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DETERMINING FACTORS IN THE UTILIZATION OF ARTIFICIAL INTELLIGENCE: PERCEPTIONS AND BEHAVIORS OF PROSPECTIVE PRIMARY SCHOOL TEACHERS IN COMPLETING SCIENCE ASSIGNMENTS

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Abstract

Artificial Intelligence (AI) holds significant potential to transform education, particularly in teaching methodologies and task completion. This study aims to identify the factors influencing the perceptions and behaviors of elementary education students in utilizing ChatGPT and Gemini to complete science-related assignments. The research design employs a quantitative approach with both descriptive and causal methodologies. Data testing and analysis are conducted using Structural Equation Modeling (SEM), P-value, and Prediction-Oriented Segmentation (POS). Path analysis results reveal that perceived benefits significantly impact perception (.403) and behavior (.406). AI effectiveness significantly affects perception (.303) but minimally influences behavior (.018). Preference for AI usage positively influences behavior (.305), whereas dependence on AI negatively impacts perception (-.050). Restrictions on AI usage reduce perception (-.077) but increase behavior (.115). The p-value analysis indicates that the perceived benefits of AI use significantly influence behavior (.000) and perception (.000), supporting the hypothesis that perceived benefits play a crucial role in enhancing AI adoption and fostering positive attitudes toward its use. Conversely, AI effectiveness significantly affects perception (.000) but not behavior (.862). Dependence, restrictions, and the impact of AI show no significant effects on either behavior or perception, except for AI usage preferences, which significantly influence behavior (.033). Segment analysis reveals that perceived benefits influence behavior in Segment 1 (.510) and perception in Segment 2 (.493). AI effectiveness negatively impacts behavior in Segment 2 (-.633) but shows moderate effects in Segment 1 (.214). Preferences for AI usage exert a more substantial influence on behavior in Segment 2 (.614), while the effects of dependence and restrictions vary across segments. The perceived benefits of AI encourage technology adoption among students, while dependence and restrictions introduce complexities in formulating AI-based educational policies.

Keywords: Artificial intelligence, ChatGPT, gemini, behaviors.

INTRODUCTION

The utilization of artificial intelligence (AI) technology across various aspects of life has undergone remarkable advancements over the past decades, offering transformative potential to replace human tasks and activities in numerous fields (Dwivedi et al., 2021). In the realm of education, the paradigm has shifted significantly with the advent of digital learning (Firdaus, 2023). Among the most widely adopted AI applications are generative language models such as ChatGPT and Gemini AI (World Bank, 2024), which leverage machine learning algorithms to interact with users via text, generate responses, and solve specific problems (Alsajri et al., 2024; Imran & Almusharraf, 2024). The integration of AI into education has increasingly extended to the learning process, including completing academic assignments, such as science tasks (Firdaus et al., 2024). This phenomenon is particularly evident among elementary education students utilizing ChatGPT and Gemini AI to complete assignments. Consequently, understanding the factors influencing perceptions and behaviors regarding the use of these AI tools in completing science tasks is essential.

Knowledge of AI technology is pivotal in effectively leveraging these applications in educational settings. Perceptions of the effectiveness and benefits offered by ChatGPT and Gemini AI play a critical role in shaping decisions to adopt this technology in learning processes (Baskara, 2025; Bayer et al., 2024). Knowledge about AI is a key driving factor for its adoption in education, as sufficient understanding enables individuals to utilize the technology optimally (Arora et al., 2024; Gao, 2023). Moreover, research has shown that students with excellent AI knowledge tend to demonstrate more positive perceptions of its use (Gao, 2023).

Student behavior in utilizing AI to complete science tasks is another crucial factor to consider. According to Choi et al. (2023), user behavior towards AI technology heavily depends on its efficiency and effectiveness factors. Students who perceive that ChatGPT and Gemini AI accelerate task completion are likelier to consistently adopt these tools (Nikolic et al., 2024). However, usage restrictions and dependence on these technologies can also influence behavior. Usage restrictions, whether technical (e.g., limited access or capacity) or ethical (e.g., concerns about plagiarism), may reduce students' willingness to rely on these technologies (Tripathi & Thakar, 2024; Rane et al., 2023).

The impact of AI usage in education requires a more profound analysis. Several studies suggest that the use of AI in learning can have positive effects, such as enhancing conceptual understanding and learning efficiency (Wang et al., 2024). Research by Luckin (2018) indicates that AI implementation in education can improve students' learning experiences by providing faster and more accurate feedback. However, concerns have been raised regarding potential negative impacts, such as excessive dependency on technology or limitations arising from a lack of understanding of AI's operations. Negative consequences may include over-reliance on technology, which could diminish students' critical thinking abilities in problem-solving (Zhai et al., 2024; Calzada, 2024). Critical thinking, however, is one of the key benchmarks for student success in the current learning era (Firdaus, 2022). Therefore, it is crucial to explore how students perceive the impact of AI use in supporting education.

Students' preferences in selecting technology to support learning and their views on AI technology's potential benefits and risks are relevant variables in this study. Research by Alam & Mohanty (2023) emphasizes that individual preferences for technology are often influenced by ease of use, accessibility, and effectiveness in completing academic tasks. Hence, the primary issue in this research focuses on understanding the factors influencing the utilization of Artificial Intelligence (AI), specifically ChatGPT and Gemini AI, among elementary education students in completing science-related tasks.

The use of AI among students is increasing alongside technological advancements; however, its impact on students' perceptions and behaviors in completing educational tasks has not been extensively discussed in the literature. Previous studies indicate that perceptions of new technology significantly influence how individuals interact with and adopt such technologies (Venkatesh et al., 2003). Students' perceptions of AI usage's effectiveness, benefits, and impacts are key determinants in its adoption. The effectiveness of these technologies relates to students' ability to complete science tasks more efficiently and effectively, while perceived benefits influence how frequently students use these technologies in their learning process (Davis, 1989). Research by Hwang et al. (2020) examines how acceptance of AI affects its effectiveness in learning contexts, showing that students with excellent knowledge of AI are likelier to utilize the technology effectively.

Furthermore, the potential limitations and dependency on AI usage may significantly influence students' behavior. Several studies have indicated that excessive reliance on technology can diminish critical thinking skills and independence (Carr, 2011). Restrictions on access to or use of AI also emerge as critical factors, as not all students have equal access to this technology, whether in terms of devices or internet connectivity (Hochschild, 2017). This approach is essential to understanding the opportunities and challenges of integrating AI technology into education, particularly in the context of science teaching and learning.

One of the reasons why this research is important is that AI holds immense potential to revolutionize learning processes, both in teaching and in completing tasks. The effectiveness of AI usage in education, as described by Popenici and Kerr (2017), can facilitate more personalized teaching, accelerate access to information, and reduce students' cognitive load. Analyzing the variables of ChatGPT and Gemini AI's effectiveness will provide insights into how students perceive these tools in completing assignments and whether they find them helpful or disruptive to the learning process. As Atchley et al. (2013) noted, students tend to be more enthusiastic about using technology if they perceive significant benefits, such as easier access to information or time efficiency. However, these benefits are not universally experienced by all individuals, influencing their behavior toward adopting such technologies. Additionally, students' preferences for using AI to support their learning are another critical aspect to consider. As Lai (2021) explains, users' preferences for adopting educational technology are heavily influenced by personal experiences and perceptions of the technology.

Although some research has explored the impact of AI technology in education, few studies have combined the analysis of psychological factors, such as students' perceptions and behaviors, in the context of completing specific tasks, such as science assignments. The research gap lies in the lack of in-depth investigation into factors influencing AI utilization, including variables such as usage limitations, dependency on technology, and students' preferences in choosing AI to support the learning process. This study aims to address this gap by conducting a comprehensive analysis using SEM models to identify the factors affecting the perceptions and behaviors of elementary education students in utilizing ChatGPT and Gemini AI to complete science assignments.

METHOD

Research Design

The research design employs a quantitative approach with both descriptive and causal methodologies. The descriptive approach is utilized to depict students' perceptions and behaviors regarding the use of AI in completing science assignments. In contrast, the causal approach is applied to identify cause-and-effect relationships between various variables, such as the benefits, effectiveness, impacts, and preferences for AI usage on students' behaviors and perceptions.

This study examines the relationships between variables and explores the factors influencing AI utilization using Structural Equation Modeling (SEM), with SmartPLS 4 as the analytical tool.

Additionally, student segments with varying responses to AI are identified through Prediction-Oriented Segmentation (POS) to analyze variations in the influence of variables based on the differing characteristics of students.

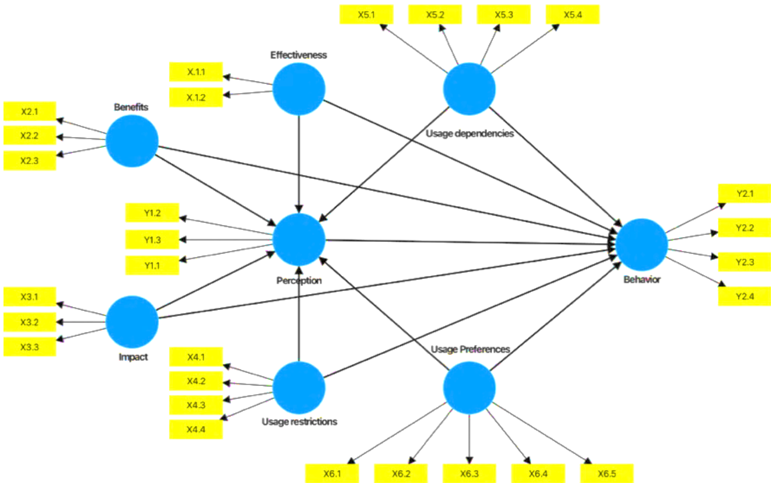

Figure 1. Research framework.

Populations and Sampling Techniques

The population used in this study consists of all fifth-semester Elementary Education students at Trunojoyo University, Madura, enrolled in science courses and using or having knowledge of ChatGPT and Gemini AI as elements of the learning process. Although they have not received specific training on AI, Elementary Education students are familiar with the use of digital tools. This study used a purposive sampling technique, which selects students who meet certain criteria (Ritchie et al., 2013). This study used 100 samples obtained based on the qualifications of students who actively participate in science courses, have knowledge and experience in using AI (especially ChatGPT and Gemini AI) during learning, and are willing to participate in the study. The number of participants consisted of 55% female and 15% male and the majority had good access to computers and the internet. The purpose of this sampling was to determine that the study focuses on students with the appropriateness of the research topic and their direct experience in using AI in academic activities.

Research Instrument

The questionnaire was constructed using a Likert scale to measure students' attitudes and perceptions toward the use of artificial intelligence, ranging from 1 (Strongly Disagree) to 4 (Strongly Agree). This instrument was pre-tested to ensure its validity and reliability before being used in data collection. The questionnaire was designed to measure the variables involved in this study. This measurement instrument was developed by the researcher based on several literature reviews on user perceptions and behaviors toward artificial intelligence in academic contexts in the world of education. Instrument development began with identifying appropriate indicators from the literature, which were then formulated into statement items. The questionnaire was structured to measure the variables involved in this study, which include:

X1: Effectiveness of using ChatGPT & Gemini AI

X2: Benefits of using ChatGPT & Gemini AI

X3: Impact of using ChatGPT & Gemini AI

X4: Restrictions on the use of ChatGPT & Gemini AI

X5: Dependency on the use of ChatGPT & Gemini AI

X6: Preferences and use of AI in supporting learning

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Y1: Perception

Y2: Behavior

Data Collection Procedure

The questionnaire was developed based on appropriate theoretical foundations regarding the use of technology in education and the variables to be measured in this study. Prior to distribution, the questionnaire instrument underwent a pilot test on a small sample to identify and identify potential issues and ensure the clarity of each question. The questionnaire was then distributed online to students selected using a purposive sampling technique. Students were instructed and asked to complete the questionnaire independently, answering each question based on their personal experiences and perspectives on the use of artificial intelligence in science learning.

Data collection was conducted over a two-month period, with respondents completing the questionnaire online through a secure and confidential survey platform, Google Forms. Researchers ensured the honesty and accuracy of responses by including a research ethics statement at the beginning of the questionnaire, explaining that there were no right or wrong answers, that participation was voluntary, anonymous, and would not affect the academic grades of the elementary education students participating in the questionnaire. Furthermore, respondents were asked to complete the questionnaire based on their personal understanding and experiences without any influence from other parties. Researchers also reviewed the submitted results to ensure completeness and consistency of responses to maintain data quality. Respondents who did not meet the criteria or showed inconsistent response patterns were eliminated from the final data analysis

Data Analysis

The collected data was analyzed descriptively to provide a general overview of the respondents' characteristics, including the frequency distribution, mean value, and standard deviation of each measured variable. This descriptive analysis was used to understand each respondent's response patterns and to identify and determine general trends in education students' perceptions and behaviors toward the use of artificial intelligence. Data validity and reliability were ensured through several stages. Prior to the main analysis, the construct validity and internal reliability of the instrument were checked using confirmatory analysis within a Structural Equation Modeling (SEM) framework. Outer loadings, average variance extracted (AVE), and composite reliability (CR) were analyzed to ensure adequate validity and reliability for each construct. Items with loadings below the threshold value (.7) were considered for removal. The relationships between variables in the model were tested using Structural Equation Modeling (SEM) with the aid of SmartPLS 4 software. SEM was used to measure the direct and indirect effects between research variables and to assess the extent to which the proposed theoretical model explained the observed data.

The p-value was used to test the significance of the relationships between variables. If the p-value is <.05, the relationship is considered significant (Vidgen & Yasseri, 2016). This approach is used to test whether the data can support the hypothesis proposed in the study. Furthermore, to simplify the high-dimensional data and identify the main variables that explain the greatest variation in the data, Principal Component Analysis (PCA) was applied. The results of the PCA revealed the core components that influence student AI utilization. Next, Prediction-Oriented Segmentation (POS) was used to examine the variation in responses between student groups regarding AI use. The purpose of this method is to identify student segments with significantly different patterns of perception and behavior, thereby providing a deeper understanding of the determining factors in AI utilization in the context of completing science assignments.

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RESULTS

Path Analysis

Based on Figure 2, it is evident that the variable Benefits significantly influences both students' perceptions and behaviors. The perceived benefits of using AI tools such as ChatGPT and Gemini enhance students' knowledge and encourage more active utilization in academic tasks. The path coefficients are notably high, at .403 for perception and .406 for behavior. The benefits of AI usage have been proven to be a key factor influencing students' attitudes and actions toward adopting this technology.

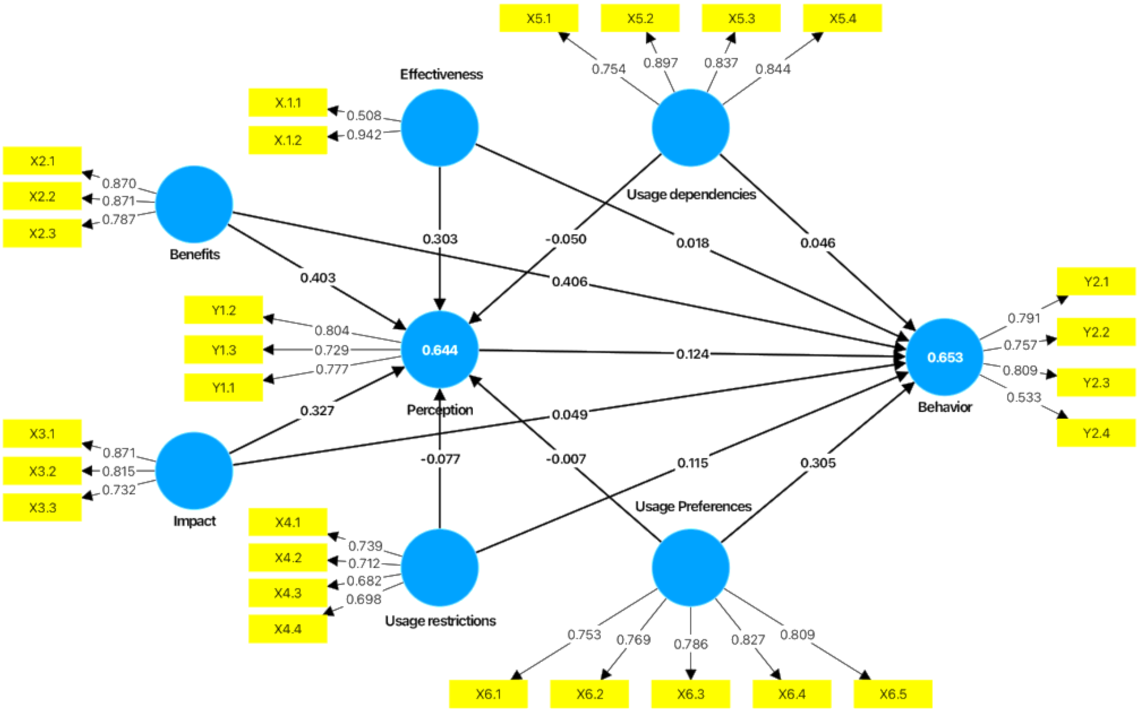

Figure 2. Path analysis.

The Effectiveness of AI usage positively impacts students' perceptions (.303) but has a minimal effect on behavior (.018). It indicates that while AI is effective in assisting, it is not sufficient to significantly drive behavioral changes or increase AI usage in the context of science tasks. Similarly, the Impact of AI usage, though felt by students (.327 for perception), shows a negligible effect on behavior (.049). It suggests that while the positive impact of AI may improve knowledge, it is not enough to induce significant behavioral changes.

Students' Perception of AI, influenced by its benefits and impact, positively affects their behavior (.124). It indicates that students with a better understanding of AI are more likely to use it in completing assignments. However, the influence of Preferences for AI usage and Dependence on AI remains relatively low. Students' preferences for using AI in learning show only a slight positive influence on behavior (.305), while dependence on AI even negatively influences students' perceptions (-.050). Excessive dependence on AI may diminish awareness or understanding of the technology's potential.

Moreover, Restrictions on AI usage negatively affect students' perceptions (-.077), meaning that the more restrictions imposed on AI usage, the lower students' perception of its utility and potential. However, these restrictions have a small yet positive effect on students' behavior (.115). This result suggests that despite AI usage limitations, students continue using these tools for task completion, albeit within the constraints imposed.

Construct Validity and Reliability

The analysis results in Table 1 highlight various indicators related to the validity and reliability of constructs within the research model. Each construct was tested using multiple measurement items evaluated based on loadings, weights, and various statistical indices such as Composite Reliability (CR), Cronbach's Alpha (CA), Average Variance Extracted (AVE), and Variance Inflation Factor (VIF).

Table 1. Construct validity and reliability.

Constructs	Items	Loadings	Weights	CA	CR	AVE	VIF
Effectiveness	X.1.1	.508	.342	.703	.818	.535	1.037
	X.1.2	.942	.877				1.037
Benefits	X2.1	.870	.445	.798	.881	.712	1.772
	X2.2	.871	.402				1.919
	X2.3	.787	.334				1.551
Impact	X3.1	.871	.482	.319	.711	.573	1.643
	X3.2	.815	.401				1.536
	X3.3	.732	.347				1.322
Usage Restrictions	X4.1	.739	.378	.734	.849	.653	1.325
	X4.2	.712	.373				1.266
	X4.3	.682	.356				1.254
	X4.4	.698	.306				1.336
Usage dependencies	X5.1	.754	.382	.659	.814	.594	1.374
	X5.2	.897	.293				3.368
	X5.3	.837	.290				2.555
	X5.4	.844	.244				2.834
Usage Preferences	X6.1	.753	.328	.852	.892	.623	1.467
	X6.2	.769	.154				1.987
	X6.3	.786	.254				1.826
	X6.4	.827	.228				2.231
	X6.5	.809	.304				1.878
Perception	Y1.1	.777	.453	.856	.902	.697	1.268
	Y1.2	.804	.458				1.339
	Y1.3	.729	.383				1.261
Behavior	Y2.1	.791	.422	.669	.801	.501	1.435
	Y2.2	.757	.327				1.447
	Y2.3	.809	.353				1.610
	Y2.4	.533	.251				1.135

Based on the results in Table 1, the construct of effectiveness is measured using X.1.1 and X.1.2. Item X.1.1 has a loading of .508 and a weight of .342, which, although relatively low, is acceptable. Item X.1.2 shows a very high loading value (.942), indicating that this item highly represents the effectiveness construct. The CA value (.703) and CR value (.818) demonstrate good reliability for this construct, although the AVE value (.535) suggests room for improvement in capturing the variance explained by the construct. The VIF value for this construct is 1.037, indicating no significant multicollinearity issues.

The construct of benefits is measured using three items: X2.1, X2.2, and X2.3. All items show high loading values, with X2.1 loading of .870, X2.2 reaching .871, and X2.3 at .787. These results indicate that the items are highly relevant and effectively reflect the benefits construct. The CA value (.798) and CR value (.881) indicate excellent reliability, while the AVE value (.712) demonstrates that this construct explains a substantial proportion of variance. The VIF values, ranging from 1.551 to 1.919, show no significant multicollinearity issues among the items measuring this construct.

The construct of impact is measured using three items (X3.1, X3.2, and X3.3), with loading values of .871 for X3.1, .815 for X3.2, and .732 for X3.3. While X3.3 has a slightly lower loading value, all items are acceptable. The CA value (.319) and CR value (.711) indicate moderate reliability, while the AVE value (.573) suggests sufficient variance explanation, though there is room for improvement in this construct. The VIF values, ranging from 1.322 to 1.643, indicate no significant multicollinearity issues.

The construct of usage restrictions is measured using four items (X4.1 to X4.4). All items demonstrate sufficiently high loading values, with X4.1 loading of .739, X4.2 at .712, X4.3 at .682, and X4.4 at .698. The CA value (.734) and CR value (.849) indicate good reliability, and the AVE value (.653) suggests that the construct explains a significant portion of the variance. The VIF values for this construct are within acceptable limits, ranging from 1.254 to 1.336.

The construct of dependency on usage is measured using four items (X5.1 to X5.4). X5.1 shows a loading of .754, X5.2 reaches .897, X5.3 is .837, and X5.4 is .844. These items are highly representative of the dependency construct. The CA value (.659) and CR value (.814) indicate good reliability, with an AVE of .594, suggesting room for improvement in this construct. The VIF for X5.1 is 1.374, indicating no multicollinearity issues, although X5.2 and X5.3 have higher VIF values (3.368 and 2.555), which may suggest potential multicollinearity concerns.

The construct of usage preference is measured using five items (X6.1 to X6.5). The loading values for these items range from .753 (X6.1) to .809 (X6.5), demonstrating good consistency in measuring this construct. The CA value (.852) and CR value (.892) indicate excellent reliability, with an AVE of .623, which is also relatively high. The VIF values for this construct range from 1.467 to 2.231, indicating no significant multicollinearity issues.

The construct of perception is measured using three items (Y1.1 to Y1.3). All items exhibit high loading values, with Y1.1 loading of .777, Y1.2 at .804, and Y1.3 at .729. The CA value (.856) and CR value (.902) indicate excellent reliability, with an AVE of .697, suggesting that this construct explains a substantial proportion of the variance. The VIF values for these items range between 1.261 and 1.339, showing no significant multicollinearity issues.

The construct of behavior is measured using four items (Y2.1 to Y2.4). The loading values range from .533 (Y2.4) to .809 (Y2.3), showing generally acceptable loading values. The CA value (.669) and CR value (.801) indicate good reliability, although the AVE (.501) is slightly lower compared to other constructs, suggesting room for improvement. The VIF values for these items range from 1.135 to 1.610, indicating no significant multicollinearity issues.

Model Fit

The results presented in Table 2 provide information regarding the model fit used in this study, both for the saturated and estimated models. Several indicators were employed to evaluate the model's goodness-of-fit, including SRMR (Standardized Root Mean Square Residual), d_ULS (Squared Euclidean Distance), d_G (Geodesic Distance), Chi-square, and NFI (Normed Fit Index).

Table 2. Model fit.

	Saturated model	Estimated model
SRMR	.106	.106
d_ULS	4.560	4.560
d_G	1.569	1.569
Chi-square	769.254	769.254
NFI	.575	.575

SRMR (Standardized Root Mean Square Residual) is an indicator that measures the difference between the observed covariance matrix and the one predicted by the model. Lower SRMR values indicate better model fit. The SRMR value for both the saturated and estimated model is .106, which is slightly higher than the ideal threshold (below .08). Nevertheless, this value falls within an acceptable range for many structural model applications, indicating that the model demonstrates a reasonably good fit despite some minor deviations from a perfect model.

d_ULS (Squared Euclidean Distance) measures the squared Euclidean distance between the observed covariance matrix and the one predicted by the model. Lower d_ULS values indicate a better fit. The

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d_ULS value for both the saturated and estimated models is 4.560. This value suggests an adequate fit between the estimated model and the observed data.

d_G (Geodesic Distance) measures the geodesic distance used to evaluate differences between the observed and predicted models. Lower d_G values indicate a better model. The d_G value is 1.569 for both models, indicating that the estimated model fits the observed data reasonably well, with values within acceptable limits for most analyses.

Chi-square (χ^2) is a statistic that measures the degree to which the estimated model aligns with the observed data. Lower Chi-square values indicate better model fit. The Chi-square value for both models is 769.254. It indicates some imperfections in model fit, which is standard in SEM analyses with large sample sizes. Typically, larger sample sizes result in higher Chi-square values, even for reasonably well-fitting models.

NFI (Normed Fit Index) measures how much the estimated model improves upon a simpler baseline model. Higher NFI values indicate better model fit. The NFI value is .575 for both models, suggesting that the estimated model has a lower fit than a simpler model. It indicates areas within the model that require improvement to enhance overall fit.

P-Values

The p-value results in Figure 3 can be interpreted to understand the various relationships between the variables in the model used to examine the factors influencing students' utilization of Artificial Intelligence (AI). Each p-value indicates whether the relationship between two variables in the model is significant or not, with the commonly used significance level being .05. Below is the interpretation of the obtained p-value results.

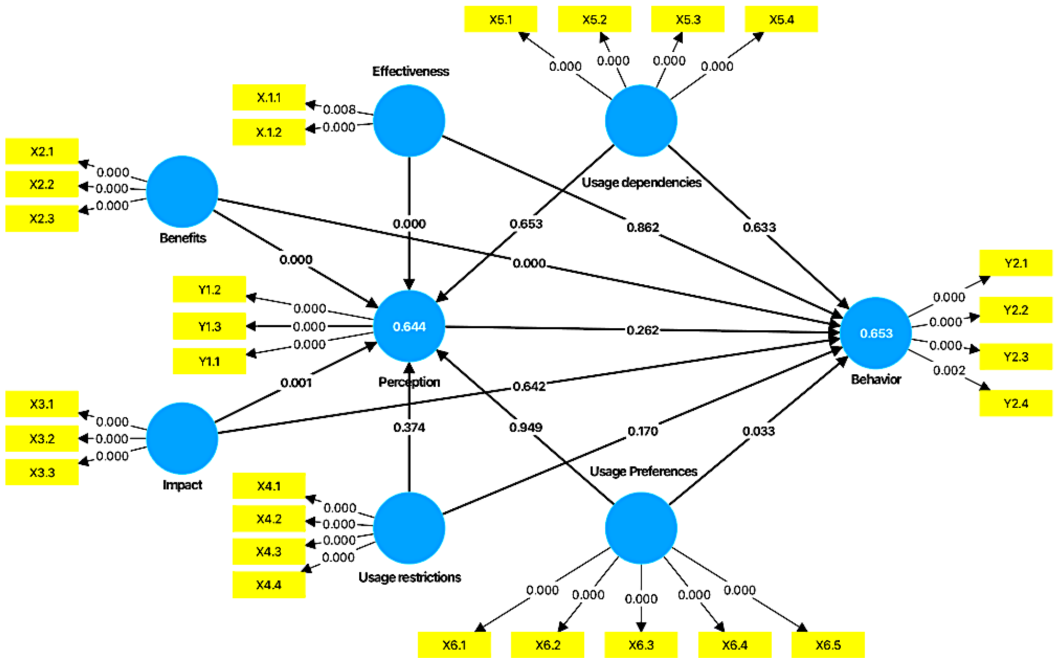

Figure 3. p-values.

Based on Figure 3, the relationship between the perceived benefits of AI usage and students' behavior in using AI for task completion shows highly significant results, with a p-value of .000. It indicates that the perceived benefits strongly influence behavior. Statistically, this relationship is highly significant, supporting the hypothesis that the greater the perceived benefits, the higher the tendency to use AI for academic tasks. Similarly, the relationship between benefits and students' perceptions of AI also shows highly significant results, with a p-value of .000. It indicates that the perceived benefits influence behavior and enhance students' perceptions of AI's potential and utility in completing tasks. Benefits are critical in shaping students' views and attitudes toward AI technology.

The relationship between the effectiveness of AI usage and students' behavior shows a p-value of .862, which exceeds the .05 significance threshold. This means that the relationship between effectiveness and behavior is not significant. This result indicates that although students find AI effective in assisting task completion, its influence on behavioral change is not strong enough to drive greater adoption in academic tasks. In contrast, the relationship between effectiveness and students' perceptions shows a highly significant p-value of .000. This suggests that effectiveness does not directly impact behavior. It significantly affects how students perceive AI technology. Students who perceive AI as more practical tend to have more positive perceptions of it, which may increase their likelihood of using it.

The relationship between the impact of AI usage and students' behavior shows a p-value of .642, more significant than .05, indicating that this relationship is insignificant. Although students recognize the impact of AI usage, the results indicate that this impact is not strong enough to alter their behavior in using AI for academic tasks. However, the relationship between impact and perception is significant, with a p-value of .001. This indicates that although the impact does not directly influence behavior, it significantly affects how students perceive AI technology. The findings suggest that students who experience positive impacts from AI are more likely to have favorable perceptions of the technology.

The relationship between students' perceptions of AI and their behavior shows a p-value of .262, which is greater than .05, indicating that the influence of perception on students' behavior is insignificant. Although positive perceptions of AI tend to foster positive attitudes, this relationship is not strong enough to directly influence behavior in the context of academic tasks.

The relationship between AI usage preferences and student behavior shows a significant p-value of .033. This result indicates that students' preferences for using AI significantly influence their behavior in integrating AI into the learning process. Students who favor using AI to support learning tend to be more active in utilizing it for academic tasks. In contrast, the relationship between AI usage preferences and students' perceptions has a p-value of .949, which exceeds .05, indicating that preferences do not significantly influence students' perceptions of AI. It suggests that even if students prefer AI, it cannot alter their perceptions of the technology.

The relationship between dependency on AI and student behavior shows a p-value of .633, more significant than .05, indicating that dependency on AI usage does not significantly influence student behavior. This means that although students may rely on AI, this dependency is not strong enough to change their behavior when using the technology. Similarly, the relationship between dependency on AI and students' perceptions shows a p-value of .653, exceeding .05, indicating that dependency on AI does not significantly influence students' perceptions of the technology.

The relationship between AI usage restrictions and student behavior shows a p-value of .170, more significant than .05. It indicates that while there are restrictions on AI usage, their influence on student behavior is not significant. It suggests that students can still find ways to utilize AI technology in their learning process, even with restrictions. Meanwhile, the relationship between AI usage restrictions and students' perceptions shows a p-value of .374, which is also greater than .05, indicating that such restrictions do not significantly impact students' perceptions of AI technology.

Prediction-Oriented Segmen (POS)

The Prediction-Oriented Segmentation (POS) analysis results, as presented in Table 3, provide further insights into how the relationships between variables in the model function across two distinct segments. Table 3 highlights the original path coefficients and how each path coefficient varies between Segment 1 and Segment 2. These differences illustrate whether the relationships between variables differ across segments and indicate how specific factors influence behavior or perception within different groups.

Table 3. Prediction-oriented segmentation.

	Original path coefficients	Segment1	Segment2
Benefits -> Behavior	.406	.510	.338
Benefits -> Perception	.403	.449	.493
Effectiveness -> Behavior	.018	.214	-.633
Effectiveness -> Perception	.303	.127	.522
Impact -> Behavior	.049	-.042	.341
Impact -> Perception	.327	.460	.138
Perception -> Behavior	.124	-.148	.779
Usage Preferences -> Behavior	.305	.297	.614
Usage Preferences -> Perception	-.007	-.042	-.136
Usage dependencies -> Behavior	.046	.120	.009
Usage dependencies -> Perception	-.050	.178	-.403
Usage restrictions -> Behavior	.115	.201	-.274
Usage restrictions -> Perception	-.077	-.139	.213

Based on the analysis results in Table 3, the relationship between benefits and behavior shows a higher path coefficient in Segment 1 (.510) than in Segment 2 (.338). This indicates that in Segment 1, the perceived benefits have a more significant influence on students' behavior in using AI than in Segment 2. Conversely, the relationship between benefits and perception is slightly stronger in Segment 2 (.493) compared to Segment 1 (.449), although the difference is not substantial.

Segment 1 shows a moderate influence between effectiveness and behavior with a coefficient of .214, while Segment 2 demonstrates a more negative relationship (-.633). This indicates that in Segment 1, the effectiveness of AI usage slightly influences students' behavior. However, in Segment 2, effectiveness has a significantly negative impact on behavior, suggesting that students in this segment may feel that although AI is effective, they are either hesitant to trust it or reluctant to use it in academic tasks. On the other hand, the relationship between effectiveness and perception is more substantial in Segment 2 (.522) than in Segment 1 (.127), indicating that the effectiveness of AI contributes more to shaping a positive view of the technology in Segment 2.

The relationship between impact and behavior shows significant differences between the two segments. In Segment 1, the impact has a small negative effect on behavior (-.042), whereas in Segment 2, the impact exhibits a more significant positive relationship (.341). This suggests that students in Segment 2 experience more positive effects from AI usage, encouraging them to use it more frequently for academic tasks. Meanwhile, the impact on perception is more significant in Segment 1 (.460) than in Segment 2 (.138), indicating that AI usage strengthens positive perceptions of the technology more in Segment 1.

The relationship between perception and behavior shows a stark contrast between the segments. In Segment 1, this relationship is negative (-.148) and insignificant, indicating that although students may have positive perceptions of AI, this is not enough to drive them to use AI for task completion. Conversely, in Segment 2, the relationship between perception and behavior is highly positive (.779), showing that students in this segment with positive views of AI are more likely to use it for academic tasks.

The relationship between AI usage preferences and behavior indicates a more substantial influence in Segment 2 (.614) than Segment 1 (.297). This suggests that students who prefer using AI for learning are more active in leveraging it, especially in Segment 2. Conversely, the relationship between preferences and perception is minimal and insignificant in both segments, with coefficients of -.042 in Segment 1 and -.136 in Segment 2, indicating that personal preferences do not significantly impact perceptions of AI usage.

The influence of dependency on behavior is small and positive in Segment 1 (.120) but negligible in Segment 2 (.009), indicating that although students in Segment 1 are more dependent on AI, this dependency is not strong enough to drive more active behavior. For the influence of dependency on perception, Segment 1 shows a positive effect (.178), while Segment 2 exhibits a negative effect (-.403), suggesting that students in Segment 2 who rely on AI tend to have negative views of the technology.

Segment 1 shows a positive effect (.201) of restrictions on behavior, meaning that students in this segment tend to use it more actively despite restrictions on AI usage. However, in Segment 2, restrictions have a negative impact on behavior (-.274), indicating that restrictions may hinder AI usage among students in this segment. For the relationship between restrictions and perception, Segment 2 shows a positive influence (.213), meaning that restrictions on AI usage can improve positive perceptions of the technology in this segment, although the relationship is insignificant in Segment 1 (-.139).

Principal Component Analysis (PCA)

The Principal Component Analysis (PCA) results presented in Table 4 provide insights into the distribution of variance within the data and how the variables in this study can be grouped into several principal components. PCA is a method used to reduce the dimensionality of complex data into a few principal components that explain the majority of the variance in the dataset.

Table 4. Principal component analysis.

	Eigenvalue	Variance proportion	Variance cumulative
Component 1	8.823	.315	.315
Component 2	4.443	.159	.474
Component 3	1.958	.070	.544
Component 4	1.267	.045	.589
Component 5	1.163	.042	.631
Component 6	1.094	.039	.670
Component 7	.963	.034	.704
Component 8	.861	.031	.735
Component 9	.775	.028	.762
Component 10	.713	.025	.788
Component 11	.594	.021	.809
Component 12	.575	.021	.830
Component 13	.523	.019	.848
Component 14	.485	.017	.866
Component 15	.447	.016	.882
Component 16	.442	.016	.897
Component 17	.413	.015	.912
Component 18	.361	.013	.925
Component 19	.319	.011	.936
Component 20	.309	.011	.947
Component 21	.280	.010	.957
Component 22	.247	.009	.966
Component 23	.231	.008	.975
Component 24	.191	.007	.981
Component 25	.166	.006	.987
Component 26	.148	.005	.993
Component 27	.109	.004	.996
Component 28	.099	.004	1.000

Principal Components

The PCA results indicate that Component 1 has the highest eigenvalue of 8.823, explaining 31.5% of the total variance in the data. This suggests that Component 1 is highly significant in representing the overall data patterns and is the most dominant component in this analysis. This component likely represents the primary factors or variables with the most significant influence on the dataset. Component 2 has an eigenvalue of 4.443 and explains 15.9% of the total variance, making it the second most influential component in the data. The total contribution of the first two components is 47.4% of the total variance, indicating that these two components alone sufficiently explain nearly half of the information in the dataset. Components 3 and 4 have eigenvalues of 1.958 and 1.267, respectively, contributing 7.0% and 4.5% to the total variance. Although their contributions are smaller than the first two components, they remain significant. The total contribution of the first four components reaches 58.9%, demonstrating that this combination of four principal components explains the majority of the patterns in the data.

Variance Distribution
Components 1 through 6 account for approximately 67.0% of the total variance, while the remaining components (7 through 28) contribute progressively smaller proportions. These smaller components have lower eigenvalues, such as Component 7 with an eigenvalue of .963 (3.4%) and Component 8 with an eigenvalue of .861 (3.1%). Subsequently, the contributions of individual components diminish incrementally, with the final component (Component 28) contributing only .004% of the total variance.

Implications of PCA Results
Several key conclusions can be drawn from the PCA results. Components 1 and 2 significantly contribute to the total variance, highlighting their importance in understanding the data structure. These components are typically used to reduce the dimensionality of high-dimensional data, facilitating more efficient analysis focusing on the most influential aspects. Meanwhile, the subsequent components, although contributing less, still carry additional helpful information for further analysis depending on the research context. However, given the decreasing contribution of each successive component, only a few principal components are usually considered for further analysis to reduce data complexity effectively.

DISCUSSION, CONCLUSION, and RECOMMENDATIONS

One of the key factors influencing students' use of AI technology is the perceived benefits. Perceived benefits, such as ease of accessing information, time efficiency, and improved task quality, are significant motivators for students to utilize AI. Students who experience clear and immediate advantages from AI usage tend to develop positive perceptions of the technology and are more likely to actively use it in completing academic tasks. This aligns with technology adoption theories, which state that perceptions of benefits strongly influence individuals' attitudes and intentions to adopt new technologies (Al-Debei et al., 2015).

Although many students consider AI usage effective in assisting with academic tasks, its influence on behavior appears to be more limited. While the effectiveness of AI in completing academic tasks is acknowledged, it is not always sufficient to profoundly transform students' work habits. Other factors, such as established learning routines, personal preferences for traditional methods, or limitations in accessing technology, often significantly impact the decision to use AI.

Although AI positively impacts students' perceptions, such as facilitating faster task completion or easier access to answers, this is not strong enough to significantly change their behavior in using the technology more intensively. The positive impact of AI tends to serve as a supplementary benefit rather than a primary driver of significant changes in how students complete tasks or interact with technology in an academic context.

Students' personal preferences regarding the use of technology, including AI, play a significant role in determining how frequently they use it. Students more inclined toward using technology in learning are typically more active in integrating AI into academic activities. These preferences reflect individual tendencies toward new technology, influencing decisions to adopt tools like AI for completing tasks (Cao et al., 2021; Mahmud et al., 2023).

However, dependence on AI, while providing convenience, can negatively impact students' perceptions of their abilities. Students who rely heavily on AI for academic tasks often feel that their understanding or knowledge of the studied material diminishes. Excessive dependence can reduce critical thinking skills or problem-solving abilities, which are crucial in an educational context. This over-reliance also indicates a tendency to depend more on technology than to develop personal capabilities (Lall, 1992; Firdaus et al., 2025).

Restrictions on AI usage can influence students' perceptions, with some students feeling that these limitations reduce the benefits they can derive from the technology. However, such restrictions can also positively impact students' behavior. Restrictions on AI usage may encourage students to be more creative and prudent in utilizing the technology while preventing excessive dependency on AI. These limitations can also serve as a form of control, helping students stay focused on academic tasks without over-relying on AI tools.

This study also highlights the importance of validity and reliability in measuring the factors influencing students' use of AI. Each construct tested, such as effectiveness, benefits, impact, restrictions, dependency, preferences, and perceptions, plays a critical role in shaping students' views of this technology. High construct validity and reliability ensure that these factors are measured accurately, clearly showing how students utilize AI in education.

The findings of this study offer valuable insights into how students use AI technology to complete academic tasks. The perceived benefits of AI usage emerge as a key factor driving students to adopt this technology, while dependency on AI and its usage restrictions demonstrate more complex impacts on students' perceptions and behaviors. When designing policies or educational programs involving AI technology, these findings underscore the importance of considering various factors, such as personal preferences, access restrictions, and the effects on students' critical thinking skills.

This research demonstrates that while the benefits of AI usage are crucial in encouraging students to use this technology, other factors such as habits, dependency, and personal preferences also play significant roles in determining how AI is integrated into students' academic lives. Therefore, educators and policymakers need to consider these factors to support more effective use of technology in learning contexts.

The primary factor driving students' utilization of AI is the perceived benefits, which significantly influence their perceptions and behaviors when using this technology. Students' perceptions of AI usage's benefits, effectiveness, and impact are critical in determining how this technology is employed in academic contexts. However, excessive dependence on AI and usage restrictions can affect perceptions and limit the optimization of its utilization. Therefore, it is essential to maintain a balance in AI usage to ensure students retain independent learning skills while maximizing the benefits of the technology.

The effectiveness and benefits of AI significantly impact students' perceptions, which in turn influence their behavior in completing academic tasks. Conversely, other factors such as impact, preferences, dependency, and usage restrictions exhibit more complex relationships and are not always significant in shaping student behavior. By strengthening positive perceptions of the benefits and effectiveness of AI and managing dependency wisely, educators and technology developers can promote the productive adoption of AI in education. This provides opportunities to design curricula that strategically integrate AI to enhance learning quality and support student skills development to address future challenges.

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Ethics and Conflict of Interest

This research was conducted with the permission obtained from the Ethics Committee of PT. Komunitas Peneliti Alinea, dated 01.11. 2024. Furthermore, all publication ethics were adhered to at every stage of the research. The authors declare that they have no conflict of interest.

Author Contribution

All authors contributed equally to the research.

Data availability

The data that support the findings of this study are available on request from the corresponding author.

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