

Analyzing the Use of Artificial Intelligence to Support Education and Scientific Writing among Students Using the UTAUT2 Model

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INFO ARTIKEL

History Article:

Submitted 08 30, 2026

Received 09 12, 2026

Published 09 18, 2026

ABSTRACT

The rapid advancement of artificial intelligence (AI) has created new opportunities to support learning and scientific writing among students. This study examines the factors influencing students' adoption of AI for educational and scientific writing purposes using the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model. A quantitative research design was employed, with data collected from 400 students using simple random sampling. A structured questionnaire measured seven UTAUT2 constructs: performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit. The results show that performance expectancy, effort expectancy, and facilitating conditions significantly influenced students' behavioral intention to use AI. Hedonic motivation and habit also emerged as substantial predictors, while price value had a moderate effect. Social influence demonstrated a relatively weaker effect. These findings confirm the relevance of UTAUT2 in explaining AI adoption among students and provide practical implications for educators and libraries in developing AI-supported resources, guidance, and services to enhance learning and scientific writing productivity.

Keywords: Artificial Intelligence; Students; Education; Scientific Writing; Technology Acceptance

How to Cite:

Krismiyanto, A., & Purnomo, G. W. (2026). Analyzing the Use of Artificial Intelligence to Support Education and Scientific Writing among Students Using the UTAUT2 Model. LANCAH: Jurnal Inovasi Dan Tren, 4(2), 490-517. <https://journal.lembagakita.com/ljit/article/view/8605>

INTRODUCTION

The use of artificial intelligence (AI) across various sectors has increased rapidly in recent decades, particularly in education, libraries, research, and scientific writing. AI technologies provide a broad range of tools that can enhance learning effectiveness, facilitate information retrieval, support research activities, and assist users in preparing scientific writing. From automated recognition and information retrieval to complex data analysis and content generation, AI has considerable potential to transform how educational institutions and libraries support students' academic activities. In educational and research environments, AI can assist students in accessing and processing information, developing learning materials, analyzing academic data, and supporting the preparation of scientific documents. However, the availability of AI technologies and their technical capabilities do not automatically lead to effective adoption. Students' perceptions of usefulness, ease of use, social environment, available resources, enjoyment, perceived value, and previous usage patterns may determine whether they are willing to adopt and continue using AI. Understanding these factors is therefore essential for ensuring that AI technologies are implemented effectively and responsibly in educational and academic contexts.

Artificial intelligence is generally associated with the development of computer systems capable of performing tasks that traditionally require human intelligence. Devianto and Dwiasnati (2020) describe artificial intelligence as a field concerned with enabling computers to perform tasks that are typically associated with human capabilities. This perspective emphasizes the capacity of AI to replicate, support, or augment human abilities across different contexts, including education, research, and scientific writing. In education, Raup et al. (2022) emphasize that AI technologies, including artificial neural networks and genetic algorithms, can be applied to address a wide range of problems, from robotics to financial analysis. Baihaqi et al. (2021) further highlight the importance of introducing AI to students to prepare them for the changing demands of the workplace in the era of Industry 4.0. Similarly, Dewi (2020) argues that AI implementation in libraries can encourage libraries to become more technologically literate and responsive to emerging technologies. These developments indicate that AI is increasingly relevant to students' academic activities because it can facilitate information access, improve learning processes, support research, and assist scientific writing. Nevertheless, the increasing availability of AI applications raises an important question concerning not only what AI can do, but also why and under what conditions students are willing to use it.

The issue of technology acceptance is particularly important because the successful implementation of AI depends substantially on users' behavioral responses. One of the most widely used theoretical frameworks for examining technology acceptance is the Unified Theory of Acceptance and Use of Technology (UTAUT), which was subsequently extended into UTAUT2. Venkatesh *et al.* (2012) developed UTAUT2 by integrating and extending several technology acceptance theories. The framework incorporates performance expectancy, effort expectancy, social influence, and facilitating conditions, while additionally introducing hedonic motivation, price value, and habit. These constructs provide a comprehensive framework for explaining behavioral intention and technology use because they capture functional, cognitive, social, contextual, motivational, economic, and behavioral dimensions of technology adoption. In the context of AI, the application of UTAUT2 is particularly relevant because students may evaluate AI not only according to whether it improves their academic performance, but also according to how easy it is to use, whether its use is socially encouraged, whether adequate technological resources are

available, whether using it is enjoyable, whether its benefits justify its costs, and whether AI use has become a habitual part of their academic activities.

Previous studies have demonstrated the potential of AI to support information retrieval, service personalization, academic data analysis, scientific writing, and library services. Huang et al. (2019), for example, demonstrated the potential of AI to enhance information retrieval. Their study illustrates the functional value of AI in improving access to and processing of information, but its primary emphasis was on the technological dimension rather than on the behavioral acceptance of AI by users. Johnson et al. (2020) and Smith and Thompson (2019) similarly identified the potential benefits of AI in service personalization and academic data analysis. However, these studies did not comprehensively examine the influence of performance expectancy, effort expectancy, hedonic motivation, and habit as interconnected determinants of technology acceptance. Thus, although the functional benefits of AI have been increasingly recognized, the behavioral mechanisms explaining users' willingness to adopt AI remain insufficiently explored.

Research focusing on AI in scientific writing and library services has likewise established the relevance of AI applications in academic environments. Chen et al. (2020) and Lee and Kim (2021) highlighted the potential of AI in supporting scientific writing and developing AI-based tools for libraries. These studies demonstrate that AI can be positioned as an important academic support technology, particularly for information access and knowledge production. However, they did not comprehensively examine facilitating conditions, social influence, and price value as factors that may shape users' acceptance of AI. These omissions are important because students' adoption of AI may depend not only on perceived usefulness but also on whether they receive social encouragement, have adequate technological and institutional support, and perceive the benefits of AI as proportionate to the resources or costs required for its use.

Other studies have approached AI integration and technology adoption from broader behavioral and organizational perspectives. Wang and Li (2018) emphasized the importance of examining technology adoption through a systematic approach, but their study did not provide a comprehensive quantitative assessment of the factors underlying AI acceptance. Brown et al. (2021) and Garcia and Rodriguez (2019) also contributed to understanding AI use and technology adoption, but did not examine the simultaneous influence of intrinsic motivation, effort expectancy, and performance expectancy. Similarly, Martinez et al. (2020) and Singh and Patel (2021) demonstrated the potential success of AI integration in library services, but did not sufficiently identify the barriers and behavioral factors affecting users' adoption of these technologies. Taken together, these studies indicate that AI adoption has been investigated from different perspectives, but the determinants of students' behavioral intention to use AI remain fragmented across technological, functional, motivational, and contextual dimensions.

A systematic comparison of these previous studies reveals an important distinction between research on the capabilities of AI and research on the acceptance of AI. Studies such as Huang et al. (2019) primarily demonstrate what AI can contribute to information retrieval, whereas Johnson et al. (2020) and Smith and Thompson (2019) emphasize its potential for personalization and academic data analysis. Chen et al. (2020) and Lee and Kim (2021) demonstrate the relevance of AI to scientific writing and library services. Meanwhile, Wang and Li (2018), Brown et al. (2021), Garcia and Rodriguez (2019), Martinez et al. (2020), and Singh and Patel (2021) provide further perspectives on technology adoption and AI integration. Although these studies collectively establish the growing importance of AI, they differ in terms of their

research focus and do not provide an integrated explanation of the multiple factors that may influence students' acceptance of AI. In particular, the existing studies have not sufficiently brought together functional expectations, perceived effort, social influence, facilitating conditions, hedonic motivation, perceived value, and habitual behavior within a single empirical model focused on students' use of AI for educational and scientific writing.

The comparison also demonstrates that the existing literature tends to address AI adoption in separate domains. Some studies concentrate on technological performance and information retrieval, while others emphasize AI-enabled services, academic data analysis, scientific writing, or library applications. Consequently, the literature provides substantial evidence regarding the potential usefulness of AI but comparatively less integrated evidence regarding the behavioral determinants of students' willingness to use AI across educational and scientific writing activities. Furthermore, several previous studies have relied primarily on technical or qualitative approaches, thereby leaving a need for comprehensive quantitative examination of technology acceptance. This fragmentation constitutes an important research gap because students' adoption of AI is unlikely to be explained by a single perceived benefit. Rather, adoption may emerge from the interaction of cognitive evaluations, social pressures, contextual support, motivational responses, perceived economic value, and established usage habits.

Based on this systematic comparison, the present study addresses three interrelated gaps in the existing literature. First, previous research has established the functional and technical potential of AI but has paid comparatively limited attention to the behavioral mechanisms underlying students' acceptance and use of AI. Second, studies examining AI in education, libraries, information retrieval, and scientific writing have generally focused on specific applications rather than simultaneously examining multiple technology-acceptance determinants. Third, although UTAUT2 provides a comprehensive framework for understanding technology adoption, its seven relevant constructs have not been sufficiently examined together in the specific context of students' use of AI for educational and scientific writing. Therefore, the contribution of the present study lies in moving beyond an assessment of whether AI is useful and toward an empirical examination of why students intend to adopt AI and which factors most strongly shape that intention.

To address these gaps, this study applies the UTAUT2 framework by examining the effects of performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit on students' behavioral intention to use AI. Performance expectancy represents students' perceptions regarding the extent to which AI can improve their educational and scientific writing activities, while effort expectancy concerns the perceived ease associated with using AI. Social influence captures the extent to which important individuals or groups encourage AI use, whereas facilitating conditions represent the availability of resources and support required for AI utilization. Hedonic motivation reflects the degree of enjoyment or satisfaction derived from using AI, price value represents students' evaluation of the benefits obtained relative to the costs or resources involved, and habit reflects the extent to which AI use becomes an established pattern of behavior. Examining these constructs simultaneously enables the study to provide a more comprehensive explanation of the determinants of AI acceptance than approaches that focus on individual technological benefits.

The research question addressed in this study is: What are the key factors influencing students' acceptance and use of AI to support education and scientific writing? Based on the UTAUT2 framework, the study proposes that performance expectancy, effort expectancy, social influence, facilitating conditions,

hedonic motivation, price value, and habit significantly influence students' behavioral intention to use AI. By empirically testing these relationships within a single quantitative model, the study seeks to identify which factors are most important in explaining students' willingness to adopt AI for academic purposes. This approach also enables the study to distinguish between functional determinants of adoption and broader social, contextual, motivational, economic, and behavioral determinants.

Accordingly, this study aims to provide a comprehensive quantitative analysis of the factors influencing students' acceptance and use of AI for educational and scientific writing. The study employs a quantitative survey design using simple random sampling to obtain data from 400 students. The relationships among the proposed variables are analyzed using structural equation modeling (SEM) to identify the key factors influencing students' behavioral intention to adopt AI. By applying UTAUT2 to the emerging context of AI-supported education and scientific writing, this study extends existing technology-acceptance research from conventional digital technologies toward AI-based academic tools. More specifically, the study contributes empirical evidence concerning the relative importance of the seven UTAUT2 constructs within a context in which AI is increasingly used for information access, learning, research, and scientific writing.

Ultimately, the study is expected to generate both theoretical and practical contributions. Theoretically, it extends the application of UTAUT2 by examining the simultaneous influence of performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit in explaining students' behavioral intention to use AI for educational and scientific writing. Empirically, it provides quantitative evidence that complements previous technical, application-oriented, and qualitative studies of AI adoption. Practically, the findings can assist educational institutions and libraries in designing and implementing AI-supported technologies that are aligned with students' needs and preferences. By identifying the factors that most strongly influence AI adoption, the findings can inform the development of AI literacy programs, user guidance, academic support, and AI-enabled library and educational services. Thus, this study is expected to contribute not only to the theoretical development of technology acceptance research but also to the practical and responsible integration of AI into education, research, libraries, and scientific writing.

METHODS OF RESEARCH

Research Methods

This study employed a quantitative research approach to examine the factors influencing students' acceptance and use of artificial intelligence (AI) for educational and scientific writing purposes in Malang City, Indonesia. The research was conducted among students from several higher education institutions in Malang City to obtain a broader representation of students with diverse academic backgrounds and experiences in using AI. The survey instrument was developed based on the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) proposed by Venkatesh *et al.* (2012). The constructs examined in this study included performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, habit, behavioral intention, and actual AI use.

Research Population

The population of this study comprised students enrolled at several higher education institutions in Malang City, Indonesia. Malang is one of Indonesia's major educational centers, with a diverse student population from various academic disciplines and higher education institutions. The target population included students who had experience using or were familiar with AI-based technologies for educational activities, information seeking, research, or scientific writing.

The selection of students from several higher education institutions was intended to provide a broader empirical context for examining AI acceptance beyond a single institutional setting. This approach also allows the study to capture variations in students' perceptions, experiences, and patterns of AI use across different educational environments.

Research Sample

The sample was selected using a probability sampling approach with a simple random sampling technique. Students from several higher education institutions in Malang City who met the study criteria were eligible to participate. Simple random sampling was employed to provide eligible members of the target population with an equal probability of being selected as respondents, thereby reducing selection bias and improving the representativeness of the sample.

For structural equation modeling (SEM), sample size should be considered in relation to the number of indicators included in the research model. Kline (2015) emphasizes the importance of an adequate sample size for obtaining stable and reliable parameter estimates in SEM. A commonly applied rule of thumb suggests obtaining between five and ten observations for each questionnaire item, although appropriate sample size may also depend on model complexity, data quality, and the estimation approach.

The questionnaire used in this study consisted of 36 measurement items. Based on the five-to-ten-times rule, the minimum and maximum sample sizes were calculated as follows: Minimum: $36 \text{ items} \times 5 = 180$ respondents; and Maximum: $36 \text{ items} \times 10 = 360$ respondents.

Based on these considerations, the study targeted a minimum of 180 student respondents from several higher education institutions in Malang City. This sample size was considered adequate for the planned SEM analysis and sufficient to provide an empirical basis for examining the proposed relationships within the UTAUT2 framework.

Data Collection Technique

Data were collected using a structured questionnaire distributed to students from several higher education institutions in Malang City. The questionnaire consisted of two main sections: respondent demographic characteristics and measurement items representing the constructs in the UTAUT2 model. The demographic section collected information such as age, gender, academic level, field of study, higher education institution, and experience with AI. The second section measured students' perceptions and behavioral responses regarding AI use for educational and scientific writing purposes. Each measurement item was assessed using a five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree.

Data Collection Procedure

The questionnaire was distributed online to facilitate access to students from different higher education institutions across Malang City. The survey link was disseminated through social media, student

networks, academic communities, and other appropriate online communication channels. Respondents were informed about the purpose of the study and were asked to participate voluntarily. Data collection was conducted over a one-month period to obtain a sufficient number of valid responses for subsequent analysis.

To ensure that the respondents matched the research objectives, screening questions were included at the beginning of the questionnaire. Only students who were currently enrolled at a higher education institution in Malang City and had experience using or were familiar with AI-based technologies were included in the analysis.

Data Analysis Technique

The collected data were analyzed using SmartPLS through partial least squares structural equation modeling (PLS-SEM). PLS-SEM was selected because it enables the simultaneous examination of relationships among multiple latent constructs and is appropriate for testing theoretically derived models such as UTAUT2. The analysis began with data screening to assess the completeness of responses, missing values, duplicate responses, and potential response errors. Responses that did not meet the inclusion criteria or contained substantial missing information were excluded from further analysis. Subsequently, the measurement model was assessed to evaluate the validity and reliability of the constructs. Convergent validity was examined using outer loadings and average variance extracted (AVE), while discriminant validity was assessed using the Fornell-Larcker criterion and the heterotrait-monotrait (HTMT) ratio. Internal consistency reliability was evaluated using Cronbach's alpha and composite reliability. The structural model was then assessed to examine the hypothesized relationships among the UTAUT2 constructs, behavioral intention, and actual AI use. Path coefficients, significance levels, coefficient of determination (R^2), and other relevant PLS-SEM criteria were examined to evaluate the explanatory and predictive capacity of the model. Finally, hypothesis testing was conducted using bootstrapping procedures in SmartPLS, with the significance and direction of the path coefficients used to determine whether the proposed relationships were statistically supported.

Research Model and Hypotheses

The research model is based on the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) proposed by Venkatesh *et al.* (2012). The model incorporates seven primary constructs that explain behavioral intention and technology use: performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit. In this study, these constructs are adapted to the context of students' use of artificial intelligence (AI) to support education and scientific writing. The model further incorporates behavioral intention as a mediator between the UTAUT2 constructs and actual AI use, while facilitating conditions and habit are also hypothesized to have direct effects on actual AI use.

Performance expectancy (PE) refers to the extent to which students believe that using AI will improve their effectiveness and productivity in learning, information searching, research, and scientific writing. Students who perceive AI as beneficial for improving the quality and efficiency of their academic activities are expected to develop a stronger intention to use the technology. Therefore, the first hypothesis is proposed: **H1:** Performance expectancy has a positive effect on students' behavioral intention to use AI.

Effort expectancy (EE) refers to the perceived ease associated with learning and using AI. When students perceive AI as easy to understand, learn, and operate, they are more likely to develop a positive

intention to use the technology. Ease of use can reduce the cognitive and practical effort required to integrate AI into learning and scientific writing activities. Accordingly, the second hypothesis is proposed: **H2**: Effort expectancy has a positive effect on students' behavioral intention to use AI.

Social influence (SI) refers to the extent to which students perceive that important people in their social and academic environment, such as friends, lecturers, classmates, or academic peers, encourage or support their use of AI. Positive perceptions and recommendations from significant others may influence students' attitudes and intentions toward adopting AI. Therefore, the third hypothesis is proposed: **H3**: Social influence has a positive effect on students' behavioral intention to use AI.

Facilitating conditions (FC) refer to the availability of technological infrastructure, resources, knowledge, and technical support required for students to use AI effectively. Students are more likely to develop an intention to use AI when they have adequate access to devices, internet connectivity, relevant knowledge, and supporting resources. Thus, the fourth hypothesis is proposed: **H4**: Facilitating conditions have a positive effect on students' behavioral intention to use AI.

Hedonic motivation (HM) refers to the enjoyment, pleasure, or satisfaction that students derive from using AI. AI applications that are perceived as engaging, interesting, and enjoyable may encourage students to develop stronger intentions to use them in their academic activities. Therefore, the fifth hypothesis is proposed: **H5**: Hedonic motivation has a positive effect on students' behavioral intention to use AI.

Price value (PV) refers to students' assessment of the benefits obtained from using AI relative to the monetary or other costs associated with accessing and using the technology. When students perceive that the benefits of AI outweigh the costs involved, they are expected to have a stronger intention to adopt the technology. Accordingly, the sixth hypothesis is proposed: **H6**: Price value has a positive effect on students' behavioral intention to use AI.

Habit (HB) refers to the extent to which students tend to use AI automatically as a result of prior learning and repeated experience with the technology. Repeated use may make AI adoption increasingly automatic and reduce the need for conscious deliberation when deciding whether to use the technology. Habit is therefore expected to influence both students' behavioral intention and their actual use of AI. The seventh hypothesis is proposed: **H7**: Habit has a positive effect on students' behavioral intention to use AI. In addition, because habitual behavior may directly translate into repeated technology use, the ninth hypothesis is proposed: **H9**: Habit has a positive effect on students' actual use of AI.

Facilitating conditions (FC) may also have a direct effect on actual AI use. Although adequate infrastructure and technical support can strengthen students' behavioral intention, these conditions may also directly enable students to translate their intentions into actual technology use. Students with sufficient access to technological resources and appropriate support are expected to be more capable of using AI in their educational and scientific writing activities. Therefore, the eighth hypothesis is proposed: **H8**: Facilitating conditions have a positive effect on students' actual use of AI.

Behavioral intention (BI) refers to the extent to which students intend or are willing to use AI to support their educational and scientific writing activities. Behavioral intention represents students' motivational readiness to engage with AI and is expected to be a key predictor of actual technology use. Students with stronger intentions to use AI are more likely to translate those intentions into actual usage behavior. Therefore, the tenth hypothesis is proposed: **H10**: Behavioral intention has a positive effect on students' actual use of AI.

The proposed research model provides a comprehensive framework for examining the factors influencing students' acceptance and use of AI across several higher education contexts in Malang City. By examining the relationships among performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, habit, behavioral intention, and actual AI use, the study seeks to identify the factors that most strongly influence students' adoption of AI for educational and scientific writing purposes. The findings are expected to provide practical insights for higher education institutions, educators, and libraries in developing AI literacy programs, academic support, and AI-enabled services that are responsive to students' needs.

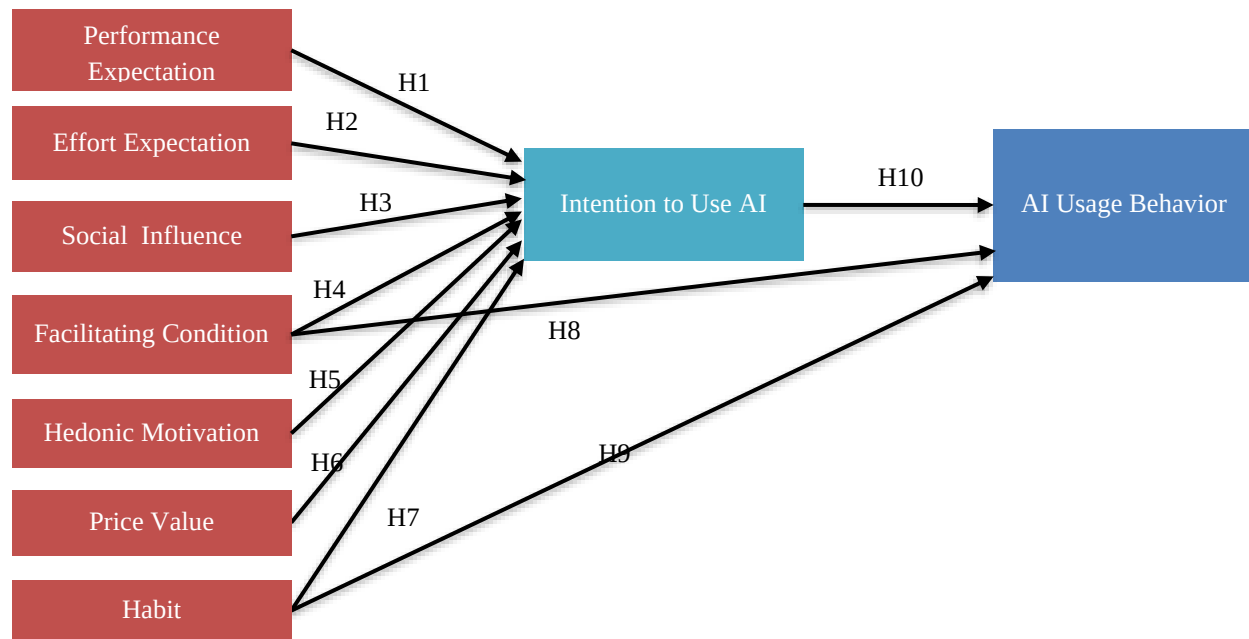


Figure 1. Research Model
Source: Adapted from Venkatesh et al. (2003, 2012)

RESULT AND DISCUSSION

Results

Respondent Characteristics

The study involved 200 student respondents who had experience using artificial intelligence (AI) for academic activities, including learning and scientific writing. The respondents provided self-reported assessments of performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, habit, behavioral intention to use AI, and actual AI use. The characteristics of the respondents are presented in Table 1.

The respondent profile was examined to ensure that the sample was consistent with the target population of the study. The descriptive characteristics included relevant demographic and academic information, such as gender, age, study program or academic field, semester or level of study, and experience or frequency of AI use, where applicable. These characteristics provide contextual information for interpreting the subsequent structural model results.

Before conducting the PLS-SEM analysis, the collected data were screened to ensure that the responses were suitable for further analysis. The analysis considered the completeness of responses and the consistency of the measurement data. Responses that did not meet the predetermined data-quality criteria were excluded prior to the final estimation. The final dataset consisted of 200 valid respondents and was subsequently analyzed using SmartPLS 3.9.

Measurement Model Assessment

The measurement model was assessed using convergent validity, internal consistency reliability, and discriminant validity. The initial assessment identified several indicators with outer loading values below the minimum threshold of 0.50, namely EE2 (0.311), H1 (0.176), H2 (0.036), and BI4 (0.246). Because these indicators did not satisfy the minimum loading criterion, they were removed from the measurement model. The model was then re-estimated to determine whether the remaining indicators satisfied the required measurement criteria.

Following the removal of the low-loading indicators, the second-stage assessment demonstrated improved measurement performance. All remaining indicators met the required validity criteria. Convergent validity was assessed using outer loadings and average variance extracted (AVE), while internal consistency reliability was evaluated using composite reliability. Discriminant validity was subsequently examined by comparing the loading of each indicator on its associated construct with its loadings on other constructs.

As presented in Table 1, all constructs obtained AVE values above 0.50, ranging from 0.524 to 0.828. These results indicate that the constructs achieved satisfactory convergent validity. Composite reliability values ranged from 0.797 to 0.946, exceeding the commonly accepted threshold and indicating satisfactory internal consistency reliability.

The lowest AVE was observed for hedonic motivation (0.524), while the highest was obtained for habit (0.828). Although hedonic motivation had the lowest AVE, the value remained above the minimum criterion, indicating that the construct retained adequate convergent validity. Facilitating conditions demonstrated the highest AVE (0.815) and composite reliability (0.946), indicating particularly strong measurement consistency.

Overall, the measurement model demonstrated satisfactory convergent validity and internal consistency reliability. The results provided an adequate measurement basis for subsequent assessment of the structural model. However, measurement validity and structural collinearity were considered separately to ensure that satisfactory measurement properties did not obscure potential problems among the predictor constructs.

Collinearity and Common Method Bias Assessment

Because the data were collected through self-reported questionnaires from a single group of respondents, the possibility of common method bias (CMB) was considered. Common method bias refers to systematic variance that may arise from the measurement method rather than from the constructs being measured. Such bias can potentially inflate or distort the observed relationships among variables, particularly when predictor and criterion variables are collected from the same respondents using the same measurement procedure (Podsakoff et al., 2003).

To address this concern, the study considered the full-collinearity assessment approach proposed for PLS-SEM by Kock (2015). This approach uses variance inflation factor (VIF) values to assess whether excessive collinearity may indicate the presence of common method bias. In addition to the CMB assessment, structural-model collinearity was examined because excessive collinearity among predictor constructs can distort path coefficients and produce unstable or unexpected coefficient signs.

The collinearity assessment indicated that several predictor constructs in the behavioral intention equation had relatively high VIF values. In particular, performance expectancy had a VIF of 9.928, followed by habit (6.949), price value (5.477), facilitating conditions (4.654), hedonic motivation (4.057), social influence (3.685), and effort expectancy (3.675). These values indicate that multicollinearity among the predictors of behavioral intention requires careful consideration when interpreting the structural path coefficients.

The presence of high structural VIF values is particularly relevant to the estimated coefficient for performance expectancy. The path coefficient of performance expectancy on behavioral intention was $\beta = 1.235$, which exceeds the conventional range generally expected for a standardized path coefficient. Therefore, the magnitude of this coefficient should not be interpreted as a conventional standardized effect size without considering the potential influence of multicollinearity. The high VIF value for performance expectancy provides a plausible methodological explanation for the unusually large coefficient.

Importantly, structural multicollinearity and common method bias are conceptually related but should not be treated as identical. Structural VIF values primarily assess collinearity among predictors in the structural model, whereas the full-collinearity procedure is used to evaluate potential common method bias. Therefore, the structural VIF results are interpreted as evidence of a collinearity concern rather than, by themselves, as proof of the presence or absence of common method bias.

Given these findings, the results of the hypothesis testing are interpreted with caution. Statistical significance indicates that a relationship is supported under the estimated model, but the magnitude and substantive meaning of coefficients should be considered alongside the collinearity diagnostics. This approach is particularly important for performance expectancy, habit, and other constructs that exhibit relatively high VIF values.

Algorithm Test Analysis

To analyze the use of artificial intelligence (AI) in supporting education and scientific writing among students, the UTAUT2 model was tested using SmartPLS. The objective of this analysis was to identify the key factors influencing students' acceptance and use of AI for educational and scientific writing purposes.

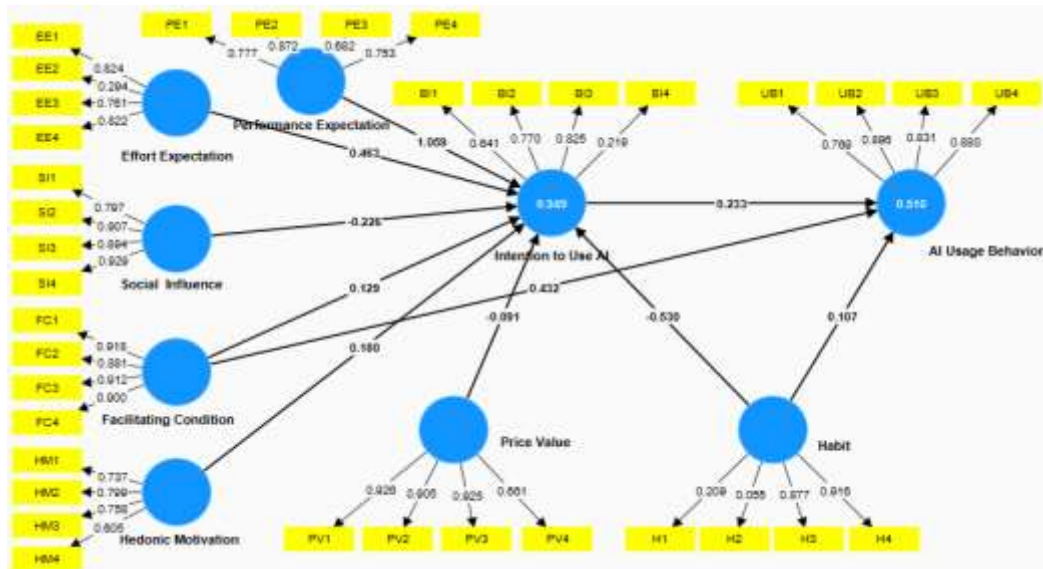


Figure 2. Results of the First Model Assessment

Source: SmartPLS 3.9 analysis, 2026

Based on the first-stage assessment presented in Figure 2, several indicators had outer loading values below the minimum threshold of 0.50. These indicators were EE2 (0.311), H1 (0.176), H2 (0.036), and BI4 (0.246). Because these indicators did not meet the minimum loading criterion of 0.50, they were removed from the measurement model. The model was subsequently re-estimated to ensure that all remaining indicators met the required validity and reliability criteria. The removal of indicators with low outer loadings was intended to improve the measurement accuracy and reliability of the model and, consequently, strengthen the validity of the subsequent analysis. A second-stage assessment was therefore conducted to confirm that all remaining indicators satisfied the required measurement criteria.

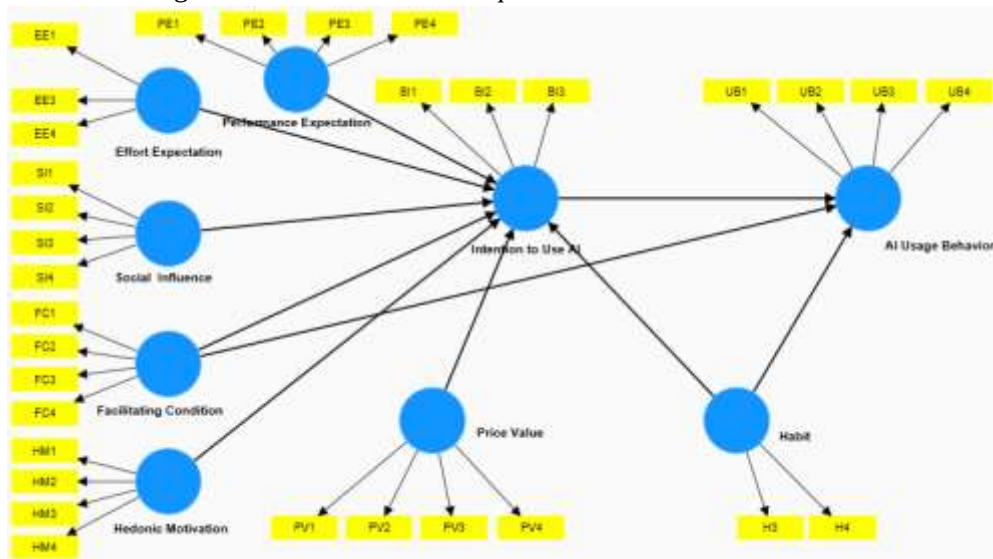


Figure 3. Results of the Second Model Assessment

Source: SmartPLS 3.9 analysis, 2026

Following the second-stage assessment presented in Figure 3, all remaining indicators met the required validity criteria. According to Wiyono (2011), outer loading values ranging from 0.50 to 0.60 can be considered acceptable for assessing convergent validity. After establishing convergent validity, discriminant validity was assessed using cross-loadings. An indicator was considered to demonstrate adequate discriminant validity when its loading on the intended construct was higher than its loadings on other constructs. After the indicators satisfied these criteria, the analysis proceeded to the evaluation of the measurement and structural models, as presented in Table 1.

Table 1. Results of the PLS Algorithm Assessment

Construct	AVE	Composite Reliability	R Square (R ²)	Assessment
Performance Expectancy	0.606	0.859		Reliable
Effort Expectancy	0.660	0.853		Reliable
Social Influence	0.786	0.936		Reliable
Facilitating Conditions	0.815	0.946		Reliable
Hedonic Motivation	0.524	0.813		Reliable
Price Value	0.743	0.919		Reliable
Habit	0.828	0.906		Reliable
Behavioral Intention to Use AI	0.571	0.797	0.959	Reliable
Actual AI Use	0.717	0.910	0.500	Reliable

Source: SmartPLS 3.9 analysis, 2026

Table 1 presents the results of the PLS algorithm assessment using SmartPLS 3.9. The constructs were evaluated based on average variance extracted (AVE), composite reliability, and coefficient of determination (R²). All constructs demonstrated AVE values above 0.50, indicating adequate convergent validity. In addition, all composite reliability values exceeded the commonly accepted threshold, indicating satisfactory internal consistency reliability.

Performance expectancy had an AVE of 0.606 and a composite reliability of 0.859, indicating that the indicators measuring this construct demonstrated adequate convergent validity and internal consistency. This result suggests that students' perceptions regarding the ability of AI to improve their academic performance and productivity were measured consistently. Effort expectancy recorded an AVE of 0.660 and composite reliability of 0.853, indicating satisfactory validity and reliability. This finding suggests that students' perceptions of the ease of learning and using AI were consistently represented by the measurement items.

Social influence had an AVE of 0.786 and composite reliability of 0.936, indicating a high level of convergent validity and internal consistency. Facilitating conditions recorded the highest AVE (0.815) and composite reliability (0.946) among the constructs, demonstrating particularly strong measurement quality. This result indicates that the availability of technological resources, infrastructure, knowledge, and technical support was measured consistently. Hedonic motivation had an AVE of 0.524 and composite reliability of 0.813, indicating acceptable convergent validity and reliability despite having the lowest AVE among the constructs. Price value demonstrated an AVE of 0.743 and composite reliability of 0.919, indicating that students' perceptions of the benefits of AI relative to its associated costs were measured reliably. Habit had an AVE of 0.828 and composite reliability of 0.906, demonstrating strong convergent validity and internal consistency.

Behavioral intention to use AI had an AVE of 0.571 and composite reliability of 0.797, with an R² value of 0.959. This R² value indicates that performance expectancy, effort expectancy, social influence,

facilitating conditions, hedonic motivation, price value, and habit collectively explained 95.9% of the variance in students' behavioral intention to use AI. This represents a very high level of explanatory power and indicates that the proposed UTAUT2 constructs collectively account for a substantial proportion of students' behavioral intention.

Actual AI use had an AVE of 0.717 and composite reliability of 0.910, with an R^2 value of 0.500. This indicates that the predictors included in the structural model explained 50.0% of the variance in actual AI use. Although this represents a moderate level of explanatory power, it also suggests that other factors not included in the current model may contribute to students' actual use of AI. Nevertheless, the model provides a meaningful basis for examining the determinants of AI use for educational and scientific writing.

Overall, the measurement model demonstrated satisfactory validity and reliability across all constructs. The high R^2 value for behavioral intention indicates that the UTAUT2 constructs have strong explanatory power in predicting students' intention to use AI, while the R^2 value for actual AI use indicates moderate explanatory power. These findings provide an adequate foundation for further assessment of the structural model and hypothesis testing.

Predictive Relevance

The predictive relevance of the structural model was assessed using the Q^2 value. In PLS-SEM, a Q^2 value greater than zero indicates that the model has predictive relevance for the endogenous construct being assessed. The analysis produced a Q^2 value of 0.445, which is greater than zero. This result indicates that the model possesses predictive relevance for the endogenous constructs included in the analysis.

The positive Q^2 value provides additional evidence that the structural model contains information that contributes to predicting the observed values of the endogenous constructs. However, predictive relevance should be interpreted separately from explanatory power. The R^2 values describe the proportion of variance explained by the predictors, whereas Q^2 evaluates predictive relevance. Therefore, the Q^2 result complements rather than replaces the assessment of R^2 and the structural path coefficients.

Hypothesis Testing

The structural model was evaluated using the bootstrapping procedure in SmartPLS 3.9 to assess the direction and statistical significance of the hypothesized relationships. Table 2 reports the original sample (O), sample mean (M), standard deviation (STDEV), t-statistics, and p-values for each structural path. The results indicate that several determinants significantly influenced students' behavioral intention to use AI, whereas some relationships were statistically non-significant.

Table 2. Bootstrapping Results

Structural Path	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T-Statistics (O/STDEV)	P-Values
Performance Expectancy → Behavioral Intention to Use AI	1.235	1.229	0.096	12.856	0.000
Effort Expectancy → Behavioral Intention to Use AI	0.448	0.446	0.047	9.575	0.000
Social Influence → Behavioral Intention to Use AI	-0.246	-0.241	0.039	6.252	0.000
Facilitating Conditions → Behavioral Intention to Use AI	0.082	0.081	0.060	1.380	0.168

Structural Path	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T-Statistics (O/STDEV)	P-Values
Hedonic Motivation → Behavioral Intention to Use AI	0.144	0.136	0.048	2.999	0.003
Price Value → Behavioral Intention to Use AI	-0.067	-0.055	0.066	1.009	0.313
Habit → Behavioral Intention to Use AI	-0.639	-0.638	0.081	7.906	0.000
Facilitating Conditions → Actual AI Use	0.448	0.445	0.129	3.478	0.001
Habit → Actual AI Use	0.130	0.130	0.131	0.993	0.321
Behavioral Intention to Use AI → Actual AI Use	0.190	0.193	0.163	1.166	0.244

Source: SmartPLS 3.9 analysis, 2026

Table 2 shows that performance expectancy had a positive and statistically significant relationship with behavioral intention to use AI ($\beta = 1.235$, $t = 12.856$, $p < 0.001$). This result suggests that students who perceive AI as useful for improving academic performance and productivity tend to demonstrate stronger intentions to use AI. The finding is consistent with the Technology Acceptance Model and UTAUT, which identify perceived usefulness or performance expectancy as an important determinant of technology adoption (Davis, 1989; Venkatesh et al., 2003). It is also compatible with the task-technology fit perspective, which emphasizes that technology is more likely to be accepted when users perceive that it enhances the performance of relevant tasks (Goodhue & Thompson, 1995).

However, the estimated path coefficient of 1.235 requires cautious interpretation. In a standardized PLS-SEM structural model, path coefficients are generally expected to fall within the interval from -1 to $+1$. Therefore, a coefficient exceeding 1 may indicate potential estimation or model-specification issues, particularly substantial collinearity among predictor constructs. Accordingly, the magnitude of $\beta = 1.235$ should not be interpreted as a conventional standardized effect size without first examining the model diagnostics. In particular, the variance inflation factor (VIF) for the predictor constructs should be inspected to determine whether multicollinearity contributes to the unusually high coefficient. The measurement model, construct correlations, discriminant validity, and structural-model specification should likewise be reviewed before drawing substantive conclusions from the magnitude of this coefficient. Nevertheless, the very low p-value and high t-statistic indicate that the estimated relationship is statistically significant in the model as specified.

The effort expectancy construct also demonstrated a positive and statistically significant effect on behavioral intention to use AI ($\beta = 0.448$, $t = 9.575$, $p < 0.001$). This finding indicates that students are more likely to intend to use AI when they perceive the technology as easy to learn, understand, and operate. The result is consistent with UTAUT and the Technology Acceptance Model, which emphasize that perceived ease of use reduces the cognitive effort associated with technology adoption (Davis, 1989; Venkatesh et al., 2003). It is also consistent with the technology acceptance literature, which suggests that usability can contribute to users' willingness to engage with emerging technologies (Venkatesh & Bala, 2008).

In contrast, social influence had a negative and statistically significant effect on behavioral intention to use AI ($\beta = -0.246$, $t = 6.252$, $p < 0.001$). Thus, although the relationship is statistically significant, its direction is opposite to the conventional positive relationship proposed in UTAUT. The finding suggests

that social messages surrounding AI use may not uniformly encourage adoption. Instead, students may receive social cues that emphasize academic integrity risks, excessive dependence on AI, misinformation, privacy concerns, or uncertainty about the legitimacy of AI-assisted academic work. Such concerns can transform social influence from an adoption-promoting mechanism into a source of resistance or caution. This interpretation is compatible with research showing that distrust and perceived risks associated with emerging technologies can negatively shape technology-related attitudes and behavioral responses (Dinev et al., 2015). It also accords with the role of uncertainty and risk perceptions in shaping responses to unfamiliar technologies (Hofstede, 2011).

The finding can further be understood through the broader technology-resistance literature. When users receive negative information or warnings about a technology from peers or influential social groups, these messages may strengthen resistance rather than adoption, particularly when the technology is perceived as controversial or potentially threatening to established practices (Gursoy et al., 2019). Therefore, the negative coefficient does not necessarily indicate that social influence is irrelevant. Rather, it suggests that the content and valence of social influence matter. In the context of AI use in higher education, social influence may operate through both supportive and discouraging messages. This finding consequently provides an important qualification to the conventional UTAUT assumption that social influence primarily encourages behavioral intention (Venkatesh et al., 2003).

Facilitating conditions did not have a statistically significant effect on behavioral intention to use AI ($\beta = 0.082$, $t = 1.380$, $p = 0.168$). Although the coefficient was positive, the evidence was insufficient to establish a significant relationship. This finding suggests that the availability of resources, technical assistance, and supporting infrastructure may function more as enabling conditions than as direct motivational factors. This interpretation is consistent with UTAUT, in which facilitating conditions are conceptually associated with the resources and organizational support necessary for technology use (Venkatesh et al., 2003). It is also consistent with the task-technology fit perspective and technology acceptance research, which distinguish between the availability of supporting conditions and the psychological motivation to adopt a technology (Goodhue & Thompson, 1995; Venkatesh & Bala, 2008).

Hedonic motivation had a positive and statistically significant effect on behavioral intention to use AI ($\beta = 0.144$, $t = 2.999$, $p = 0.003$). This indicates that students' positive experiences, enjoyment, or satisfaction when interacting with AI can contribute to their willingness to use it. The finding is consistent with UTAUT2, which extends traditional technology acceptance models by recognizing hedonic motivation as a determinant of behavioral intention (Venkatesh et al., 2012). It also supports the argument that users' affective experiences with technology can complement more utilitarian considerations such as performance and effort expectancy (Venkatesh & Bala, 2008).

Price value showed a negative but statistically non-significant relationship with behavioral intention to use AI ($\beta = -0.067$, $t = 1.009$, $p = 0.313$). The negative direction suggests that higher perceived cost relative to benefits may potentially reduce intention; however, the relationship is not statistically supported in this study. This result may reflect the accessibility of free or relatively low-cost AI tools, reducing the salience of monetary considerations in students' adoption decisions. The finding should therefore be interpreted in light of the UTAUT2 concept of price value, in which users evaluate whether the perceived benefits of a technology justify its monetary cost (Venkatesh et al., 2012). In an educational context where students can access AI services at little or no direct cost, other factors such as usefulness, ease of use, trust, and academic appropriateness may become more influential (Davis, 1989; Venkatesh & Bala, 2008).

Habit had a negative and statistically significant effect on behavioral intention to use AI ($\beta = -0.639$, $t = 7.906$, $p < 0.001$). This result differs from the conventional expectation that established technology-use habits facilitate continued behavioral intention. The negative relationship may indicate that students' existing academic habits are still strongly oriented toward conventional practices, such as independent searching, manual information processing, conventional writing practices, and direct interaction with lecturers or learning resources. Consequently, established routines may create resistance when AI requires students to modify familiar ways of completing academic tasks. This interpretation is consistent with Ouellette & Wood (1998), who explain that habitual behavior is strongly associated with repeated responses in stable contexts, and with Limayem *et al.* (2007), who emphasize the role of habit in shaping technology-use behavior. In the present context, the negative coefficient suggests that established academic routines may compete with rather than facilitate the formation of AI-related behavioral intention.

For actual AI use, facilitating conditions had a positive and statistically significant effect ($\beta = 0.448$, $t = 3.478$, $p = 0.001$). This result differs from the non-significant relationship between facilitating conditions and behavioral intention. The distinction is theoretically meaningful because access to infrastructure, technical resources, and organizational support may not be sufficient to make students *intend* to use AI, but these conditions can directly determine whether students are actually able to use it. The finding is consistent with UTAUT, which conceptualizes facilitating conditions as resources and support that enable technology use (Venkatesh *et al.*, 2003), and with task-technology fit, which emphasizes the importance of the availability of appropriate technological resources for effective task performance (Goodhue & Thompson, 1995).

Habit had a positive but statistically non-significant effect on actual AI use ($\beta = 0.130$, $t = 0.993$, $p = 0.321$). Although the direction is positive, the statistical evidence does not support a meaningful direct relationship. This result suggests that students' actual AI use may be relatively situational rather than automatically triggered by established habits. AI may be used when students encounter particular academic tasks for which the technology is perceived as useful, rather than simply because AI use has become an established routine. This finding provides a more nuanced interpretation of habit in technology adoption and complements the view of Limayem *et al.* (2007) that habitual behavior becomes influential when repeated technology use is sufficiently established.

Finally, behavioral intention to use AI had a positive but statistically non-significant effect on actual AI use ($\beta = 0.190$, $t = 1.166$, $p = 0.244$). Although students may express an intention to use AI, intention does not necessarily translate into actual use in the present context. This finding highlights a potential intention-behavior gap. The distinction between intention and actual behavior is recognized in technology acceptance research, where behavioral intention represents a motivational state rather than a guarantee that the behavior will occur (Venkatesh *et al.*, 2003). Similarly, Bhattacharjee & Premkumar (2004) demonstrate that technology-related beliefs and intentions may evolve as users encounter practical experiences and constraints. In the academic context, students may intend to use AI but refrain from doing so because of assignment-specific restrictions, concerns about academic integrity, uncertainty regarding appropriate use, insufficient skills, limited access, or the perception that AI is not suitable for a particular task.

Overall, the results indicate that performance expectancy (PE), effort expectancy (EE), and hedonic motivation (HM) have positive and statistically significant relationships with behavioral intention to use AI (BI). These findings suggest that students' intentions to use AI are positively associated with their perceptions of its usefulness for academic activities, the ease of using AI, and the enjoyment or satisfaction

experienced when interacting with AI-based technologies. In contrast, social influence (SI) and habit demonstrate statistically significant negative relationships with BI. Thus, although these relationships are statistically significant, their directions are contrary to the expected positive relationships proposed in the hypotheses.

However, the interpretation of the magnitude of the path coefficients should be made with caution. The structural model indicates potential multicollinearity among several predictors of BI, particularly PE and Habit, as reflected in their relatively high VIF values. This issue is also consistent with the unusually large coefficient observed for the PE → BI relationship. Therefore, the present findings provide stronger evidence regarding the statistical significance and direction of the relationships than regarding the relative strength or magnitude of the effects. Further interpretation of the coefficients should consequently be considered alongside the collinearity assessment to avoid overstating the substantive contribution of individual predictors.

Accordingly, the findings support a more differentiated understanding of AI adoption in higher education. Rather than relying only on broad initiatives to increase students' intention to use AI, institutions should address the specific mechanisms identified in the structural model. Lecturers can provide task-specific guidance on when and how AI may appropriately support learning activities, while explicitly distinguishing acceptable assistance from prohibited forms of AI-generated academic work. Libraries can complement this role by providing AI-oriented research support, including guidance on responsible AI-assisted searching, information verification, source evaluation, citation practices, and academic integrity. Institutional policy makers should develop clear and operational AI-use guidelines for different types of assessments instead of relying on general statements about responsible AI use. Meanwhile, educational technology developers and institutional IT units should prioritize reliable access, usability, technical support, and integration with existing academic workflows. These measures address not only students' perceptions of AI but also the practical conditions that determine whether AI can be used appropriately and effectively in academic settings.

Discussion

Hypothesis 1: Performance expectancy has a positive and significant effect on behavioral intention to use AI

The findings indicate that performance expectancy has a positive and significant effect on students' behavioral intention to use AI. This result suggests that students are more inclined to use AI when they perceive that the technology can enhance the effectiveness and efficiency of their academic activities. The finding is consistent with Venkatesh *et al.* (2003), who identify performance expectancy as a central determinant of technology acceptance. Similarly, Davis (1989) argues that perceived usefulness plays an important role in shaping users' willingness to adopt and use technology.

In the context of higher education and scientific writing, the result indicates that students evaluate AI largely in terms of the academic value it can provide. AI may be perceived as useful when it assists students in completing routine academic tasks, developing and organizing ideas, searching for relevant information, supporting data analysis, improving writing processes, and facilitating access to academic resources. This interpretation is also consistent with Goodhue & Thompson (1995), who emphasize that technology is more likely to contribute to individual performance when its capabilities are aligned with the

tasks that users need to accomplish. Thus, students' intention to use AI may be strengthened when they can clearly identify a connection between AI capabilities and specific academic tasks.

However, this finding should be interpreted alongside the potential issue of common method bias (CMB), as the constructs in this study were measured using self-reported responses collected from the same respondents. The use of a single measurement source can introduce systematic variance that may influence the observed relationships among constructs (Podsakoff et al., 2003). This concern is particularly relevant to technology-adoption research because performance expectancy and behavioral intention are both perceptual constructs commonly measured through self-report instruments. Accordingly, the relationship between performance expectancy and behavioral intention should not be interpreted solely on the basis of statistical significance. A full-collinearity assessment should be reported as an additional diagnostic to evaluate whether substantial common method bias may be present, particularly within a PLS-SEM framework (Kock, 2015).

The practical implication is that institutions should demonstrate the specific academic value of AI rather than promoting AI adoption merely as the use of a new technology. Lecturers can integrate structured AI-based activities into assignments, for example by asking students to use AI to generate alternative explanations of complex concepts, identify weaknesses in an initial argument, develop potential research questions, or provide feedback on the organization of a draft. These activities should be accompanied by requirements for students to verify AI-generated information, consult authoritative sources, and critically evaluate the accuracy and relevance of the output. Such an approach positions AI as an academic support tool rather than a substitute for students' intellectual work.

Libraries can further strengthen students' performance expectancy by providing AI-assisted research workshops focused on practical academic tasks. These workshops may include the use of AI for developing search keywords, identifying potential research directions, organizing literature, synthesizing information, and planning research activities, while emphasizing source verification, information literacy, and responsible use of AI. At the institutional level, AI policies should therefore communicate concrete and measurable academic use cases, including examples of appropriate and inappropriate applications of AI in learning and scientific writing. By demonstrating how AI can contribute to learning efficiency, research productivity, and the quality of academic work, institutions can help students develop a more realistic understanding of AI's academic utility and potentially strengthen their intention to use the technology.

Hypothesis 2: Effort expectancy has a positive and significant effect on behavioral intention to use AI

The significant positive effect of effort expectancy indicates that students' willingness to use AI is strengthened when the technology is perceived as easy to learn and operate. This finding supports Venkatesh *et al.* (2003), who identify effort expectancy as an important determinant of technology adoption, and is consistent with Davis (1989), who establishes perceived ease of use as an important factor in technology acceptance.

This finding is particularly relevant because AI applications differ considerably in terms of interfaces, functions, prompting requirements, output quality, and interaction mechanisms. Students may be willing to use AI when they can quickly understand how to interact with the system without requiring extensive technical knowledge. Venkatesh & Bala (2008) emphasize that reducing complexity and providing clear

guidance can strengthen users' acceptance of technology. Thus, the issue is not simply whether students have access to AI, but whether they can use it confidently and efficiently.

The practical implication is that AI adoption programs should be designed around specific user tasks rather than generic technology demonstrations. Lecturers can provide short prompt templates and examples of appropriate AI use for different stages of learning and scientific writing. Librarians can develop step-by-step research guides covering tasks such as developing search terms, comparing information sources, summarizing documents, and checking references. Institutions can also provide short tutorials, frequently asked questions, and user support for commonly used AI applications. These interventions can reduce students' initial learning burden and increase their confidence in using AI. Consequently, improving usability and providing task-specific guidance may be more effective than merely increasing the number of AI tools available to students.

Hypothesis 3: Social influence has a negative but significant effect on behavioral intention to use AI

Contrary to the positive direction generally proposed by UTAUT, the findings show that social influence has a significant negative relationship with students' behavioral intention to use AI. This means that stronger perceived influence from the surrounding social environment is associated with lower intention to use AI. Rather than indicating that social influence is irrelevant, the finding suggests that the direction and content of social influence are important in the context of AI adoption.

One possible explanation is that social influence surrounding AI may contain cautionary or negative messages. Students may receive warnings from lecturers, peers, or other members of the academic community concerning plagiarism, academic integrity, misinformation, privacy, dependence on AI, and inappropriate use of generated content. Dinev *et al.* (2015) suggest that distrust and concerns surrounding emerging technologies can be reinforced through social environments in which the technology is viewed cautiously. Gursoy *et al.* (2019) similarly indicate that exposure to negative information can contribute to resistance toward emerging technologies.

Cultural expectations may further strengthen this effect. Hofstede (2011) argues that environments characterized by relatively high uncertainty avoidance may demonstrate greater reluctance toward innovations involving uncertainty or perceived risks. In academic settings, this may occur when students perceive that AI use conflicts with established expectations concerning independent learning, research integrity, and conventional scientific writing. Venkatesh *et al.* (2003) emphasize the importance of social influence in technology adoption; however, the present finding indicates that its effect should not automatically be interpreted as supportive. Social influence can encourage adoption when the prevailing message is positive, but it can discourage adoption when the dominant message emphasizes risk or prohibition.

This finding has a direct implication for lecturers and institutional policy makers. Institutions should not rely on informal peer pressure or promotional campaigns to encourage AI adoption. Instead, lecturers should explicitly distinguish between acceptable and unacceptable AI use in coursework and scientific writing. For example, students should be informed when AI may be used for brainstorming, language improvement, or preliminary exploration, and when its use would violate assessment or academic-integrity requirements. Libraries can support this process by providing evidence-based AI literacy sessions that address misinformation, source verification, citation practices, privacy, and responsible prompting. At the institutional level, a clear AI-use policy should replace ambiguous messages that may cause students to

associate AI generally with misconduct. In this way, social influence can gradually shift from a source of uncertainty to a source of informed and responsible guidance.

Hypothesis 4: Facilitating conditions have a positive but non-significant effect on behavioral intention to use AI

The non-significant relationship between facilitating conditions and behavioral intention indicates that the availability of infrastructure, resources, and technical support does not by itself motivate students to develop an intention to use AI. This result does not imply that facilitating conditions are unimportant. Rather, it suggests that their role may be primarily enabling rather than motivational.

Venkatesh *et al.* (2003) identify facilitating conditions as an important factor in technology use, but their effect may become more apparent when users have already decided to adopt a technology. Goodhue & Thompson (1995) further demonstrate that task-technology fit and the perceived usefulness of technology may be more influential in determining whether a technology is accepted. Similarly, Venkatesh & Bala (2008) emphasize the importance of performance- and effort-related perceptions in shaping technology acceptance.

The finding suggests that students may regard basic access to internet connectivity, devices, and digital services as an expected condition rather than a reason to adopt AI. In other words, providing infrastructure alone is unlikely to generate demand if students do not perceive a clear academic benefit or if they are uncertain about how AI should be used.

The practical implication is that institutions should avoid treating infrastructure provision as the primary AI-adoption strategy. Investment in AI should be accompanied by demonstrable academic applications. Universities can provide access to AI tools through institutional platforms, but this access should be linked to training, academic examples, user support, and clearly defined purposes. Libraries can integrate AI support into existing research consultation services rather than creating a separate technology service that students may not understand. Thus, facilitating conditions should be designed to remove barriers to use while performance expectancy and effort expectancy are addressed through pedagogical and instructional interventions.

Hypothesis 5: Hedonic motivation has a positive and significant effect on behavioral intention to use AI

The significant positive effect of hedonic motivation indicates that students' enjoyment and satisfaction when interacting with AI contribute to their willingness to use it. This finding supports Venkatesh *et al.* (2012), who incorporated hedonic motivation into UTAUT2 as an important determinant of technology adoption. Venkatesh & Bala (2008) also emphasize that motivational factors can influence technology use beyond purely functional considerations.

Although students primarily use AI for academic rather than entertainment purposes, the quality of interaction remains important. Conversational interfaces, rapid feedback, personalized responses, and interactive problem-solving may make AI more engaging than conventional tools. An AI application that is technically capable but difficult, frustrating, or monotonous may be less attractive to students than one that provides a smooth and satisfying interaction.

The practical implication is that AI-supported learning should be designed as an engaging academic experience without sacrificing academic rigor. Lecturers can use interactive AI activities to encourage

students to compare alternative explanations, critique AI-generated answers, or engage in simulated question-and-answer exercises. Libraries can develop interactive AI literacy sessions rather than relying exclusively on conventional lectures. For developers and institutional technology teams, usability testing with students should include not only functional performance but also interaction quality and user satisfaction. However, hedonic motivation should support—not replace—critical evaluation. An enjoyable AI experience must still require students to verify information and retain responsibility for academic decisions.

Hypothesis 6: Price value has a negative but non-significant effect on behavioral intention to use AI

The non-significant effect of price value indicates that cost–benefit considerations do not constitute a major determinant of students’ intention to use AI in the context examined. Although the coefficient is negative, its lack of statistical significance indicates that the direction should not be interpreted as evidence that higher perceived value reduces AI adoption.

Venkatesh *et al.* (2012) explain that price value becomes particularly relevant when users directly compare the benefits of a technology with the financial cost required to use it. In the present context, many AI services may be available without direct payment or through free and relatively inexpensive versions. As a result, students may not perceive price as a sufficiently important differentiating factor. Venkatesh & Bala (2008) further suggest that perceived functional benefits can become more important when users consider a technology highly relevant to their goals. Davis (1989) similarly emphasizes the importance of usefulness and ease of use in technology acceptance.

The practical implication is that institutions should not assume that reducing cost alone will increase AI adoption. If universities provide subsidized or institutionally licensed AI services, the investment should be justified through clear academic functions, privacy protections, user support, and integration with existing educational and library services. Procurement decisions should therefore consider educational value and responsible-use features rather than focusing solely on subscription price. For students, the important issue is whether an AI service provides reliable and academically relevant benefits, not simply whether it is inexpensive.

Hypothesis 7: Habit has a negative but significant effect on behavioral intention to use AI

The significant negative relationship between habit and behavioral intention is one of the more distinctive findings of this study. Rather than strengthening students’ intention to use AI, stronger established habits are associated with lower intention. This result can be understood through the concept of behavioral persistence: students who are accustomed to conventional approaches to learning, information searching, research, and scientific writing may be less willing to alter established routines.

Ouellette & Wood (1998) explain that habits can strongly predict repeated behavior because established behavioral patterns can operate with limited conscious deliberation. Limayem *et al.* (2007) similarly demonstrate that familiarity with existing behavioral patterns can influence technology-related behavior. In the present context, students may already be comfortable using search engines, textbooks, academic databases, conventional writing software, and established research procedures. The introduction of AI therefore requires not simply learning a new tool but modifying existing academic routines.

This finding has an important implication for lecturers and librarians: AI adoption should be framed as augmentation rather than replacement. Lecturers can introduce AI at selected stages of existing

assignments—for example, after students conduct an initial literature search, they may use AI to compare concepts or identify potential gaps, followed by verification against scholarly sources. Librarians can integrate AI into existing information-literacy instruction by teaching students how AI complements, rather than replaces, scholarly databases and authoritative information sources. Institutions should also avoid policies that require students to immediately restructure their entire academic workflow around AI. A gradual integration strategy may reduce resistance because students can observe how AI complements familiar practices.

Hypothesis 8: Facilitating conditions have a positive and significant effect on actual AI use

The significant positive relationship between facilitating conditions and actual AI use contrasts with the non-significant relationship between facilitating conditions and behavioral intention. This distinction provides an important insight into the adoption process: students may not need infrastructure to become interested in AI, but they need infrastructure to actually use it.

Venkatesh *et al.* (2003) identify facilitating conditions as an important determinant of technology use, while Goodhue & Thompson (1995) emphasize the importance of matching technological capabilities with users' tasks. The present findings support this distinction by suggesting that access to devices, reliable internet connectivity, appropriate applications, knowledge, and technical support becomes critical at the point of actual implementation.

The practical implications are therefore more concrete than simply recommending “better infrastructure.” Universities should ensure reliable campus connectivity in locations where students conduct academic work, provide access to institutionally approved AI tools where appropriate, establish technical support channels, and provide guidance on account security and responsible data input. Libraries can provide AI research-support desks or consultation services where students receive assistance with selecting appropriate tools, formulating prompts, verifying outputs, and identifying authoritative sources. Institutions should also ensure that access policies do not unintentionally exclude students who cannot afford premium AI services. These interventions directly address the conditions required to transform students' potential willingness to use AI into actual academic use.

Hypothesis 9: Habit has a positive but non-significant effect on actual AI use

The non-significant effect of habit on actual AI use indicates that established behavioral patterns do not directly determine whether students actually use AI. This finding is noteworthy because habit has a significant relationship with behavioral intention in the opposite direction. The results therefore suggest that students' existing habits may influence their psychological willingness to adopt AI without necessarily determining their actual behavior.

Limayem *et al.* (2007) demonstrate that habit can influence technology-related behavior, but the strength of this relationship depends on the context and the degree to which behavior has become established. AI remains a rapidly evolving technology, and students may use different AI applications for different academic tasks rather than developing one stable pattern of use. Actual use may therefore be highly situational.

The finding also reinforces the importance of facilitating conditions. Students may use AI when a particular assignment requires rapid information processing, writing assistance, idea generation, or data analysis, but may not use it when those conditions are absent. Consequently, institutions should focus less

on attempting to create AI dependence or automatic usage habits and more on ensuring that students can recognize appropriate situations in which AI adds academic value. This approach is particularly important for responsible AI adoption because habitual use without critical judgment may increase the risk of accepting inaccurate or inappropriate outputs.

Hypothesis 10: Behavioral intention has a positive but non-significant effect on actual AI use

The non-significant relationship between behavioral intention and actual AI use indicates that students' willingness to use AI does not automatically translate into actual behavior. This finding reveals an important intention-behavior gap in AI adoption. Although students may express a willingness to use AI, their actual behavior can still be constrained by practical, ethical, academic, or contextual considerations.

Venkatesh *et al.* (2003) identify behavioral intention as an important predictor of technology use, but actual use can also depend on facilitating conditions and other contextual factors. Bhattacharjee & Premkumar (2004) similarly emphasize the importance of environmental and resource-related conditions in technology implementation and continued use. The significant effect of facilitating conditions on actual AI use in this study provides further support for this interpretation.

Several barriers may explain why intention does not translate directly into behavior. Students may be uncertain about whether AI use is permitted for a particular assignment, concerned about academic integrity, lack sufficient knowledge to use AI effectively, lack access to appropriate tools, or simply encounter academic tasks for which AI provides limited additional value. Therefore, increasing students' intention to use AI is insufficient if institutions do not simultaneously create conditions that allow students to use it appropriately.

The practical implication is that institutional AI policy should connect intention with actionable opportunities for use. Lecturers should clearly specify permissible AI use in course assignments and assessment activities. Libraries should provide practical support at the point where students conduct research rather than relying only on general AI-literacy campaigns. Academic units should provide examples of acceptable AI-assisted workflows for research and scientific writing. Institutions should also establish mechanisms through which students can obtain clarification when they are uncertain about whether a particular AI application or activity is academically appropriate. These measures can reduce the gap between students' intention and their actual behavior.

Integrated Discussion and Practical Implications

Taken together, the findings demonstrate that students' AI adoption is not governed by a single mechanism. The results distinguish between factors that primarily shape behavioral intention and factors that facilitate actual use. Performance expectancy and effort expectancy indicate that students need to perceive AI as useful and easy to operate, while hedonic motivation shows that the quality of interaction can further strengthen their intention. Conversely, the negative effects of social influence and habit indicate that students may face social reservations and established academic routines that discourage adoption. Price value does not appear to be a decisive factor in the present context.

More importantly, facilitating conditions have different roles at different stages of adoption. Their lack of a significant effect on behavioral intention but significant effect on actual use suggests that infrastructure and support operate primarily as implementation mechanisms rather than as motivational

mechanisms. Similarly, the non-significant relationship between behavioral intention and actual use demonstrates that willingness alone does not guarantee behavior. These findings suggest that AI adoption should be understood as a process in which students first recognize academic value and usability, negotiate social and behavioral barriers, and finally require appropriate conditions to translate intention into actual use.

The findings lead to several specific institutional implications. For lecturers, AI should be integrated into clearly defined academic tasks rather than introduced as a generic digital tool. Course assignments can specify when AI may be used for brainstorming, feedback, language improvement, or preliminary analysis, while requiring students to verify AI-generated information and remain responsible for the final academic product. This approach can strengthen performance expectancy and effort expectancy while addressing concerns associated with social influence and academic integrity.

For librarians, AI adoption should be incorporated into existing information-literacy and research-support services. Rather than merely teaching students how to operate AI tools, librarians can provide task-based guidance on AI-assisted literature discovery, prompt formulation, source verification, citation checking, information evaluation, and responsible use of AI-generated content. Libraries can also provide individual or group consultations for students who need assistance integrating AI with scholarly databases and authoritative information sources. Such services directly address the facilitating conditions found to be important for actual AI use.

For institutional policy makers, the findings indicate the need for a clear and differentiated AI governance framework. Policies should distinguish between acceptable, restricted, and prohibited uses of AI in learning, assessment, research, and scientific writing. Institutions should communicate these rules consistently through lecturers, libraries, academic departments, student orientation, and digital platforms. Clear policies can reduce uncertainty and prevent negative social influence from being driven by ambiguous or overly general messages about AI.

For educational technology developers and institutional IT units, usability should be treated as a central adoption requirement. AI services should provide intuitive interfaces, clear instructions, user feedback, privacy protections, and technical support. Because facilitating conditions significantly affect actual use, institutions should also prioritize reliable connectivity, appropriate access arrangements, and support mechanisms. However, infrastructure investment should be accompanied by demonstrations of concrete academic value; infrastructure alone is unlikely to generate adoption when students do not perceive a clear benefit.

Finally, the findings suggest that AI adoption should be pursued through a responsible augmentation strategy rather than technological replacement. Students' established academic habits should not necessarily be eliminated; instead, AI can be introduced gradually as an additional resource that complements information searching, learning, research, and scientific writing. This approach acknowledges the negative relationship between habit and behavioral intention while avoiding the assumption that students must immediately abandon established academic practices.

Overall, the study demonstrates that effective AI adoption requires more than increasing students' willingness to use the technology. Students need to recognize clear academic benefits, experience manageable and engaging interactions, receive reliable guidance concerning appropriate use, and have access to the practical conditions necessary for actual implementation. The findings therefore support an institutional strategy that combines task-oriented pedagogy, library-based AI research support, clear

governance, user-centered technology design, and accessible infrastructure. Such an integrated approach is more consistent with the empirical evidence than generic recommendations to simply increase AI literacy or provide technological infrastructure.

CONCLUSION

This study examined the factors influencing students' acceptance and actual use of artificial intelligence (AI) to support education and scientific writing across several higher education contexts in Malang City using the UTAUT2 framework and PLS-SEM. The findings demonstrate that students' intention to use AI is significantly influenced by performance expectancy, effort expectancy, and hedonic motivation. Performance expectancy emerged as the strongest positive predictor, indicating that students are more likely to intend to use AI when they perceive that it can improve their productivity, learning effectiveness, information searching, research activities, and scientific writing. Effort expectancy also had a significant positive effect, confirming that perceived ease of use remains an important consideration in students' willingness to adopt AI. Hedonic motivation further contributed positively to behavioral intention, suggesting that enjoyable and satisfying experiences with AI can strengthen students' willingness to use the technology.

In contrast, social influence and habit showed significant negative effects on behavioral intention, while facilitating conditions and price value did not significantly influence intention. These findings indicate that students' AI adoption decisions are not necessarily driven by social expectations or cost considerations. Instead, established habits may create resistance to changing existing learning and writing practices. Importantly, facilitating conditions had a significant positive effect on actual AI use, highlighting the critical role of access to technological infrastructure, resources, knowledge, and technical support in translating AI adoption into actual practice. Meanwhile, habit and behavioral intention did not significantly affect actual AI use. This finding suggests that having an intention to use AI does not automatically result in actual usage and that contextual and infrastructural conditions may be more important in enabling students to use AI in practice.

The study contributes theoretically by demonstrating that UTAUT2 provides a useful framework for explaining students' acceptance and use of AI, while also revealing that the effects of several UTAUT2 constructs may differ in the context of AI-supported education and scientific writing. The findings also highlight the importance of distinguishing between behavioral intention and actual technology use. From a practical perspective, the results suggest that efforts to promote responsible and effective AI use should prioritize demonstrating the academic benefits and ease of use of AI, providing engaging learning experiences, strengthening students' AI literacy, and ensuring adequate access to technological infrastructure and technical support. These measures should be developed based on students' demonstrated needs rather than relying solely on efforts to increase their intention to use AI. Overall, the findings indicate that effective AI adoption among students requires not only positive perceptions of the technology but also a supportive environment that enables students to translate those perceptions into meaningful and responsible use for educational and scientific writing purposes.

REFERENCES

- Baihaqi, W. M., Sulistiyana, F., & Fadholi, A. (2021). Pengenalan artificial intelligence untuk siswa dalam menghadapi dunia kerja di era Revolusi Industri 4.0. *RESWARA: Jurnal Pengabdian Kepada Masyarakat*, 2(1), 79–88. <https://doi.org/10.46576/rjpkkm.v2i1.876>
- Bhattacharjee, A., & Premkumar, G. (2004). Understanding changes in belief and attitude toward information technology usage: A theoretical model and longitudinal test. *MIS Quarterly*, 28(2), 229–254.
- Brown, A., Green, R., & Hill, M. (2021). AI and accessibility in educational resources. *Computers & Education*, 160, 104–112.
- Chen, X., Wu, Z., & Liu, H. (2020). Developing AI tools for library use: A practical approach. *Information Processing & Management*, 57(3), 102–114.
- Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319–339. <https://doi.org/10.2307/249008>
- Devianto, Y., & Dwiasnati, S. (2020). Kerangka kerja sistem kecerdasan buatan dalam meningkatkan kompetensi sumber daya manusia Indonesia. *Jurnal Telekomunikasi dan Komputer*, 10(1), 19. <https://doi.org/10.22441/incomtech.v10i1.7460>
- Dewi, A. O. P. (2020). Kecerdasan buatan sebagai konsep baru pada perpustakaan. *Anuva: Jurnal Kajian Budaya, Perpustakaan, dan Informasi*, 4(4), 453–460. <https://doi.org/10.14710/anuva.4.4.453-460>
- Dinev, T., McConnell, A., & Smith, H. J. (2015). Informing privacy research through information systems, psychology, and behavioral economics: Thinking outside the "APCO" box. *Information Systems Research*, 26(4), 639–655. <https://doi.org/10.1287/isre.2015.0600>
- Garcia, M., & Rodriguez, A. (2019). AI in library management: Strategies and outcomes. *Library Management*, 40(6), 401–413.
- Goodhue, D., & Thompson, R. (1995). Task-technology fit and individual performance. *MIS Quarterly*, 19(2). <https://aisel.aisnet.org/misq/vol19/iss2/5/>
- Gursoy, D., Chi, C. G., & Karadag, E. (2019). The impact of technology on travel and tourism: A comprehensive literature review. *Tourism Management Perspectives*, 29, 70–76.
- Hofstede, G. (2011). Dimensionalizing cultures: The Hofstede model in context. *Online Readings in Psychology and Culture*, 2(1). <https://doi.org/10.9707/2307-0919.1014>
- Huang, J., Chen, Y., & Xu, L. (2019). Enhancing information retrieval efficiency with AI in libraries. *Journal of Library Science*, 35(4), 123–134.
- Johnson, R., Jones, P., & Smith, K. (2020). Personalization of library services through AI: A case study. *Library and Information Science Research*, 42(2), 201–215.
- Kline, R. B. (2015). *Principles and practice of structural equation modeling* (4th ed.). Guilford Press.
- Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. *International Journal of E-Collaboration*, 11(4), 1–10. <https://doi.org/10.4018/IJEC.2015100101>
- Lee, H., & Kim, S. (2021). AI as a tool for scientific writing support. *Journal of Educational Technology*, 45(1), 67–80.
- Limayem, M., Hirt, S. G., & Cheung, C. M. K. (2007). How habit limits the predictive power of intention: The case of information systems continuance. *MIS Quarterly*, 31(4), 705–737.
- Martinez, F., Gomez, S., & Torres, L. (2020). Successful AI integration in library services. *Library Hi Tech*, 38(2), 289–303.
- Ouellette, J. A., & Wood, W. (1998). Habit and intention in everyday life: The multiple processes by which past behavior predicts future behavior. *Psychological Bulletin*, 124, 54–74. <https://doi.org/10.1037/0033-2909.124.1.54>
- Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied*

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- Psychology*, 88(5), 879–903. <https://doi.org/10.1037/0021-9010.88.5.879>
- Raup, A., Ridwan, W., Khoeriyah, Y., Supiana, S., & Zaqiah, Q. Y. (2022). Deep learning dan penerapannya dalam pembelajaran. *JiIP - Jurnal Ilmiah Ilmu Pendidikan*, 5(9), 3258–3267. <https://doi.org/10.54371/jiip.v5i9.805>
- Singh, R., & Patel, K. (2021). Implementing AI in academic libraries: Challenges and opportunities. *College & Research Libraries*, 82(1), 15–28.
- Smith, T., & Thompson, L. (2019). AI in academic data analysis: Benefits and challenges. *Educational Technology Research and Development*, 67(3), 456–470.
- Venkatesh, V., & Bala, H. (2008). Technology Acceptance Model 3 and a research agenda on interventions. *Decision Sciences*, 39(2), 273–315. <https://doi.org/10.1111/j.1540-5915.2008.00192.x>
- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425–478. <https://doi.org/10.2307/30036540>
- Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, 36(1), 157–178.
- Wang, Y., & Li, J. (2018). Adoption of AI in libraries: A quantitative analysis. *Journal of Academic Librarianship*, 44(5), 600–612.