information provided is sufficiently accurate and aligned with academic needs.

Moreover, the use of ChatGPT contributes to enhancing students' understanding and productivity, as reflected by 88.6% of participants expressing positive responses toward its role in supporting learning. Additionally, the majority acknowledged its efficiency in accelerating information retrieval**,** with 35.7% strongly agreeing and 61.4% agreeing[11].

Validity Test

According to Sugiyono (2013), validity refers to a trustworthy tool for measuring things, which means it can accurately assess what it's meant to assess. A reliable tool demonstrates how closely the actual information from the subject matches the information that the researcher shares [9].

Validity testing is done to find out how well a research tool can properly measure what it is supposed to measure. When deciding on the results of this validity test, researchers look at the correlation coefficient (r calculated) and compare it to the r table value. They also consider the significance probability value. With 102 people taking part in the survey (N = 102), the degrees of freedom (df) calculated is 100 (df = N - 2). This is based on a significance level of 5% (a = 0.05$) for a two -tailed test, the r table value is 0.195. A statement item is declared valid and can be used in research if it meets the criteria of r count > r table (0.195) and Sig. value (2-tailed) < 0.05. If the analysis results show that the r count value is smaller than r table, then the item is declared invalid. According to these standards, here is a brief overview of the results from the validity tests for each statement in the research variable:

Tabel 1.
Results of the Validity Test of Artificial Intelligence Variables (X)

Statement Items	R-value	R-table value (a=0.05)	Sig. (2-tailed)	Information
Item 1	0.819	0.195	0.0o1	Valid
Item 2	0.534	0.195	0.001	Valid
Item 3	0.634	0.195	0.0o1	Valid
Item 4	0.819	0.195	0.0o1	Valid
Item 5	0.401	0.195	0.0o1	Valid

Tabel 2.
Results of the Validity Test of Student Productivity Variables (Y)

Question Items	R-value	R-table value (a=0.05)	Sig. (2-tailed)	Information
Item 1	0.586	0.195	0.0o1	Valid
Item 2	0.734	0.195	0.001	Valid
Item 3	0.687	0.195	0.0o1	Valid
Item 4	0.705	0.195	0.0o1	Valid
Item 5	0.683	0.195	0.0o1	Valid
Item 6	0.585	0.195	0.0o1	Valid
Item 7	0.294	0.195	0.0o1	Valid
Item 8	0.491	0.195	0.0o1	Valid
Item 9	0.480	0.195	0.0o1	Valid
Item 10	0.532	0.195	0.0o1	Valid

From looking at Tables 1 and 2, we notice that the r values for all the items related to Variable X and Variable Y are higher than the r value in the table, which is 0.195. Also, the significance values (Sig.) for each item are less than 0.05. This means we can say that all the items in this survey are valid and appropriate for use in future testing

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of hypotheses.

Reliability Test

Reliability is a series of measurements or a series of measuring instruments that have. When the same measurements are taken multiple times using the measuring tools, it helps to ensure that the results are consistent. Test reliability shows how consistent a test is, meaning how much you can trust the results it gives. To keep getting similar scores even when tested in different situations. Therefore, it can be said that reliability is a way to check or see how something works. is the object of measurement. A test can be considered reliable if it consistently gives the same results when taken under similar conditions. Same results (consistent, stable). The measurement results must stay the same, relative to the original. If the measurement is given to the same subject even though it is carried out by different people. People, at different times, and in different places. A measuring instrument with high reliability is called a reliable measuring instrument [12].

This test aims to determine the extent to which a research instrument produces consistent results when repeated measurements are taken at different times. This test uses the Cronbach's Alpha method, where a variable is considered reliable if its Cronbach's Alpha value is > 0.60. The following are the reliability test results for each variable:

Tabel 3.
Reliability Test Results

Reliability Test	Cornbach's Alpha	N of Items
Item 1	0.819	0.195
Item 2	0.534	0.195

Based on Table 3 above, it can be seen that the Cronbach's Alpha value for variable X is 0.673 and for variable Y is 0.772. Because both variables have Cronbach's Alpha values greater than 0.60, it can be concluded that all research instruments used in this study are reliable. This indicates that the questionnaire used has a good level of consistency and can be trusted for use in this study.

Classical Assumption Test

Normality Test

According to Nuryadi (2017), a normality test is a procedure to determine whether the data obtained comes from a normally distributed population. In other words, this test is used to determine whether the data distribution follows a normal distribution pattern. The basis for making decisions in a normality test is: if the calculated L value is greater than the L table, H0 is rejected; whereas if the calculated L value is less than the L table, H0 is accepted [13]. Wijayanti explained that there are several methods that can be used in normality tests. In general, these methods are divided into two: numerical and graphical. Numerical-based normality tests include: (1) the Chi-Square test for nominal or ordinal data, (2) the Kolmogorov-Smirnov test for interval or ratio data, (3) the Lilliefors test for interval or ratio data, and (4) the Shapiro-Wilk test, which is also used for interval or ratio data. Meanwhile, graphic-based normality tests can be performed using Normal Q-Q Plot, Normal P-P Plot, Detrended Q-Q Plot, histogram, boxplot, and stem-and-leaf. [12].

Tabel 4.
Normality Test Results

Variables	Statistics	DF	Sig.	Information
Y TOTAL (Kolmogorov-Smirnov)	0.083	102	0.079	Normally Distributed
X TOTAL (Shapiro-Wilk)	0.984	102	0.259	Normally Distributed

Based on the analysis results in Table 4, the normality test using the Kolmogorov-Smirnov method showed a significance value of 0.079, while the Shapiro-Wilk test produced a significance value of 0.259. Because both values are greater than 0.05, it can be concluded that the data in the X TOTAL variable is normally distributed. Thus, the normality assumption has been met so that the data can be further analyzed using parametric statistics, such as Pearson correlation or linear regression.

Liniearity Test

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According to Purnomo (2016), the linearity test is used to determine the linearity of data, namely whether two variables have a linear relationship or not. This test is used as a prerequisite in Pearson correlation analysis or linear regression. Testing in SPSS uses the Test for Linearity at a significance level of 0.05**.** Two variables are said to have a linear relationship if the significance (Linearity) is less than 0.05. The testing criteria used are if the Sig. Deviation from Linearity value > 0.05, then the relationship between the variables is declared linear. Conversely, if the Sig. value < 0.05, then the relationship is declared non-linear [14]. The following are the results of the linearity test between Variable X and Variable Y:

Tabel 5.
Linearity Test Results

Variables Relationships	Sum of Squares	DF	Mean Square	F	Sig.	Information
Y TOTAL * X TOTAL	650.476	13	50.037	2.926	0.001	Linear

Based on Table 5 above, the results of the linearity test show a significance value (Sig.) of 0.001. Considering that the significance value is smaller than 0.05 (0.001 < 0.05), it can be concluded that there is a significant linear relationship between the X TOTAL variable and the Y TOTAL variable. By fulfilling this linearity assumption, the regression model can be used to predict the relationship between the two variables.

Hypothesis Testing

Pearson Product Moment Correlation

Pearson correlation analysis, also known as product moment correlation, is an analysis to measure the closeness of a linear relationship between two variables that have a normal data distribution. The data used is an interval or ratio type [14]**.** The Pearson Product Moment correlation test is used to determine the strength and direction of the relationship between Variable X (Total) and Variable Y (Total). The basis for decision making is if the Sig. (2-tailed) value is <0.05, then there is a significant relationship. In addition, the strength of the relationship is seen from the correlation coefficient value (r), where the closer to 1, the stronger the relationship. The following are the results of the Pearson correlation test in this study:

Tabel 6.
Results of Pearson Product Moment Correlation Test

Variables Relationships	Pearson Correlation (r)	Sig. (2-tailed)	N	Information
X TOTAL with Y TOTAL	0.374	<0.001	102	Significant

Based on Table 6 above, the Pearson Correlation value (r) is 0.374. This value indicates that the strength of the relationship between Variable X and Variable Y is in the weak category (in the range of 0.21 - 0.40).

A positive correlation value (+) indicates a unidirectional relationship, meaning that the higher the Variable X, the higher the Variable Y will be. Furthermore, the Sig. (2-tailed) value is <0.001, which is less than 0.05. Thus, it can be concluded that there is a positive and statistically significant relationship between Variable X and Variable Y.

Spearman Rank Correlation Test or Kendall’s Tau

Kendall’s tau and Spearman’s rho analyses are used to measure the strength of the relationship between two variables based on their ranks. This correlation does not require a normal data distribution and is suitable for ordinal data. To practice data processing, we use case studies, such as the Pearson correlation analysis case study [14].

Non-parametric correlation tests are used when the data is not normally distributed or ordinal. In this study, the test used was Spearman’s rho (or Kendall’s Tau) to determine the strength and direction of the relationship between Variable X (Total) and Variable Y (Total). The decision-making criteria were based on a significance value (Sig.) <0.05. The following is a summary of the test results:

Tabel 7.
Results of Pearson Product Moment Correlation Test

Test Method	Variable Relationship	Correlation Coefficient (p)	Sig. (2-tailed)	N	Information
Spearman’s rho	X TOTAL * Y TOTAL	0.414	<0.001	102	Significant
Kendall’s tau	X TOTAL * Y TOTAL	0.349	<0.001	102	Significant

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Based on Table 7 above, the results of the Spearman's rho test show a correlation coefficient value of 0.414 with a significance value (Sig.) of <0.001. Since the Sig. value is <0.05, it can be concluded that there is a significant relationship between Variable X and Variable Y.

The coefficient value of 0.414 falls into the moderate relationship category (ranging from 0.41 to 0.60) with a positive direction. Meanwhile, Kendall's tau_b test also supports this result with a coefficient value of 0.349 and a significance value <0.001, indicating that the relationship between the variables is statistically significant.

Coefficient of Determination Test

The coefficient of determination analysis is used to figure out how much the data points fit the model or trend line. The independent variable X can help explain the changes in the dependent variable Y. The value used To determine this contribution, the R-square value is used. R-square (R2) is also known as the The coefficient of determination explains how much of the dependent variable's variation can be explained by the independent variables in the model. It shows the proportion of the variance in the dependent data that is predictable from the independent variables. Explained by the independent data. This item shows how well the independent variables can explain the changes in the dependent variable [14].

When using multiple linear regression, the adjusted R-square value is examined. Why is that? The R-square value changes depending on how many independent variables are included. The greater The more independent variables there are, the higher the R-square value tends to be. Therefore, to obtain the A true value, which is a correction factor, is used to create an adjusted R-square. The following are the results of the coefficient of determination test in this study:

Tabel 8.
Results of The Determination Coefficient Test

Model	R	R Square	Adjusted R Square	Standard Error of The Estimate
1	0.374	0.140	0.131	4.306

Based on Table 8 above, the R Square value is 0.140 . This indicates that the contribution or influence of Variable X on Variable Y is 14% ($0.140 \times 100\%$). Meanwhile, the remaining 86% ($100\% - 14\%$) is explained by other variables or other factors outside this research model that were not examined. The R value of 0.374 also indicates that the relationship between variables X and Y has a correlation level that is in the weak category.

Extended Discussion

The statistical findings provide a basis for understanding AI not merely as a stand-alone application, but as a component of students' personal academic information management. In this context, a Management Information System is reflected in the way students collect information, classify learning materials, schedule assignments, prepare responses, and evaluate the quality of outputs. AI platforms can support each of these activities by shortening the time required to locate initial information, converting complex material into more accessible explanations, generating alternative structures for assignments, and helping users organize a sequence of work. The positive correlation identified in this study therefore indicates that students who use AI more effectively tend to report higher productivity. Nevertheless, the magnitude of the relationship also confirms that technological assistance is only one element within a broader learning system.

Interpretation of AI Adoption Patterns

The dominance of ChatGPT, used by 83.3% of respondents, shows that conversational AI has become the principal entry point for students who require rapid academic assistance. Its interface resembles ordinary dialogue, allowing users to formulate questions without mastering complex technical commands. This ease of interaction is especially relevant for early-semester students who are still adapting to university terminology, independent learning expectations, and the volume of academic information. Gemini AI, selected by 49% of respondents, also occupies an important position, while Claude AI, Notion AI, and Zotero AI are used by smaller proportions. Because respondents could select more than one platform, these percentages indicate a multi-tool environment rather than mutually exclusive adoption.

The use of several platforms can be interpreted as a form of functional specialization. Students may employ one application for initial explanations, another for comparing ideas, another for organizing notes, and a reference-oriented tool for managing sources. This pattern is consistent with the broader development of AI in higher education, where applications are increasingly embedded across teaching, information retrieval, feedback, administration, and learning support [16]. From a Management Information Systems perspective, the value of AI is not determined only by how frequently a particular tool is opened, but by whether information generated by the tool is integrated into a controlled academic workflow. Students who compare outputs, record important information, verify sources, and connect the results to course requirements are more likely to obtain genuine productivity benefits than students who simply copy the first generated response.

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The adoption pattern also demonstrates the importance of perceived usefulness and ease of use. Research on university students has shown that learners generally view conversational AI as useful for obtaining explanations, generating ideas, and supporting complex thinking, although perceived usefulness varies according to task type and user competence [19]. In the present study, the high utilization of ChatGPT may therefore reflect both functional value and low barriers to entry. However, high adoption should not automatically be interpreted as high-quality use. A student may use AI frequently but still apply weak prompts, accept inaccurate information, or fail to connect the output with learning objectives. Consequently, future measurement should distinguish frequency, duration, diversity of functions, verification behavior, and the degree of cognitive engagement during AI-assisted activities.

AI as a Personal Academic Information Management Tool

The findings become more meaningful when AI use is viewed as part of a personal information cycle. The first stage is information identification, in which students determine what they need to know. The second stage is information acquisition through lectures, textbooks, scholarly databases, learning management systems, and AI platforms. The third stage is information evaluation, which requires checking relevance, accuracy, authority, and consistency. The fourth stage is organization, including note-taking, categorization, citation management, and task scheduling. The final stage is information application, where students transform verified material into an assignment, presentation, analysis, or decision. AI can contribute at every stage, but it cannot replace the student's responsibility to determine whether the information is academically appropriate.

For early-semester students, the information cycle is often difficult because they are simultaneously learning disciplinary content and university study procedures. AI may reduce the initial cognitive burden by explaining unfamiliar concepts, proposing search keywords, summarizing long passages, or producing a preliminary outline. These functions can improve the efficiency of an academic information system because they reduce the time between identifying a problem and producing an actionable plan. Kasneci et al. explain that large language models provide opportunities for personalized support, rapid feedback, and adaptive educational assistance, while also creating risks associated with unreliable information, bias, and uncritical dependence [15]. The current results align with this balanced position: productivity increases as AI utilization increases, but the relationship is not strong enough to justify treating AI as the primary determinant of academic success.

A productive workflow should therefore position AI between problem identification and human evaluation rather than at the end of the learning process. For example, a student may ask AI to clarify a concept, use the explanation to identify relevant keywords, search for authoritative literature, compare the literature with the generated answer, and then write an original synthesis. In such a workflow, AI accelerates preliminary processing while the student retains control of evidence selection and reasoning. Conversely, when AI directly produces a final answer that is submitted without verification, apparent speed may increase while genuine learning productivity decreases. The distinction between output quantity and learning quality is essential when interpreting self-reported productivity.

Meaning of the Weak-to-Moderate Relationship

The Pearson correlation of 0.374 indicates a positive but weak relationship between AI utilization and student productivity. This result should not be understood as evidence that AI has little value. In educational research, productivity is influenced by many interrelated factors, including learning motivation, self-regulation, prior academic ability, course difficulty, lecturer support, internet quality, study environment, assessment design, health, and available time. A single technological variable would not be expected to explain all of these influences. The positive direction and significance below 0.001 show that the relationship is unlikely to be random within this sample, while the moderate Spearman coefficient suggests that higher levels of AI use are generally associated with higher productivity rankings.

The coefficient of determination provides a clearer interpretation of practical contribution. An R Square value of 0.140 means that AI utilization accounts for 14% of the observed variation in productivity, while 86% is associated with factors outside the model. This percentage is substantial enough to justify institutional attention because a supportive technology can produce meaningful efficiency gains even when it is not the dominant predictor. At the same time, the result prevents an exaggerated conclusion. Providing access to an AI platform alone will not automatically create productive students. Institutions must combine technology access with learning strategies, academic guidance, digital literacy, and appropriate assessment.

The result also implies that the relationship may differ among subgroups. Students with strong self-regulation may use AI to accelerate planning and checking, whereas students with weak self-regulation may use the same tool to postpone work or avoid deeper engagement. Students with stronger prior knowledge may detect incorrect outputs more easily, while beginners may accept plausible but inaccurate explanations. Chan and Hu found that students recognize both the benefits and the challenges of generative AI, including personalized support and efficiency alongside concerns about accuracy, over-reliance, privacy, and fairness [17]. These differences help explain why a positive average relationship can remain limited in strength.

Consistency Across Pearson, Spearman, and Kendall Tests

The use of Pearson, Spearman, and Kendall correlation tests strengthens the interpretation of the findings because all three tests show a positive and statistically significant association. Pearson correlation evaluates a linear relationship using total scores, while Spearman's rho and Kendall's tau evaluate ordered relationships and are less dependent on strict distributional assumptions. The Pearson coefficient of 0.374, Spearman coefficient of 0.414, and Kendall coefficient of 0.349 are not identical because the tests use different calculation principles, but their directions are consistent. This convergence reduces the possibility that the conclusion depends solely on one statistical technique.

Spearman's rho reaching the moderate category may indicate that the general ranking of respondents is more consistent than the exact distance between their scores. In practical terms, students with relatively higher AI utilization tend to occupy relatively higher positions in productivity, although increases are not perfectly proportional. Kendall's tau produces a lower coefficient because it evaluates concordant and discordant pairs more conservatively. The agreement among these tests supports the central conclusion that AI utilization is positively associated with productivity while preserving a cautious interpretation of effect strength.

Validity and Reliability of the Measurement Instruments

All statement items met the validity requirements because the calculated correlation values exceeded the r-table value of 0.195 and the significance values were below 0.05. This indicates that the questionnaire items were sufficiently connected to the variables they were intended to measure. The reliability coefficients of 0.673 for AI utilization and 0.772 for student productivity also exceeded the stated threshold of 0.60. The productivity scale therefore demonstrated a stronger level of internal consistency, while the AI utilization scale remained acceptable for exploratory research.

The difference between the two reliability coefficients may reflect the multidimensional nature of AI utilization. Students can use AI for searching, summarizing, translating, generating ideas, editing language, scheduling, or producing complete responses. These functions are related, but they are not identical behaviors. A future instrument could improve measurement precision by separating AI utilization into dimensions such as frequency, task diversity, prompt competence, verification practices, ethical awareness, and integration with other academic systems. Productivity could similarly be divided into efficiency, output quality, time management, perceived workload, and independent learning. A multidimensional model would help determine which aspect of AI use has the strongest relationship with each productivity outcome.

AI, Time Management, and Assignment Completion

One of the most direct pathways through which AI can affect productivity is time management. Early-semester students often spend considerable time interpreting assignment instructions, identifying the required structure, and deciding where to begin. AI can reduce this start-up time by translating instructions into a sequence of tasks, suggesting a preliminary schedule, or generating questions that guide further research. When used appropriately, these functions reduce administrative friction and allow students to allocate more time to reading, analysis, revision, and consultation.

The benefit is particularly relevant when students face several assignments with overlapping deadlines. AI can help create task lists, estimate stages of completion, and propose priorities based on urgency and complexity. However, such recommendations should remain under user control because the system does not fully understand personal circumstances, course expectations, or the actual difficulty of each task. Productivity gains arise when students use AI recommendations as a planning aid and then revise them according to realistic academic conditions.

Faster completion also needs to be interpreted carefully. A task completed quickly is productive only when it satisfies learning outcomes and quality standards. Rapid generation of text may create an illusion of efficiency if students later spend additional time correcting inaccuracies, restructuring weak arguments, or resolving citation problems. Reviews of ChatGPT in education have similarly reported that AI can support explanations, material preparation, and tutoring, but can also generate incorrect information and create assessment challenges [18], [20]. The most effective time-saving strategy is therefore not automatic answer production, but a controlled division of labor in which AI handles routine support and students perform evaluation, judgment, and final synthesis.

Assignment Quality and the Role of Human Judgment

The relationship between AI and assignment quality depends on the stage at which the tool is used. During idea generation, AI can provide alternative perspectives and help students overcome difficulty starting a task. During drafting, it can suggest structures, transitions, or examples. During revision, it can identify unclear sentences, inconsistent terminology, and possible omissions. These functions may improve presentation quality, especially for students who need additional language support. Nevertheless, surface improvement does not guarantee conceptual accuracy, originality, or alignment with the assessment rubric.

Human judgment remains necessary because generative AI produces responses based on patterns in training data rather than direct understanding of the specific course context. It may invent references, simplify contested issues, present outdated information, or produce confident statements without adequate evidence. Farrokhnia et al. describe this dual character through a SWOT analysis: personalized and immediate responses create educational opportunities, whereas limited contextual understanding, bias, inaccurate content, and threats to higher-order thinking create significant weaknesses and risks [22]. Students must therefore treat AI output as provisional material that requires comparison with lecture content, textbooks, scholarly articles, and lecturer guidance.

A useful quality-control procedure consists of four questions. First, is the answer relevant to the assignment question? Second, is every factual statement supported by a reliable source? Third, does the argument reflect the student's own reasoning and course concepts? Fourth, can the student explain and defend the submitted work without relying on the AI conversation? If any answer is negative, the work should be revised. This procedure transforms AI from an answer generator into a tool for iterative improvement and helps ensure that productivity does not come at the cost of academic competence.

Early-Semester Transition and Independent Learning

The focus on early-semester students is important because this group is undergoing a transition from highly structured school learning to more independent university learning. Students must learn to interpret syllabi, locate scholarly sources, manage long-term assignments, participate in academic discussion, and take responsibility for deadlines. AI can act as a temporary scaffold during this transition by providing explanations and procedural guidance. For example, it may clarify the difference between a summary and a critical analysis, demonstrate how to divide a research question into subtopics, or propose a checklist for reviewing an assignment.

Scaffolding is beneficial when support is gradually reduced as competence increases. If students continuously depend on AI for every decision, the scaffold may become a permanent substitute for independent learning. The current weak-to-moderate correlation suggests that productive outcomes are more likely when AI is combined with personal learning capacity rather than used in isolation. Educational institutions should therefore teach students not only how to operate AI tools but also when not to use them. Some activities, such as recalling foundational concepts, practicing calculations, developing original interpretations, and reflecting on personal learning difficulties, may require deliberate effort without immediate AI assistance.

The development of independence can be supported through staged assignments. Students may first complete an individual attempt, then use AI to compare explanations, and finally document which suggestions were accepted or rejected. This sequence preserves initial thinking while still allowing technological support. It also creates evidence of learning processes and encourages metacognition. The goal is not to prohibit AI, but to ensure that students remain able to plan, reason, and produce work when the technology is unavailable or unsuitable.

Digital Literacy, Prompt Competence, and Source Verification

Digital literacy is a central moderating factor between AI use and productivity. Students need to understand that a fluent response is not necessarily a correct response. They must be able to formulate specific questions, provide sufficient context, request alternative explanations, identify uncertainty, and verify important claims. Prompt competence is therefore not simply a technical skill; it includes the ability to define the academic problem accurately. Weak questions often produce generic answers, while carefully structured questions can generate more useful material for further evaluation.

Source verification should be integrated into every AI-assisted workflow. When an AI system mentions a theory, statistic, or publication, students should search for the original source through a library database, publisher website, or recognized scholarly index. References that cannot be located should not be included. Students should also compare important claims with more than one authoritative source, particularly when the topic is current, controversial, or technically complex. This practice reduces the risk of fabricated citations and helps students develop conventional information-literacy skills.

Digital literacy also includes privacy awareness. Students should avoid entering confidential personal data, unpublished research data, examination questions, or information belonging to other individuals into external AI platforms unless institutional policy permits it.

In a formal Management Information System, data governance is as important as system functionality. Universities should explain which categories of information are safe to process, which tools have been approved, and how students can protect accounts and academic records. Responsible data practices strengthen trust and allow productivity benefits to be achieved without creating unnecessary security risks.

Critical Thinking and Academic Integrity

The principal risk identified in the study is that excessive reliance may weaken critical thinking, creativity, and independence. This risk emerges when students accept generated text without questioning assumptions, evidence, or logical connections. AI can produce a coherent answer even when the underlying reasoning is incomplete. Critical thinking therefore requires students to examine what is missing, identify alternative interpretations, and distinguish evidence from assertion. An effective instructional strategy is to ask students to critique an AI response, locate errors, improve the argument, and explain the basis for every revision.

Academic integrity is also affected because generative AI can produce original-looking text that may not be detected by conventional similarity checking. Cotton, Cotton, and Shipway emphasize that universities need proactive policies, training, assessment redesign, and clear procedures to address the opportunities and risks of ChatGPT [21]. A purely punitive approach is insufficient because students may be uncertain about acceptable assistance. Courses should explicitly state whether AI may be used for brainstorming, language editing, coding support, data interpretation, or complete drafting, and should specify disclosure requirements.

Transparency can be encouraged through an AI-use statement attached to assignments. Students can briefly

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identify the tool used, the purpose of use, the prompts or stages involved, and how the output was verified and revised. This practice does not automatically make every use acceptable, but it provides a basis for evaluating process integrity. Assessment design can also emphasize oral explanation, local case analysis, process logs, drafts, and reflective justification. Such activities make it more difficult to substitute generated text for genuine understanding while allowing students to learn responsible use.

Institutional Integration into Management Information Systems

At the institutional level, AI should be integrated with academic information services through governance rather than left entirely to individual experimentation. Integration does not necessarily mean connecting every public AI tool directly to student records. It means establishing a coordinated ecosystem that includes approved platforms, access guidance, help services, library support, ethical rules, and learning analytics. The institution should define the academic purposes for which AI is encouraged, restricted, or prohibited and communicate these rules consistently across courses.

A practical governance structure can involve lecturers, information technology units, library staff, quality assurance teams, and student representatives. Lecturers contribute disciplinary and assessment requirements; technology units evaluate security and reliability; libraries support source verification and citation; quality assurance teams monitor alignment with academic standards; and students provide information about actual usage patterns. This collaborative model is consistent with the state of AI in higher education, where successful adoption requires attention to pedagogy, ethics, infrastructure, and stakeholder capability rather than technology alone [16].

Institutional dashboards or learning management systems may provide optional AI-supported functions such as frequently asked questions, study planning, feedback on practice tasks, or navigation to approved resources. However, automated recommendations should be transparent, and students should know when they are interacting with AI. Sensitive decisions involving grades, disciplinary action, or student welfare should not be delegated solely to automated systems. Human oversight remains essential because academic decisions require contextual judgment and accountability.

Equity and Accessibility Considerations

AI may improve accessibility by providing explanations at different levels of complexity, supporting language revision, and offering assistance outside ordinary class hours. These benefits can help students who require additional time or alternative forms of explanation. However, unequal access to devices, stable internet connections, paid features, and advanced digital skills can create new disparities. A student with continuous access to premium tools may receive different support from a student who relies on limited free access.

Institutions should therefore assess AI adoption from an equity perspective. Basic guidance and approved tools should be accessible to all students, and essential course requirements should not depend on paid services that only some students can afford. Training should be designed for beginners rather than assuming prior experience. Accessibility features should also be evaluated for students with disabilities. Equity-oriented implementation ensures that AI contributes to productivity across the student population instead of concentrating benefits among already advantaged users.

A Practical Framework for Responsible AI-Supported Productivity

Based on the findings, responsible AI-supported productivity can be organized into five stages. The first stage is Define, where the student clarifies the learning objective, assignment requirement, and expected output. The second stage is Ask, where AI is used to obtain explanations, generate alternatives, or structure a plan. The third stage is Verify, where every important claim and reference is checked against authoritative academic sources. The fourth stage is Transform, where the student rewrites, analyzes, and connects the material using personal reasoning. The fifth stage is Disclose, where the student records the nature of AI assistance when required by institutional or course policy.

The Define stage prevents the tool from directing the entire task. Students should read the assignment instructions and rubric before opening an AI platform. During the Ask stage, prompts should include relevant context, requested depth, constraints, and the type of support needed. Students can request several alternatives rather than treating the first answer as final. During Verify, they should identify unsupported claims, search for original literature, and compare the generated explanation with course materials.

The Transform stage is the point at which productivity becomes learning. Students should reorganize the material, connect it to evidence, add local or disciplinary context, and remove content that they cannot justify. They should be able to explain why a particular argument was chosen and how the conclusion follows from the evidence. Finally, the Disclose stage creates accountability and helps lecturers distinguish permitted assistance from prohibited substitution. This framework allows institutions to benefit from the speed of AI while maintaining human authorship and academic responsibility.

The framework also suggests that productivity indicators should include both efficiency and quality. Possible indicators include time required to complete a task, number of revisions, accuracy of cited sources, rubric scores, ability to explain the work orally, and retention of concepts after the task. Measuring only perceived speed may overestimate the benefit of AI. A combined indicator would provide a more valid assessment of whether technology genuinely improves learning productivity.

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Implications for Lecturers and Educational Institutions

Lecturers can use the results to redesign learning activities around guided AI use. Introductory sessions can demonstrate how the same question produces different outputs depending on prompt quality, how hallucinated references can be detected, and how generated arguments can be evaluated. Assignments may require students to compare an AI response with scholarly literature, correct errors, and justify revisions. These activities transform the technology into an object of critical learning rather than an invisible shortcut.

Institutions should provide continuing professional development because lecturers also need confidence in using and evaluating AI. The systematic review by Montenegro-Rueda et al. concludes that ChatGPT can positively affect teaching and learning, but successful implementation depends on appropriate understanding and training [20]. Training should address pedagogical design, ethical boundaries, assessment, privacy, and inclusive access. Without staff preparation, different courses may apply inconsistent rules that confuse students and weaken academic integrity.

Support services can also be coordinated. Libraries may offer workshops on verifying AI-generated references, writing centers can teach revision and attribution, and technology units can publish security guidance. Academic advisors can help early-semester students integrate AI into realistic study plans. A coordinated approach is more effective than isolated warnings because it connects responsible use with the practical academic problems students are trying to solve.

Limitations and Directions for Future Research

The findings should be interpreted in light of several limitations. First, the study uses a cross-sectional questionnaire, so it identifies association rather than causation. Students who are already productive may be more willing or able to use AI effectively. Second, productivity is self-reported and may differ from objective indicators such as grades, completion time, error rates, or lecturer evaluations. Third, 80% of respondents came from one institution, which limits generalization to universities with different disciplines, infrastructure, policies, and student characteristics.

The study also groups several AI platforms and functions within one utilization variable. Future research could compare generative chatbots, reference managers, note-taking tools, and learning analytics separately. Experimental or longitudinal designs could examine changes over a semester, compare AI-supported and non-AI-supported tasks, and determine whether productivity gains persist after the tool is removed. Qualitative interviews would help explain why some students achieve strong benefits while others experience dependence or confusion.

Future models should include additional variables that may explain the remaining 86% of productivity variation. Relevant factors include self-regulated learning, motivation, digital literacy, prior achievement, lecturer support, perceived usefulness, academic integrity awareness, internet access, and task complexity. Moderation analysis could test whether digital literacy strengthens the relationship between AI use and productivity, while mediation analysis could examine whether time management or information-search efficiency explains the relationship. Such research would produce a more complete model and support evidence-based institutional policy.

Despite these limitations, the present study contributes empirical evidence from Indonesian early-semester students and demonstrates that AI utilization has a statistically significant positive relationship with productivity. The results support neither unrestricted enthusiasm nor total rejection. Instead, they indicate that AI is most valuable when embedded in a structured information-management process, accompanied by verification, ethical awareness, and active human judgment. This balanced interpretation is consistent with international research that identifies substantial educational opportunities alongside risks requiring deliberate management [15], [17], [18], [22].

4. Conclusion

Based on the research results, it can be concluded that the use of Artificial Intelligence (AI) in Management Information Systems has a significant positive impact on the productivity of early semester students. This is proven by the results of statistical tests that indicate a relationship between the variables of AI use and student productivity, both through Pearson, Spearman, and Kendall correlation tests. However, the level of strength of the relationship is still classified as weak to moderate, with a Pearson correlation value of 0.374 and an influence contribution (R Square) of 14%. This means that AI does play a role in increasing productivity, but there are still other factors that are more dominant in influencing student academic performance. In practice, the use of AI has been proven to help students manage their time, speed up assignment completion, and improve the quality of their work. The high level of adoption of various AI platforms among respondents also indicates that this technology has become a vital part of modern learning systems, particularly in supporting students' academic activities. However, on the other hand, this study also highlights the potential risks of using AI inappropriately, such as over-reliance, which can diminish critical thinking skills, creativity, and independent learning. Therefore, a balanced and proportional strategy for utilizing AI is needed, where technology is used as a tool, not as a substitute for thinking. Furthermore, it is crucial for students to have good digital literacy and an awareness of academic ethics in using technology. Educational institutions also have a crucial role in guiding the use of AI through policies that support innovation

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while maintaining academic integrity. Thus, the use of AI is expected to provide optimal benefits in increasing student productivity without compromising the quality of the learning process itself.

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