THE ROLE OF ARTIFICIAL INTELLIGENCE IN HIGHER EDUCATION: A SURVEY STUDY FROM INDONESIA

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STATEMENT OF WORK'S ORIGINALITY

I honestly declare that this thesis proposal, which I have written, does not contain the work or part of the work of others, except those properly cited in quotations and references, in accordance with the standards of academic writing.

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MOTTO

“If you don’t take risks, you can’t create a future.”

— Monkey D. Luffy

DEDICATIONS

With heartfelt gratitude, I dedicate this thesis proposal to:

1. My eternal source of strength, Allah SWT, who has granted me the breath of life and continuously surrounds me with His infinite protection and grace.
2. My dearest parents, whose unwavering love, wise guidance, prayers, and constant support have encouraged me every step of the way throughout my academic journey.
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LIST OF KEY TERMS & ABBREVIATIONS

AI	**:** *Artificial Intelligence* — Technology that mimics human intelligence to perform tasks automatically.
TAM	**:** *Technology Acceptance Model* — A theoretical framework used to explain how users come to accept and use new technologies.
PEU	**:** *Perceived Ease of Use* — The degree to which a person believes that using a particular system would be free of effort.
PU	**:** *Perceived Usefulness* — The degree to which a person believes that using a particular system would enhance their performance.
ATU	**:** *Attitude Toward Use* — A user's positive or negative feelings about using a particular technology.
BI	**:** *Behavioral Intention* — The degree of intention a person has to use a system in the future.
AU	**:** *Actual Use* — The extent to which a system or technology is actually used by the user.
PLS-SEM	**:** *Partial Least Squares – Structural Equation Modeling* — A statistical method used for modeling complex variable relationships, especially in exploratory studies.
SmartPLS	**:** A software application used to perform PLS-SEM analysis, especially suitable for small to moderate sample sizes and non-normal data.
Outer Model	**:** The measurement model in PLS-SEM that evaluates the reliability and validity of the indicators for each latent construct.
Inner Model	**:** The structural model in PLS-SEM that tests the hypothesized relationships between latent variables.
AVE	**:** *Average Variance Extracted* — A metric that assesses convergent validity by measuring the amount of variance captured by a construct versus the variance due to measurement error.
HTMT	**:** *Heterotrait-Monotrait Ratio* — A method used to evaluate discriminant validity between constructs in PLS-SEM.
Cronbach's Alpha	**:** A measure of internal consistency and reliability of items within a construct.
Composite Reliability	**:** An index used in PLS-SEM to evaluate the internal consistency reliability of constructs based on their indicators.

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ABSTRACT

The rapid advancement of Artificial Intelligence (AI) has introduced various tools capable of transforming learning processes in higher education. However, the acceptance and adoption of AI among university students are influenced by multiple interrelated factors. This study aimed to analyze the determinants of AI adoption in the learning process by employing the Technology Acceptance Model (TAM), which comprises Perceived Ease of Use (PEU), Perceived Usefulness (PU), Attitude Toward Use (ATU), Behavioral Intention (BI), and Actual Use (AU). A quantitative research approach was applied through the distribution of structured online questionnaires to 200 university students in Indonesia. Data analysis was conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS software. The findings indicate that PEU significantly influences both PU and ATU, while PU positively affects ATU. ATU strongly predicts BI, and BI significantly influences AU. The R^2 values for PU (0.361), ATU (0.621), BI (0.489), and AU (0.582) suggested that the model possesses moderate to substantial predictive power. Furthermore, the effect size (f^2) analysis revealed that PEU had a medium effect on PU and a small-to-medium effect on ATU, PU had a medium effect on ATU, ATU had a large effect on BI, and BI had a substantial effect on AU. These results affirmed the applicability of TAM in explaining AI adoption within the Indonesian higher education context. The study concludes that enhancing the ease of use and perceived benefits of AI can promote positive attitudes, strengthen behavioral intentions, and increase sustained usage. Practical recommendations are offered for institutions, educators, and students to support the effective and ethical integration of AI in education.

Keywords: Artificial Intelligence, Technology Acceptance Model, Higher Education, AI Adoption, PLS-SEM, Indonesia, Student Perception

CHAPTER I

INTRODUCTION

1.1 Background of the Study

Artificial intelligence (AI) is now being used in higher education to improve learning, administration, and students' academic experience. With its ability to analyze data and provide automated solutions, AI makes the education system more efficient and innovative. As the future of higher education takes shape, it is important to explore how students themselves perceive the benefits of AI in their learning experience. Since AI becomes more integrated into universities, Chan & Hu (2023) found that students recognized the benefits of AI in enhancing their learning experience, particularly through personalized assistance, support in generating ideas and writing, and assistance in research and data analysis. From personalized learning platforms and virtual learning assistants to entertainment apps and online communication tools, AI now plays a more prominent role in students' daily activities than ever before (Bhutoria, 2022). In addition, AI is seen as a useful resource for generating ideas, improving writing skills, and assisting in the research process, including gathering information and analyzing data. This shows the growing importance of AI in facilitating more efficient and independent learning and improving students' overall academic performance.

The use of AI in higher education is changing the way students learn and organize their daily schedules. Klimova & Pikhart (2025) highlight tool such as AI-based tutoring systems and writing assistants allow students to access educational content more easily and learn on their own. This helps students become

more independent learners and manage their academic and personal time more effectively. As a result, AI has the potential to reduce stress and support student well-being by making learning more flexible and less overwhelming. As AI, industry, and education rapidly evolve, society is moving towards a future where AI will be an essential part of everyday life and learning (Guo et al., 2025). AI is rapidly developing and becoming an important part of everyday life and education. In the future, AI will likely play a significant role in the way we live and learn. In addition, Afrin (2023) also states it is important to understand that AI in education does not replace human teachers with robots. Instead, AI involves using artificial intelligence (computer knowledge) to support learners and teachers, making education more effective and organized. There is no doubt that AI will play a significant role in the future of education with many AI tools being developed to aid the learning process. This research seeks to investigate the role of Artificial Intelligence (AI) in higher education, with a specific focus on its support for student learning. It examines the ways in which AI facilitates the learning process, enhances students' academic experiences, and contributes to their overall educational development. In summary, this research looks at how AI can make learning more effective and personalized at the university level.

At present, the future of universities is closely linked to the development of new technologies and intelligent machines with advanced computing capabilities. Advances in AI present both opportunities and challenges for teaching and learning. In the context of higher education, AI has great potential to offer substantial benefits if applied appropriately and effectively (Taşçi & Çelebi, 2020). In education, AI is

used as a tool and support system to improve the learning process. AI helps make teaching more effective and organized. AI can also adapt to the needs of each student, helping them learn better and more efficiently (Putri & Hasan, 2022). With AI as a learning aid, teachers and educators can deliver lessons more clearly, and students can understand the material more easily. According to Alneyadi et al. (2023) and Nguyen (2023), Artificial Intelligence (AI) has the potential to significantly transform teaching and learning by making the process more personalized, engaging, and efficient. AI enables educational experiences to be tailored to individual student needs, thereby enhancing both the effectiveness and appeal of learning. Advances in learning and the role of AI are being used to support and enhance the learning experience of students and teachers. While AI can benefit both students and teachers, it is also important to think about how male and female students might experience it differently. For example, they might use AI in different ways or face different challenges. Many countries have begun to adopt AI technology in their higher education systems to improve teaching and learning, demonstrating the global impact and growing importance of AI in academia. These developments are progressively influencing global education.

A number of universities and colleges around the world, including those in Italy, have begun integrating AI into their educational systems. According to Wang et al. (2023), universities are adopting Intelligent Tutoring Systems (ITS) to enhance teaching and student support. These AI tools personalize learning by adapting content to each student's pace and needs, making them especially beneficial for international students. An additional example can be seen at a

university in Bangladesh, where the implementation of AI is anticipated to significantly influence the educational landscape. This includes the integration of advanced technologies such as AI-driven learning platforms, virtual teaching assistants, and intelligent tutoring systems, all of which are contributing to the transformation of traditional teaching methods and enhancing the way faculty deliver instruction. These technologies support AI-assisted teaching and AI-assisted learning, and offer innovative educational solutions (Fiandini et al., 2023). Higher education in Japan has adopted AI tools to enhance learning. AI systems support language and communication skills through interactive platforms. Generative AI tools like ChatGPT are reshaping creativity and education. A study in Japan highlights their growing role in supporting student learning, writing, and research in higher education (Saito, 2024). Another study from Spain shows that the emergence of digital technologies and generative AI has challenged traditional teaching and learning methods, encouraging educators to rethink their approaches for better integration of these tools (Sánchez-Vera et al., 2024). A relevant instance is demonstrated by a university in Bangladesh, where AI is expected to have a significant impact on education by introducing advanced tools such as AI-powered learning platforms, virtual teaching assistants, and intelligent tutoring systems that are reshaping the teaching methods of faculty. These technologies support AI-assisted teaching and AI-assisted learning, and offer innovative educational solutions (Fiandini et al., 2023). In another university in Turkey, the use of AI-powered virtual assistants and chatbots in higher education has improved both learning and administrative support (Görgülü, 2025). These tools help students

access academic information, manage tasks, and receive instant responses to inquiries, reflecting the country's efforts to enhance educational services through AI. This approach helps tailor educational content to individual needs, allowing learners from different backgrounds to access materials that match their pace and proficiency. As a result, AI is not only changing the way knowledge is delivered, but also promoting inclusivity and flexibility in higher education. While AI supports personalized learning, it is crucial to assess its different effects on male and female students to ensure fairness in educational access and success. Thus, it is essential to examine how AI is utilized in university learning to ensure it enhances educational quality and supports meaningful student outcomes.

The integration of AI into academic life has significantly influenced how university students in Indonesia overcome common learning challenges, particularly in the area of academic writing. Based on real experiences and student observations, the use of AI tools is becoming a practical solution to address these obstacles. Thus, it is essential to investigate the factors that shape how students adopt and interact with AI technologies in the higher education learning process. Based on the researcher’s personal experience as a private university student in Indonesia, one common challenge encountered was constructing grammatically correct English sentences. This issue was also echoed by a student from a state university, indicating that she had difficulties in applying English grammar rules. Therefore, students use alternative AI-based tools like Grammarly to help with grammatical structure difficulties in academic writing. The university students also use tools such as ChatGPT to develop writing skills, receive feedback, and assist

with various writing-based tasks. The use of ChatGPT, in particular, provides an opportunity to improve learning through efficiency and interactive engagement. In addition, the results of discussions with a number of students from state universities in Indonesia found many conveniences in using AI in their learning process. For instance, the application of tools such as DeepSeek which is almost similar to ChatGPT in analyzing and helping student prepare accurate and precise solutions to compose topics and sentences in academic writing. Although AI technologies such as DeepSeek possess advantages, it also exhibits certain deficiencies. For example, it can sometimes provide incorrect information and still need to be checked carefully, and lack applications in data privacy and freedom of information. In addition, a university student also experienced difficulties in writing his essays and thesis that require citation accuracy and sentence paraphrasing. He used one of the applications called QuillBot which helps improve his essays, papers, and thesis writing through the right level of language and citation. Unfortunately, he found weaknesses in the features of this application, indicating that access to further functions in the QuillBot application requires payment for premium services. Not all students can afford to pay for premium features of this AI application. These experiences reflect how AI applications are increasingly becoming part of students' academic routines and learning strategies. In line with the aim of this study, such insights provide a valuable foundation for identifying students' perceptions of the role of AI in the learning process and examining the key factors that influence their intention to use AI-based tools in higher education settings.

1.2 Identification of Problem

Based on the study of the research above, there are several problems that can be identified in this study, such as:

1) University students have difficulty in constructing grammatical correct and applying English grammar rules in sentences.
2) University students occasionally encountered inaccurate information and required rigorous verification of their academic writing using Deepseek AI tools, alongside a deficiency in applications concerning data protection and freedom of information.
3) A university student also experienced difficulties in writing his essays and thesis that require citation accuracy and sentence paraphrasing.
4) University students found limitations in the use of AI applications that make the use of AI cannot be maximized if they do not access its premium features. Meanwhile, not all students can afford to pay for the premium features of this AI application

1.3 Limitation of the Problem

This study is limited to the context of university-level education and does not extend to other levels such as primary or secondary education. It focuses solely on survey data that capture students' experiences with AI, based on key factors they identified during its application in academic learning. Additionally, the scope of the study does not include analysis of other demographic or socioeconomic variables, concentrating instead on students' interaction with AI technologies within the higher education setting.

1.4 Formulation of the Problem

The formulation of this research is in these following questions:

1) Do the roles of AI applications affect perceived ease of use, perceived usefulness, attitude toward use, behavioral intention, and actual use of the students' learning process?
2) What factors decide the students' overall intention to use AI applications in the learning process?

1.5 Objectives of the Study

Based on the formulation of the study above, this study attempts to achieve the following research objectives:

1) Identify the students' perception of the role of AI applications in the learning process.
2) Identify the factors affecting the students' intention of the role of AI applications in the learning process

1.6 Significance of the Study

The results of this study can help teachers and students understand how students of different genders use and experience AI in learning. This can help create a more equitable and effective AI-based education system. This study can help improve student satisfaction by showing what students expect and what challenges they face when using AI. This study was limited to survey data only to prove the factors involved in the issue under study. Therefore, it is expected that future researchers can explore broader data findings using more varied research instruments with depth of data. The findings are also expected to guide future

research on the relationship between technology, education, and gender for future discussions.

CHAPTER II

LITERATURE REVIEW

2.1 Role of AI in Higher Education

AI in education refers to the use of intelligent systems to enhance teaching and learning. AI is reshaping the core methods and processes involved in education, including how teaching is delivered and how learning takes place. This transformation spans various aspects, such as personalized instruction, automated grading, virtual tutors, and data-driven insights into student progress. By integrating AI, educational systems can become more adaptive, efficient, and accessible for diverse learners (Muldner et al., 2020). While AI technologies are advancing rapidly, the pace of reform in the education sector remains gradual, highlighting the need for alignment between technological innovation and educational transformation (Yu & Lu, 2021). As the role of AI in education continues to grow, the focus has shifted toward augmented intelligence, which emphasizes the synergy between human capabilities and AI systems. Unlike fully autonomous AI, augmented intelligence supports rather than replaces human decision-making, especially in educational environments. In higher education, AI tools assist educators and learners by tailoring instruction, simplifying administrative tasks, and supporting academic research, ultimately creating a more collaborative and effective learning process (Jupalli et al., 2022). Furthermore, AI has been progressively adopted to address existing challenges and improve the quality of teaching and learning (Afrin, 2023). The integration of AI in higher education offers significant potential for enhancing learning experiences and outcomes. However,

to fully realize these benefits, institutions must ensure that technological advancements align with pedagogical goals and inclusive practices. Besides promoting equity, AI supports innovative assessments with real-time feedback and adaptive learning (Ayeni et al., 2024). These tools help educators address student needs more effectively, though proper training and infrastructure are essential. In conclusion, AI is transforming higher education by enabling personalized, equitable, and data-driven learning. To fully benefit, institutions must combine technology with professional development and inclusive policies. Understanding how intelligent technologies are changing education is important before exploring the different types of AI tools used in teaching and learning. The next section will explain the main kinds of AI systems and how they are applied in universities.

2.2 Kinds of AI in Higher Education

Artificial Intelligence in education includes a broad range of technologies aimed at supporting and improving various aspects of the educational process, from teaching and learning to administration and student support. These tools enable personalized instruction, automate repetitive tasks such as grading, and provide data-driven insights that help educators make informed decisions.

1. Intelligent Tutoring Systems (ITS)

   One of the most impactful AI applications in education is the Intelligent Tutoring System (ITS), which adapts content and feedback to each student's pace and performance. According Grenander et al. (2021), ITS can analyze student responses to identify misconceptions and provide personalized, contextual feedback. This enhances learning by supporting

individual needs and improving understanding. By offering real-time support and mimicking one-on-one human tutoring, ITS helps bridge learning gaps. Yu & Lu (2021) argue that the integration of such intelligent technologies is increasingly viewed as a critical component in achieving sustainable, inclusive, and high-quality educational outcomes.

2. Automated Assessment Systems

Another significant AI application is automated assessment systems, which evaluate student work and provide tailored feedback without requiring human involvement. These systems streamline the grading process by assigning scores and offering immediate, consistent feedback, particularly useful in large-scale or online courses (Hahn et al., 2021). This automation helps educators save time and supports students with timely insights to guide their learning.

3. AI-Powered Educational Tools and Learning Analytics

In addition, the rapid advancement of artificial intelligence technologies, along with the increasing volume and complexity of student data, has enabled Artificial Intelligence in Education (AIED) and AI-powered educational tools to play a crucial role in enhancing the design and delivery of education (Khosravi et al., 2023). This technology not only reshapes how instruction is structured but also makes learning more adaptive, efficient, and personalized. By leveraging data-driven insights, AI helps educators better understand student needs, streamline administrative tasks, and create more effective and inclusive learning environments.

4. Natural Language Processing (NLP) and Large Language Models (LLMs)

   Advances in AI have greatly impacted education and research. As Katz et al. (2023) note, "Building on this progress, recent advances in Natural Language Processing (NLP) and Large Language Models (LLMs) have further transformed the landscape of education and research." These technologies have deepened our understanding of how AI can be applied to improve communication, automate content generation, and support academic tasks. Alqahtani et al. (2023) emphasize that NLP and LLMs enable more natural and meaningful interactions between humans and machines, allowing them to function as powerful tools for enhancing both teaching effectiveness and research productivity.

5. Generative AI Models

   One of the notable advancements within AI in education is the use of generative modeling, a machine learning technique that focuses on producing new content that mirrors the characteristics of its training data (Chan & Colloton, 2024). Instead of simply recognizing patterns, generative models learn the underlying structure of the data and use it to create realistic outputs such as text, images, or code that resemble human work. In the context of education, this enables tools like ChatGPT to support students in writing tasks, brainstorming, and content generation, thereby enhancing creativity and learning efficiency.

6. Virtual Assistants and AI Chatbots

   Building on the capabilities of generative models in educational tools, another important use of AI in education is virtual assistants, also known as

AI chatbots (Chukwuere, 2024). These chatbots help students by answering questions, providing personalized guidance, and assisting with administrative tasks. The use of generative AI chatbots in higher education has changed the way education works, improving student support, efficiency, and research. These intelligent systems are designed to enhance both traditional and online learning settings by addressing key challenges such as student engagement, instructor workload, and personalized learning (Davar et al., 2025). Virtual assistants can provide real-time answers to students' academic or administrative questions, guide them through course materials, and automate repetitive tasks for educators. By offering personalized and timely support, these tools contribute to more interactive, efficient, and learner-centered educational experiences.

In summary, various types of AI technologies ranging from intelligent tutoring systems and automated assessments to virtual assistants and generative models are transforming the educational landscape. These tools not only enhance instructional delivery and streamline administrative functions but also provide more personalized and adaptive learning experiences. Given these transformative capabilities, it is essential to explore the broader benefits that the integration of AI brings to the learning process, both for educators and students alike.

2.3 Conceptualization of AI-tools in Higher Education

The integration of Artificial Intelligence in higher education is reshaping teaching, learning, and administration. This section conceptualizes AI by defining its key technologies, applications, and alignment with educational goals. AI now

serves as a practical tool to personalize learning, streamline assessments, and support institutional decisions, setting the stage for exploring its benefits and challenges in higher education (Allen et al., 2020). AI systems used in higher education can generally be divided into two categories based on their complexity and interaction capabilities. Among these, mindful AI-robots represent a more advanced form of artificial intelligence, designed to interact with users in a more human-like and intuitive manner. The so-called mindful AI-robots are able to perform more complex tasks, respond to user prompts in a meaningful way, and are often designed to act and look like humans. On the other hand, mindless AI-robots handle simpler tasks and tend to function more like traditional machines. In the following, a brief overview of AI tools is provided based on Delcker et al. (2024), including their main functionalities and examples of practical applications in higher education learning processes

2.3.1 Mindless AI

Mindless AI refers to artificial intelligence systems that function without consciousness, self-awareness, or true understanding. These systems rely entirely on algorithms, data patterns, and statistical models to perform tasks such as language processing, image recognition, and decision-making. Despite their ability to simulate intelligent behavior, they do not possess thoughts, intentions, or emotions. Some of the types are:

1) Translation text generators are AI tools that convert written text from one language to another, enabling students to better understand course materials or complete assignments in a required language. A study by

Loock & Léchauguette (2021) found that 83% of undergraduate language students used machine translation tools like Google Translate for homework. Rather than banning them, the study recommends teaching students how to use these tools properly.

2) Summarizing and rephrasing text generators are AI tools designed to simplify complex content by extracting key ideas and restating information in a clearer form. Glickman & Zhang (2024) show that AI tools, like chatbots, help researchers quickly find and summarize important information, improving understanding and productivity.
3) Writing assistants are AI-based tools designed to enhance writing quality by detecting and correcting grammar and spelling errors in real time. These tools provide immediate feedback that helps users produce clearer and more accurate text. According to Xu (2025), AI tools are predominantly used in academic writing to improve readability and grammar, with 22% of usage focused on grammar checking.
4) Text generators are AI tools create written content from short prompts and are frequently used for blogs or social media posts. According to Woo et al. (2024), these tools can help students improve their writing by generating ideas and organizing content, making them useful aids when used properly.

2.3.2 Mindful AI-robots

Mindful AI robots are a type of artificial intelligence designed to show signs of awareness, understanding, and the ability to interact more naturally

with humans. Unlike mindless AI, which works only through data and fixed rules, mindful AI tries to imitate human-like thinking, emotions, and ethical behavior. The types are:

1) Chatbots are intelligent conversational computer systems designed to imitate human communication in order to provide automated guidance and support through online platforms. Caldarini et al. (2022) stated due to their numerous benefits, chatbots have been widely adopted across various industries to offer virtual assistance to users
2) Virtual avatars are digital representations used in online classes to portray teachers and students, enhancing interaction and engagement. Garcia (2025) found that avatar design and realistic behavior affect how students perceive instructor credibility and teaching effectiveness in virtual learning environments.
3) Social-humanoid robots mimic human behavior and have features like hands, legs, and faces. They are used in education to improve interaction and engagement. Yun et al. (2023) highlight the importance of designing these robots with motivational gestures to enhance learning experiences.

2.3.3 AI-competencies and AI-ethics

The European Digital Competence Framework 2.2 (DigComp 2.2) outlines key digital skills for citizens, highlighting AI literacy in three areas: knowledge, skills, and attitudes. Knowledge includes understanding AI and related regulations; skills involve using and managing AI tools effectively; and

attitudes refer to forming opinions on AI's benefits and risks for active social and political participation (Vuorikari et al., 2022). This framework helps people understand what digital skills are important today, especially in relation to artificial intelligence (AI). It includes three main areas. First, people should have basic knowledge of how AI works and be aware of important rules, like data protection. Second, they should have the ability to use AI tools in everyday life, including choosing the right tools and using them effectively. Lastly, it is important for people to develop the right attitude by understanding both the benefits and risks of AI, so they can take part in discussions and decisions about how AI is used in society.

2.4 University Students' Intention of Using AI in the Learning Process

Artificial Intelligence (AI) has significantly influenced higher education by introducing digital tools that enhance academic productivity, streamline learning tasks, and support personalized instruction. Initially viewed as a means to increase efficiency (Lee, 2020), AI has now become embedded in students' academic routines, shaping how they access resources, organize information, and complete assignments (Bhutoria, 2022). Platforms such as ChatGPT, Grammarly, and other AI-powered writing tools allow students to generate content, receive feedback, and enhance academic writing. The integration of AI in learning environments has also contributed to institutional benefits such as automation and adaptive systems (Juma & Patel, 2023). However, while students generally respond positively to these tools with reported improvements in engagement, academic outcomes, and independent learning (Nurtanto et al., 2025). Effective adoption depends on more than technical

availability. It requires understanding the psychological and behavioral factors that shape students' willingness to accept and utilize these technologies.

To investigate this, the study adopts the Technology Acceptance Model (TAM) as the theoretical lens. TAM is a widely recognized model for analyzing technology adoption and user behavior. According to Davis & Granić (2024), the model proposes five key constructs that influence acceptance: Perceived Ease of Use (PEU), Perceived Usefulness (PU), Attitude Toward Use (ATU), Behavioral Intention (BI), and Actual Use (AU). These constructs form the foundation for exploring how AI tools affect students' perceptions, attitudes, and behavioral outcomes in higher education. While TAM is not the only model available, its empirical validity and structured framework make it highly suitable for this research context.

2.4.1 Perceived Ease of Use (PEU)

Perceived Ease of Use refers to students' belief that AI tools are simple and intuitive to operate. As noted by Davis & Granić (2024), ease of interaction significantly increases the likelihood of technology adoption. In this study, PEU is applied to understand whether students perceive tools like ChatGPT, Grammarly, or DeepSeek as user-friendly and helpful without requiring advanced technical knowledge. PEU is considered one of the early determinants that shape students' intention to adopt AI in learning environments.

2.4.2 Perceived Usefulness (PU)

Perceived Usefulness represents the degree to which students believe that AI tools enhance their learning effectiveness or academic performance. Within the TAM framework, this construct is central, as students are more likely to use AI tools if they believe these technologies improve outcomes such as writing quality, task completion speed, and understanding of materials. Tools like Grammarly or ChatGPT, which assist in drafting and paraphrasing, are examples of applications that can significantly improve learning productivity. When students see measurable benefits in their academic work, their confidence in using such tools grows. PU also contributes to the credibility of AI as a learning partner rather than a novelty.

2.4.3 Attitude Towards Use (ATU)

Attitude Toward Use refers to students' overall judgment positive or negative—toward the use of AI technologies in their learning process. This includes emotional responses such as enthusiasm, skepticism, or anxiety, as well as openness to future use. Students who have positive prior experiences with user-friendly and beneficial AI tools are more likely to develop trust and comfort in integrating such tools into daily learning activities. ATU acts as a psychological bridge between beliefs (PEU and PU) and behavioral outcomes. Therefore, this construct is vital in determining how students evaluate AI not just functionally, but also personally and socially in the learning context.

2.4.4 Behavioral Intention (BI)

Behavioral Intention refers to students expressed readiness or plan to use AI tools in their academic tasks. It serves as a predictor of actual behavior, indicating how likely students are to continue using AI for learning. This may include intentions to use tools regularly for grammar checks, idea development, writing assistance, or summarizing academic sources. A strong behavioral intention suggests a level of confidence and reliance on AI to enhance learning. Understanding BI also helps institutions predict the long-term viability of AI adoption and how well such tools are being integrated into student learning culture.

2.4.5 Actual Use (AU)

Actual Use (AU) refers to how frequently and consistently students incorporate AI tools into their academic activities. Unlike intention, which reflects planning or readiness, AU measures real engagement and usage behavior. It includes direct actions such as using AI to complete assignments, write theses, conduct research, or improve writing structure. By tracking AU, this study can assess whether student perceptions and intentions translate into habitual use. High levels of actual use indicate that AI tools are not only accepted but also embedded in students' learning strategies.

TAM provides a structured and validated framework for analyzing technology adoption behavior. This model is adopted in the study to examine how students perceive and interact with AI tools in academic settings. The five constructs PEU, PU, ATU, BI, and AU collectively offer insights into the

psychological, behavioral, and functional dimensions that influence AI integration in higher education. By applying TAM, this research aims to explain not only whether AI is used but also why and how students decide to adopt it as part of their academic routines.

2.5 Review of Relevant Studies

To explore the factors that contribute to the benefits, challenges, and expectations of integrating AI into learning processes from a gender perspective, it is important to examine existing studies that have addressed similar themes. While many previous works have focused on the general impact of AI in education, reviewing these studies helps establish a foundation for analyzing how these dynamics may differ across gender lines in higher education settings.

The first study by Mayasari et al. (2023), entitled '*Pengaruh Kecerdasan Buatan dan Teknologi Pendidikan terhadap Peningkatan Efektivitas Proses Pembelajaran Mahasiswa di Jawa Timur*', aimed to analyze the impact of AI and educational technology on the effectiveness of student learning. The participants were university students in East Java, though the exact number was not specified. The study used a quantitative survey design, and data were collected through questionnaires. The data were analyzed using statistical techniques, including regression analysis. The findings showed that students had positive perceptions of AI and that frequent use of educational technology was linked to improved learning outcomes. The study also emphasized the importance of fair access and student participation, which are relevant for exploring gender-based differences in AI integration in higher education.

The second study conducted by Mahmudi et al. (2023), entitled *'Integration of Artificial Intelligence Technology in Distance Learning in Higher Education'*, aimed to examine both the potential and limitations of AI integration in university-level distance education. The study involved 20 university students experienced in AI-supported learning. It employed a quantitative survey design, with data collected via structured questionnaires. The data were analyzed using descriptive statistics to identify patterns of AI use and perceptions. The findings indicated frequent use and high satisfaction with AI tools especially virtual and augmented reality while also revealing common challenges in adoption. Although gender was not directly addressed, the study's focus on benefits, challenges, and expectations makes it a relevant reference for gender-based analysis.

The third study conducted by Wang et al. (2023) a study entitled '*University Students' Intentions to Learn Artificial Intelligence: The Roles of Supportive Environments and Expectancy–Value Beliefs*', which aimed to evaluate how supportive educational environments and expectancy–value beliefs influence students' intentions to learn AI. The research involved 494 university students as participants. It employed a quantitative design, consisting of two complementary approaches: a variable-centered approach (Study 1) and a person-centered approach (Study 2). Data were collected through an online survey that included questions about students' perceptions of their learning environment and their motivational beliefs related to AI learning. For data analysis, Study 1 utilized structural equation modeling (SEM), while Study 2 applied latent profile analysis. The findings revealed that students who perceived their learning environments as supportive and

held strong expectancy–value beliefs were more likely to express strong intentions to learn AI. Furthermore, the study found that male and younger students demonstrated higher levels of intention to engage in AI learning compared to their peers.

The fourth study by Herawati et al. (2024), entitled '*Exploring the Role of Artificial Intelligence in Education, Students Preferences and Perceptions,*' aimed to examine university students' perceptions and preferences regarding the use of AI in education. The participants were 200 students from the Faculty of Teacher Training and Education at Bengkulu University. The study used a quantitative descriptive survey design, and data were collected through an online questionnaire using a student perception scale adapted from Buabbas et al. (2023). Data analysis was conducted through descriptive statistics and the Chi-Square test. The findings showed that most students held positive views about AI's role in enriching learning and improving access to resources, although concerns remained about teacher replacement, reduced human interaction, and data privacy. While gender was not directly examined, the results offer valuable insights for analyzing AI use from a gender-based perspective.

The fifth study by Sîrghi et al. (2024) entitled '*Challenges of Artificial Intelligence on the Learning Process in Higher Education*' aimed to explore students' readiness and perceptions of AI adoption in Romanian higher education. The participants were university students in Romania exact number not specified in summary. The study used a quantitative survey design, with data collected through online questionnaires measuring satisfaction, perceived usefulness, and AI

compatibility with learning needs. Data analysis was conducted using descriptive and inferential statistics. The findings showed that while students generally supported AI integration, key factors such as satisfaction, perceived usefulness, and alignment with learning preferences influenced their readiness. Challenges included unequal access, institutional preparedness, and privacy concerns. Although gender was not the focus, the study offers valuable insights into core factors that can be analyzed further through a gender lens.

The sixth study by Aldossary et al. (2024) entitled '*The Role of Generative AI in Education: Perceptions of Saudi Students*,' aimed to investigate the perceptions of university students in Saudi Arabia regarding the use of generative AI tools in education. The participants included 1,390 students from 15 universities across Saudi Arabia. The study employed a descriptive quantitative research design using a survey method. Data were collected through online questionnaires distributed to the students. Descriptive statistical techniques were used to analyze the data. The results indicated that students generally held positive perceptions of generative AI, showing high levels of awareness and acceptance. Students majoring in computer sciences demonstrated greater concern regarding potential challenges, while those from agricultural sciences showed stronger awareness of the impact of GenAI on achieving sustainable development goals.

Based on the six previous studies above, the research issue focused on the integration of AI in the context of higher education, using a quantitative survey design with various analytical methods. While these studies provide valuable insights into how AI is being adopted in academic environments, most have not

thoroughly examined the specific factors influencing students' engagement with AI tools. Therefore, this study contributes by identifying key variables such as perceived usefulness, ease of use, and behavioral intention that shape students' acceptance and utilization of AI in university learning. This approach aims to support a more comprehensive and practical understanding of AI adoption in education.

2.6 Theoretical Framework

This study adopts the TAM to explore how university students accept and use AI in higher education. According to Davis and Granić (2024), TAM includes five core constructs: PEU, PU, ATU, BI, AU. The model begins with the Role of AI Applications, which serves as an exogenous variable influencing PEU and PU. When AI tools are perceived as easy to use and useful, students tend to develop a positive attitude (ATU) toward them. This attitude shapes their intention (BI) to use AI tools, which then leads to their actual use (AU) in academic tasks. TAM provides a structured explanation of how students' perceptions and attitudes drive their adoption of AI, making it a relevant framework for this study.

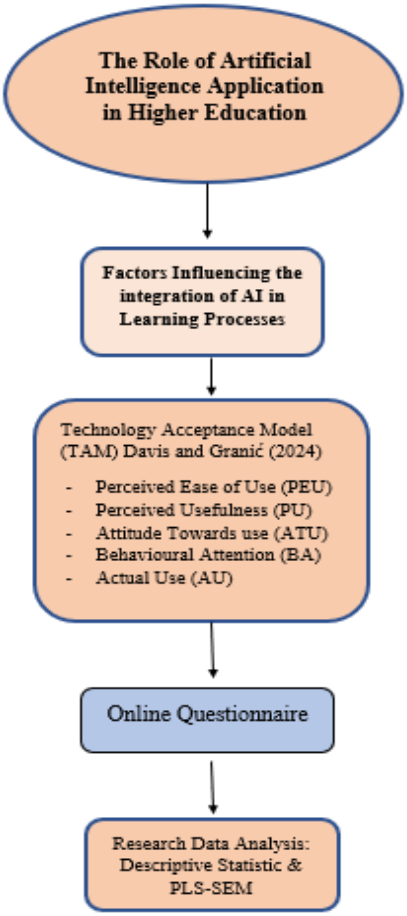


Figure 2.1 Theoretical Framework of the Study

This visual representation outlines the hypothesized relationships between constructs and shows how AI integration may influence actual use through cognitive and behavioral paths. It also guides the development of questionnaire items, which were distributed through online surveys. Data were analyzed using descriptive statistics and PLS-SEM to assess both the measurement and structural models.

2.7 Hypothesis

In quantitative research, hypotheses are used to make predictions about relationships between variables based on theoretical reasoning. According to

Creswell & Creswell (2023), a hypothesis is "a tentative statement that specifies the expected relationship between two or more variables and is tested through statistical procedures" (p. 164). Hypotheses help researchers focus their inquiry, guide the development of survey instruments, and provide the basis for testing theoretical assumptions. In this study, hypotheses are developed based on the TAM to answer the two main research questions. The first question investigates whether the use of AI applications in education influences students' perceptions specifically Perceived PEU, PU, ATU, BI, AU. The second question seeks to identify the key factors that determine students' intention to adopt AI based applications in their learning process.

To answer the research questions, this study proposes a set of hypotheses grounded in TAM, which serves as the conceptual basis for examining how students in higher education accept and utilize AI in their academic activities. The first research question explores whether AI applications influence key student perceptions and behaviors, namely PEU, PU, ATU, BI, and AU. The second question aims to identify the most influential factors affecting students' intention to use AI tools in their learning.

To examine the relationships among the constructs in this study, the following hypotheses are formulated based on the Technology Acceptance Model (TAM). Before testing the proposed hypotheses, the null hypothesis (H_0) is stated as follows:

- **H_0:** There is no significant influence among the variables PEU, PU, ATU, BI, and AU in the context of AI-supported learning in higher education.

Accordingly, the following alternative hypotheses are developed:

- **H1: Perceived Ease of Use (PEU) positively influences Perceived Usefulness (PU).**

  Students who find AI applications easy to operate are more likely to perceive them as beneficial in improving their learning outcomes. When learners experience minimal effort in interacting with AI tools, they tend to view those tools as more valuable and effective in supporting academic tasks.

- **H2: Perceived Ease of Use (PEU) positively influences Attitude Toward Use (ATU).**

  Ease of use contributes significantly to shaping positive attitudes. If students feel that AI-based technologies are user-friendly and intuitive, they are more likely to develop a favourable attitude toward adopting them for academic purposes.

- **H3: Perceived Usefulness (PU) positively influences Attitude Toward Use (ATU).**

  When students believe that AI tools enhance their learning efficiency and academic performance, they tend to form positive evaluations and increased acceptance toward those tools. Usefulness reinforces emotional and cognitive trust in the technology.

- **H4: Attitude Toward Use (ATU) positively influences Behavioural Intention (BI) to use AI applications in the learning process.**

  A student's overall positive attitude toward AI technologies directly

contributes to their willingness to continue using such tools. This intention is shaped by their prior experiences and satisfaction with the perceived benefits of the AI system.

- **H5: Behavioural Intention (BI) positively influences Actual Use (AU) of AI tools in academic learning.**

  Students who demonstrate a strong intention to use AI tools are more likely to translate that intention into consistent usage behaviour in academic settings. This hypothesis connects the psychological readiness of learners with their actual engagement in AI-supported learning environments.

These hypotheses form the basis for empirical testing and provide a framework to better understand the key psychological and behavioural mechanisms that influence students' decisions to adopt AI technologies in higher education.

CHAPTER III

RESEARCH METHODOLOGY

3.1 Research Design

This study adopted a quantitative research approach, which emphasizes a systematic process to collect and analyze numeric data in order to examine relationships among variables. According to Creswell & Creswell (2023, p. 4), quantitative research involves investigating problems through measuring variables, applying instruments, and utilizing statistical methods to determine patterns, test hypotheses, and support or refute theoretical assumptions. This approach is structured, beginning from problem identification, moving through data collection and analysis, and culminating in interpretation. As such, it provides a rigorous foundation for examining students' perceptions and behaviors related to the use of Artificial Intelligence in higher education. Additionally, this study uses a survey design, a common form of quantitative research. As noted by Sugiyono (2021, p 142), survey research involves collecting data from a sample using structured questionnaires to describe current conditions, opinions, or behaviors of a population. This method is particularly effective for gaining insights from a broad group of respondents regarding their use of AI tools in academic settings.

To structure this study's analytical framework, it is essential to define the types of variables used within the TAM, particularly because this research applies Structural Equation Modeling with Partial Least Squares (SEM-PLS). SEM-PLS is a statistical method that enables researchers to examine complex relationships between latent constructs and is especially useful for predictive and exploratory

studies (Wong, 2019, p.6) in SEM, variables are typically classified into exogenous and endogenous types. Exogenous variables act as independent predictors; they influence other constructs but are not influenced by any other variable within the model. According to Hair et al. (2019, p. 63), exogenous variables are those that initiate causal paths without being explained by other constructs. Meanwhile, endogenous variables are the constructs that are affected by other variables and serve as outcomes within the structural model. As explained by Kline (2015, p. 63), endogenous variables are dependent elements in the model, predicted by preceding constructs and essential for testing the influence paths within the theoretical framework. This classification helps researchers trace how one construct affects another, offering a clear structure for hypothesis development.

In this study, the role of AI Applications is classified as the exogenous variable because it initiates the influence on students' perceptions. The TAM constructs PEU, PU, ATU, BI, and AU are treated as endogenous variables, as they are affected by the initial input and form a structured causal chain. More specifically, PEU and PU are viewed as exogenous within the TAM structure, while ATU, BI, and AU are endogenous, as they reflect students' evolving responses. This distinction clarifies how students' early evaluations of AI tools shape their intention and actual use in higher education.

3.2 Population and Sample

In this study, the population refers to all university students from public and private institutions in Indonesia who share relevant characteristics related to the research focus. Creswell & Creswell (2023, p. 142) define a population as all

members of a group who possess specific traits under investigation. Since surveying the entire population is often impractical, sampling is used to select a manageable and representative subset. Sugiyono (2021, p. 124) explains that sampling in survey research is a technique used to select a portion of the population that can represent the entire population, allowing researchers to draw general conclusions. This study applied purposive sampling, a type of non-probability method, by selecting participants based on their relevance to the topic students from an English education background with experience in AI-based learning.

A total of 200 English education students, aged 18 to 24 and from various academic semesters, were selected from public and private universities across Indonesia. This ensured diversity while maintaining relevance to the study's objectives. Participation was voluntary, with personal data kept confidential and used exclusively for academic purposes. The sample size was determined based on PLS-SEM recommendations. Hair et al. (2019, p. 20) suggest that a sample size between 100–200 is adequate when using SEM with multiple constructs and indicators. This ensures sufficient statistical power for model testing.

As the total population of English education students in Indonesia is not precisely known, the number of respondents in this study was calculated using a basic purposive sampling ratio formula:

$$n = \boldsymbol{N} \times \boldsymbol{r}$$

Where:

- **n** = number of selected samples
- **N** = estimated population or target group

- **r =** sampling ratio based on feasibility and research needs

Since the exact size of the population could not be determined, a sample of 200 respondents was utilized, consistent with the minimum recommendation for PLS-SEM analysis. This sample size was deemed sufficient to ensure the reliability of the findings and to provide a reasonable representation of the target population.

3.3 Data Collecting Technique

One of the essential components in this research is the source of data used to obtain accurate and relevant information. In quantitative studies, the collected data must be valid and aligned with the research objectives. Therefore, selecting the appropriate data source is a key consideration in determining the data collection method. This study relied on primary data, gathered directly from respondents through an online questionnaire distributed to English education students from various universities. The data were used to assess students' perceptions and behaviors regarding the use of AI tools in the learning process, based on the constructs of the TAM. In addition, secondary data are drawn from scholarly literature, academic journals, and theoretical sources that support the conceptual and methodological foundation of the study.

3.3.1 Instrument

This study applied an online survey to collect data. The questionnaire consists of a number of questions or statements designed to obtain information from respondents about their beliefs or views. According to Kuphanga (2024), using the same questions for all respondents allows for easier comparison and

analysis of the answers. Structured questionnaires are useful tools in quantitative research because they help collect number-based information in an organized way. Researchers can use them to get the same kind of data from many people through different ways, like sending questions by mail, using online forms, talking face-to-face, or calling by phone.

The questionnaire use in this study was designed clearly and systematically to ensure that the data collected would be both valid and reliable. According to Sugiyono (2021, p. 142), a well-structured questionnaire is essential for obtaining valid and reliable data in quantitative research. This research employ a close-ended questionnaire format, which, as explained by Creswell & Creswell (2023, p. 156), is particularly effective for collecting measurable data that can be analyzed statistically, especially in educational settings today.

The instrument consisted of structured statements in a close-ended type of questions aimed at capturing respondents' perceptions across several constructs related to AI adoption in learning. The survey was administered online through Google Forms and distributed directly to participants via personal contact networks. The target sample consisted of 200 students from both public and private universities in Indonesia, focusing on English education majors and other related fields, with no affiliation to any specific organization or community.

3.3.2 Instrument Validity

In this study, a validity test was conducted to ensure the accuracy and credibility of the questionnaire in measuring students' perceptions and

intentions toward the use of AI in higher education. As Creswell and Creswell (2023, p. 4) emphasize, validity refers to how well an instrument measures the concept it is intended to assess. Therefore, before analyzing students' behavioral responses, it is essential to confirm that the instrument accurately captures the constructs outlined in the TAM, including PEU, PU, ATU, BI, and AU.

To collect consistent and quantifiable data, this research applied a Likert scale, which allows respondents to express their level of agreement or disagreement with a series of structured statements. According to Sugiyono (2021, p.93), the Likert scale is a commonly used technique to measure attitudes, opinions, and perceptions in quantitative research. It is particularly well-suited for online surveys, as it enables the systematic gathering of subjective opinions that can be analyzed statistically. Creswell & Creswell (2023, p.157) also emphasizes that such scaling methods are effective in transforming qualitative perceptions into quantifiable data for further analysis and hypothesis testing. Therefore, the use of this method supports both clarity in data interpretation and consistency across respondents.

In this questionnaire, each item is rated on a 5-point Likert scale, ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). These numeric values form the basis for evaluating the participants' responses to constructs within the TAM framework. The assigned scores are then analyzed to determine patterns and relationships among variables, as shown in the scoring table below:

Table 3.1 Likert Scale

Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
1	2	3	4	5

3.4 Data Analysis Technique

This study used the Partial Least Squares Structural Equation Modeling (PLS-SEM) method to analyze the data. As a modern multivariate analysis technique, PLS-SEM is suitable for analyzing complex models that involve several variables and relationships between them (Wong, 2019, p. 6). It is particularly useful in exploratory research where the goal is to predict specific outcomes, especially when the data do not meet certain strict conditions, such as normal distribution or large sample sizes.

PLS-SEM can be applied to both reflective and formative measurement models. In this research, all variables from the Technology Acceptance Model (TAM) including PEU, PU, ATU, BI, and AU are measured reflectively. This method allows researchers to analyze the measurement model (to check the accuracy and consistency of the indicators) and the structural model (to test the relationships among variables) at the same time. The analysis was conducted using SmartPLS version 4, a specialized software designed to handle small to medium sample sizes and non-normally distributed data. Considering this study involved 200 university students from various regions in Indonesia, PLS-SEM was considered appropriate for processing and interpreting the data.

The analysis process included three main steps: assessing the measurement model (outer model), checking the reliability and validity of the variables, and evaluating the structural model (inner model) to test the research hypotheses.

3.4.1 Convergent Validity

Convergent validity indicates the extent to which indicators within a construct are consistent and able to explain the same concept. Hair et al. (2019, p. 134) define it as the degree to which a construct correlates positively with its associated indicators, reflecting a strong internal consistency. In the context of the PLS-SEM reflective model, this validity is crucial to ensure that each indicator contributes significantly to the construct being measured. Convergent validity is typically assessed through outer loadings, Average Variance Extracted (AVE), and communality. An indicator is considered to meet the required threshold if its outer loading is greater than 0.50 and the AVE exceeds 0.50, indicating that the construct explains more than half of the variance in its observed indicators.

In this study, convergent validity was used to ensure that each main construct in the TAM namely PEU, PU, ATU, BI, and AU has a close relationship with its indicators. This emphasis on validity is crucial because the reflective measurement model requires that each indicator accurately reflect the latent variable it represents. As explained in the findings by Hair & Alamer (2022), convergent validity ensures that indicators within a construct are not only theoretically relevant but also statistically support each other.

A high AVE score reinforces that these indicators do not stand alone but reflect a unified construct. Furthermore, according to Wong (2019, p. 7), the application of convergent validity also provides an important basis for evaluating the accuracy of instruments in PLS-based models, including in educational technology, such as this study. Thus, convergent validity is not only part of the technical analysis process but also fundamental in ensuring the reliability and accuracy of the research model as a whole.

a. *Outer Loading*

Outer loading reflects how strongly each observed variable correlates with its latent construct. A value of 0.70 or higher is generally considered acceptable, indicating a strong relationship. However, indicators with values between 0.50 and 0.70 may still be retained if their removal does not significantly increase the reliability of the construct. In the context of PLS-SEM, evaluating outer loading is essential because it helps determine whether each item contributes meaningfully to its intended construct. As explained by Wong (2019, p. 6), outer loading values provide an initial basis for identifying valid indicators, especially when developing reflective measurement models.

b. *Average Variance Extracted* (AVE)

AVE is used to assess convergent validity in reflective measurement models. It measures the average amount of variance that a construct captures from its indicators relative to the amount due to measurement error. Hair et al. (2019, p. 137) state that an AVE value of 0.50 or higher

indicates adequate convergent validity, meaning that the construct explains more than half of the variance in its indicators. This criterion ensures that the indicators of a construct share a high proportion of variance and collectively represent the underlying latent variable.

The formula for AVE is:

$$AVE = \Sigma(\lambda^2) / n$$

Where:

λ = standardized loading of each indicator

n = number of indicators

In this study, AVE will be used to evaluate the extent to which each construct accurately reflects its indicators in the context of students' intention to use AI in learning, both across male and female groups.

c. Discriminant Validity

Discriminant validity refers to the degree to which a construct is truly distinct from other constructs in a model. It is important to ensure that the indicators used for one construct are not highly correlated with those of other constructs a concern emphasized by Hair et al. (2019, p. 138) so that each construct maintains its conceptual uniqueness. In PLS-SEM, establishing discriminant validity is essential for differentiating between closely related concepts. If this validity is not achieved, it can lead to biased measurements and flawed interpretation of the model's relationships.

To assess discriminant validity, several approaches can be employed. The first is the cross-loading analysis, where an indicator is expected to load higher on its associated construct than on other constructs. Second, the Fornell-Larcker criterion compares the square root of the Average Variance Extracted (AVE) of each construct with its correlations to other constructs; discriminant validity is established if the square root of AVE is greater than these correlations (Hair et al., 2019, p. 140). Finally, the latent variable correlation matrix provides additional evidence by ensuring that constructs are not excessively correlated, which would otherwise suggest a lack of discriminant validity.

In this study, discriminant validity was examined using these three approaches cross loadings, Fornell-Larcker criterion, and latent variable correlations for the five TAM constructs, namely Perceived Ease of Use, Perceived Usefulness, Attitude Toward Use, Behavioral Intention, and Actual Use, among university students.

3.4.2 Outer Model

In the context of Partial Least Squares Structural Equation Modeling (PLS-SEM), the outer model refers to the relationship between latent variables (constructs) and their observed indicators. For reflective measurement models, evaluating the outer model is essential to ensure that the indicators used truly represent the constructs they are intended to measure. The outer model evaluation typically includes three key aspects: indicator reliability, internal consistency reliability, and convergent validity (Hair et al., 2019, p. 133). In

this section, the discussion will focus on internal consistency reliability as measured by Composite Reliability and Cronbach's Alpha.

Composite Reliability (CR) and Cronbach's Alpha (α) are both used to assess the internal consistency of items within a construct referring to how closely related the indicators are in measuring the same underlying concept. In the context of PLS-SEM, Composite Reliability is preferred over Cronbach's Alpha because it does not assume equal loadings across indicators and thus provides a more accurate estimate of construct reliability. Hair et al. (2019, p. 137) explain that a construct demonstrates satisfactory internal consistency when its CR and Alpha values are 0.70 or higher, while values between 0.60 and 0.70 may still be considered acceptable in exploratory research settings.

To strengthen the theoretical foundation, the following formulas represent the calculations for these two measures:

Composite Reliability (CR):

$$\mathbf{CR} = (\Sigma\lambda)^2 / [(\Sigma\lambda)^2 + \Sigma (1 - \lambda^2)]$$

Cronbach's Alpha (α):

$$\boldsymbol{\alpha} = [k / (k - 1)] \times [1 - (\Sigma\sigma^2_i / \sigma^2_t)]$$

Where:

$\boldsymbol{\lambda}$ = standardized loading of each indicator

k = number of indicators

This formula calculates the internal consistency of indicators by comparing the total squared factor loadings with the sum of squared loadings and their measurement errors. A higher CR value indicates that most of the variance in the observed variables is captured by the latent construct, suggesting strong reliability.

σ^2_i = variance of each item

σ^2_t = total variance of the sum of all items

Cronbach's Alpha estimates reliability based on the average inter-item correlation. It assumes equal contribution of all items to the construct and is often used as a conservative measure of internal consistency.

3.4.3 Inner Model: R-Squared (R^2)

The inner model, also referred to as the structural model in PLS-SEM, evaluates the relationships between endogenous (dependent) and exogenous (independent) latent constructs, reflecting the hypothesized paths among constructs based on theoretical frameworks such as the Technology Acceptance Model (TAM). According to Hair et al. (2019, p. 140), one of the most widely used criteria for assessing predictive accuracy and relevance is the R-Squared (R^2), which serves as the coefficient of determination indicating the proportion of variance in an endogenous construct explained by one or more exogenous constructs. These values provide insight into the model's explanatory power and overall goodness of fit.

Values of 0.75, 0.50, and 0.25 are typically interpreted as substantial, moderate, and weak levels of explanatory power, respectively, based on the guidelines outlined in the same reference. Nevertheless, these thresholds are not absolute and may differ depending on the complexity of the model and the research context. Particularly in exploratory research, lower R^2 values may still yield meaningful insights, especially when the aim is to detect initial patterns or emerging relationships among constructs.

The general formula for R-Squared is:

$$R^2 = 1 - (SSres / SStot)$$

Where:

- **SSres** = Sum of squares of residuals

- **SStot** = Total sum of squares.

In this study, the R-Squared coefficient was used to evaluate how well the constructs of Perceived Ease of Use (PEU), Perceived Usefulness (PU), Attitude Toward Use (ATU), and Behavioral Intention (BI) predict the Actual Use (AU) of AI in learning among university students. This assessment helps confirm whether the structural model provides sufficient explanatory power in the context of students' intention to use AI technology in education.

3.4.4 Effect Size (f^2)

Effect size (f^2) is used in PLS-SEM to determine the individual contribution of each exogenous (independent) construct to the R-Squared value

of an endogenous (dependent) construct. It quantifies how much a predictor variable contributes to explaining the variance of a dependent variable when it is included in or removed from the model. Hair et al. (2019, p. 147) state that f^2 values of 0.02, 0.15, and 0.35 indicate small, medium, and large effects, respectively.

The formula for f^2 is:

$$f^2 = (R^2 \text{ included} - R^2 \text{ excluded}) / (1 - R^2 \text{ included})$$

Where:

- R^2 included = R-Squared value when the predictor is included

- R^2 excluded = R-Squared value when the predictor is excluded.

In this study, f^2 was used to assess how strongly each TAM construct—Perceived Ease of Use, Perceived Usefulness, Attitude Toward Use, and Behavioral Intention—contributes to explaining the Actual Use of AI in learning. This analysis helps identify which constructs have the most significant influence on students' intention and behavior regarding AI usage

CHAPTER IV

RESEARCH FINDING AND DICUSSION

4.1 Research Finding

This section presents the results of data analysis based on the responses of 200 university students from both public and private institutions in Indonesia. The data collection was designed to capture a diverse range of perspectives regarding the adoption of artificial intelligence in the learning process.

The analysis was conducted using Partial Least Squares – Structural Equation Modeling (PLS-SEM) with the aid of SmartPLS version 4. In line with established analytical procedures, a two-stage approach was applied: the evaluation of the measurement model (outer model) to assess the reliability and validity of the constructs, and the evaluation of the structural model (inner model) to test the hypothesized relationships and predictive capabilities of the model.

The constructs examined in this study are based on the TAM framework, namely PEU, PU, ATU, BI, and AU. Through this analytical process, the study proposed to ensure that the measurement instruments are both accurate and consistent, and that the structural relationships among variables meaningfully reflect the theoretical foundations of TAM in the context of AI adoption in higher education.

4.1.1 Respondents' Demographic Information

This section provides an overview of the respondent profile that forms the basis of this study. A total of 200 university students from both public and

private institutions in Indonesia participated in the survey, representing a range of academic backgrounds and experiences. The data collection aimed to capture a diverse set of perspectives on the use of artificial intelligence in education, ensuring that the analysis reflects variations across different segments of the student population.

The demographic information gathered includes key attributes such as gender, type of institution, age, and semesters. Presenting this profile is essential for understanding the composition of the sample, as it offers context for interpreting the subsequent findings. The following subsections provide a detailed breakdown of each demographic aspect, enabling a clearer picture of the participants involved in the research.

1. Characteristics of Respondents Based on Gender

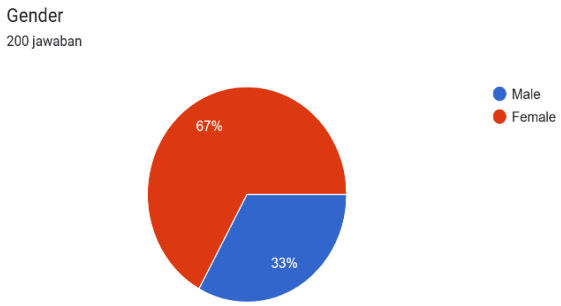


Figure 4. 1 Respondents Based on Gender

The demographic diagram presents the composition of the 200 respondents in this study. Based on the collected data, 134 respondents (67%) are female, while 66 respondents (33%) are male. This distribution indicates that the sample contains a larger proportion of male participants, although female respondents are also adequately represented.

Having a clear understanding of respondent composition is essential for interpreting survey findings accurately. The proportion shown in the demographic diagram reflects the actual participation during data collection, ensuring that the dataset is an authentic representation of the surveyed population. Such demographic information also adds transparency to the research process, as it helps contextualize the subsequent analysis of perceptions, attitudes, and behaviors toward artificial intelligence in education.

2. Characteristics of Respondents Based on Institution

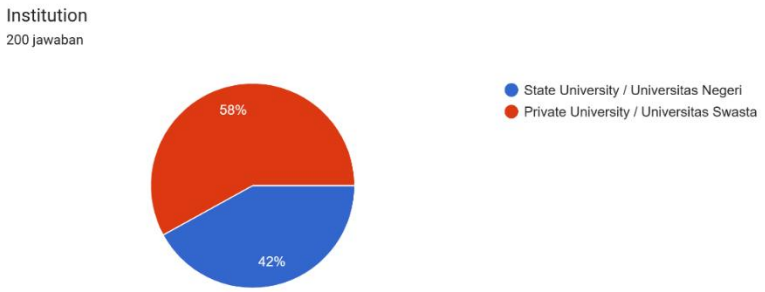


Figure 4. 2 Respondents Institutions Demographic

The demographic diagram illustrates the distribution of respondents based on their university type. Based on the 200 respondents, 116 participants (58%) are from private universities, while 84 participants (42%) are from state universities. This shows that the study sample includes a slightly higher proportion of respondents from state institutions compared to private institutions.

The inclusion of participants from both types of universities ensures that the findings reflect a broader range of academic environments. Differences in institutional resources, academic policies, and technology

integration strategies between state and private universities can influence how students perceive and adopt artificial intelligence in education. By incorporating both groups into the sample, the study gains a more comprehensive understanding of AI adoption trends across diverse educational contexts.

The majority of participants came from private universities (116 respondents; 58%), while the remainder came from public universities (84 respondents; 42%).

3. Characteristics of Respondents Based on Age

The age composition of respondents is described to provide an overview of the distribution across different age groups within the study sample. This helps to contextualize the analysis by showing the range of ages represented.

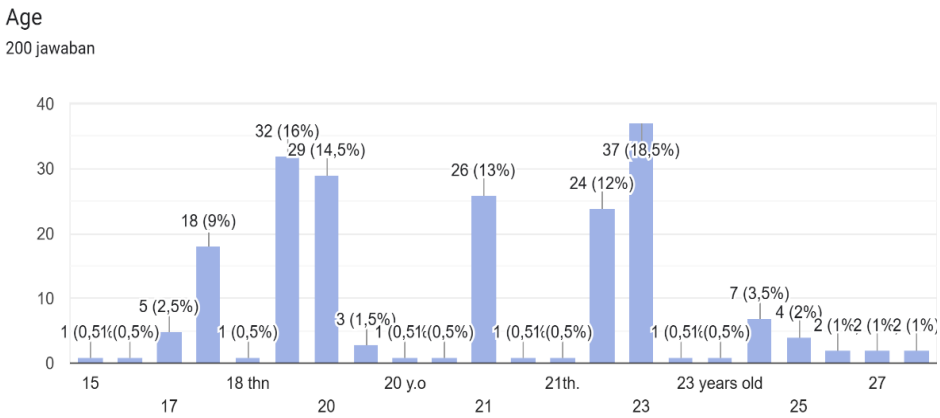


Figure 4. 3 Characteristics of Respondents Based on Ages

The demographic diagram presents the distribution of the 200 respondents according to their age categories. The largest proportion is found in the 23-year-old group with 37 respondents (18.5%), followed by

those aged 20 years with 29 respondents (14,5%), and 19 years with 32 respondents (16%). These three age groups represent the majority of participants in the study.

The next significant groups include respondents aged 21 years with 28 individuals (14%), 22 years with 24 individuals (12%), and 18 years with 19 individuals (9.5%). Meanwhile, smaller portions of the sample are represented by those aged 24 years (7 respondents, 3.5%), 25 years (4 respondents, 2%), 26 years (2 respondents, 1%), 27 years (2 respondents, 1%), and 28 years (2 respondents, 1%). The youngest participants in the dataset are 15 and 16 years old, each with 1 respondent (0.5%), while those aged 17 years account for 5 respondents (2.5%).

This distribution demonstrates that the majority of respondents are in their early twenties, which aligns with the typical profile of active university students. Nevertheless, the presence of both younger and older age groups enriches the dataset by incorporating diverse academic stages and life experiences. Such variety contributes to a more comprehensive and representative understanding of perspectives on the adoption of artificial intelligence in education.

4. Characteristics of Respondents Based on Semesters

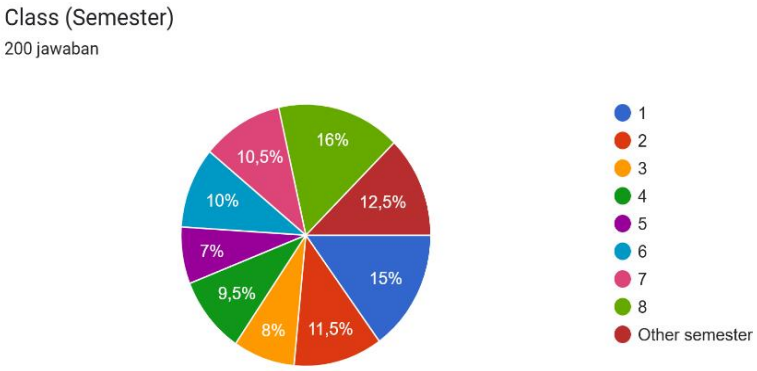


Figure 4. 4 Characteristics of Respondent Based on Semesters

Regarding semester level, the highest proportion came from Semester 8 (32 respondents; 16%), followed by Semester 1 (30 respondents; 15%), the "Other Semester" category (25 respondents; 12.5%), Semester 2 (23 respondents; 11.5%), Semester 7 (21 respondents; 10.5%), Semester 6 (20 respondents; 10%), Semester 4 (19 respondents; 9.5%), Semester 3 (16 respondents; 8%), and Semester 5 (14 respondents; 7%).

This variation indicates that the sample is diverse and represents a diverse range of students with different educational levels and backgrounds.

4.1.2 Measurement Model

There were two stages carried out in testing the research model, namely the outer model and the inner model. According to Hair et al. (2019), the outer model focuses on assessing the validity and reliability of the indicators used to measure latent variables, through tests such as convergent validity, discriminant validity, and construct reliability. Meanwhile, the inner model, as described by Hair et al. (2019), focuses on examining the relationships

among latent variables and evaluating the strength and significance of these relationships, using tests such as R^2, path coefficients, and path significance.

1. Outer Model

The outer model focuses on the relationship between latent variables and indicators. Testing the outer model aims to ensure that the instruments used to measure latent variables have good validity and reliability. There are three main types of testing in the outer model, namely convergent validity, discriminant validity, and construct reliability.

a) Convergent Validity

Convergent validity has two criteria that can be evaluated, namely using factor loading values or average variance extracted (AVE) values.

1) Loading factor value

The output of the outer loading estimation is measured from the correlation between the indicator score (instrument) and its construct (variable). An indicator is considered valid if it has a correlation value above 0.70, or 0.60 is considered sufficient.

Table 4. 1 Loading Factor Results

Indicators	Actual Use	Attitude Toward Use	Behavioral Intention	Perceived Ease of Use	Perceived Usefulness	Information
ATU1		0.852				Valid
ATU2		0.898				Valid
ATU3		0.915				Valid
AU1	0.906					Valid
AU2	0.908					Valid

Indicators	Actual Use	Attitude Toward Use	Behavioral Intention	Perceived Ease of Use	Perceived Usefulness	Information
AU3	0.888					Valid
BI1			0.883			Valid
BI2			0.878			Valid
BI3			0.880			Valid
PEU1				0.819		Valid
PEU2				0.844		Valid
PEU3				0.890		Valid
PU1					0.883	Valid
PU2					0.895	Valid
PU3					0.869	Valid

The output of the loading factor values for all statements of the variables PEU, PU, ATU, BI, and AU presented in the table 4.1 shows that each indicator has a value greater than 0.7, which means that all indicators are considered valid. This result indicates that the indicators/statements used successfully measure the correlation between the indicator scores and their respective constructs/variables, thereby supporting the construct validity of the measurement model.

2) Average variance extracted (AVE)

The AVE estimation results are shown in Table 4.2. A variable is considered valid if it has an AVE value > 0.5.

Table 4. 2 Average variance extracted

Variables	Average variance extracted (AVE)	Information
Actual Use	0.811	Valid
Attitude Toward Use	0.790	Valid
Behavioral Intention	0.775	Valid
Perceived Ease of Use	0.725	Valid
Perceived Usefulness	0.779	Valid

The Average Variance Extracted (AVE) values for each construct are as follows: Perceived Ease of Use (PEU) = 0.725, Perceived Usefulness (PU) = 0.779, Attitude Toward Use (ATU) = 0.790, Behavioral Intention (BI) = 0.775, and Actual Use (AU) = 0.811. According to Hair et al. (2019), an AVE value of 0.50 or higher indicates that a construct explains at least 50% of the variance of its indicators, thus meeting the criterion for convergent validity. In this study, all AVE values exceeded this threshold, demonstrating that, on average, more than half of the variance in the observed indicators is captured by their respective latent constructs. This confirms that the measurement items applied are valid representations of the intended theoretical concepts.

b) Discriminant Validity

Discriminant validity is used to ensure that the constructs or variables in a measurement model capture distinct concepts and do not overlap with

one another. In other words, it evaluates the degree to which different constructs in the model can be differentiated from each other. In this study, discriminant validity was assessed using latent variable correlations and cross-loading analysis.

1) Cross Loading

An indicator or statement is considered valid if its correlation with its respective construct or variable (cross-loading value) is higher than its correlation with other constructs. The following are the data analysis results generated using SmartPLS version 4, presenting the cross-loading values as shown in the table 4.3 below.

Table 4. 3 Cross Loading Results

Indicators	Actual Use	Attitude Toward Use	Behavioral Intention	Perceived Ease of Use	Perceived Usefulness	Information
AU1	**0.906**	0.721	0.633	0.678	0.668	Valid
AU2	**0.908**	0.737	0.731	0.676	0.708	Valid
AU3	**0.888**	0.679	0.652	0.650	0.688	Valid
ATU1	0.594	**0.852**	0.656	0.711	0.704	Valid
ATU2	0.758	**0.898**	0.768	0.725	0.756	Valid
ATU3	0.751	**0.915**	0.775	0.722	0.762	Valid
BI1	0.640	0.761	**0.883**	0.663	0.713	Valid
BI2	0.663	0.688	**0.878**	0.684	0.657	Valid
BI3	0.675	0.734	**0.880**	0.688	0.620	Valid
PEU1	0.574	0.693	0.771	**0.819**	0.658	Valid
PEU2	0.686	0.643	0.572	**0.844**	0.741	Valid
PEU3	0.635	0.731	0.629	**0.890**	0.698	Valid
PU1	0.656	0.740	0.675	0.741	**0.883**	Valid
PU2	0.682	0.715	0.647	0.689	**0.895**	Valid
PU3	0.686	0.752	0.671	0.740	**0.869**	Valid

The cross-loading values for the constructs Perceived Ease of Use (PEU), Perceived Usefulness (PU), Attitude

Toward Use (ATU), Behavioral Intention (BI), and Actual Use (AU) indicate that the correlation between each indicator and its corresponding construct is higher than its correlation with other constructs. The results of the convergent validity and discriminant validity tests show consistent findings, with all indicators meeting the validity criteria. This demonstrates that the measurement model employed in this study has a good fit and is capable of effectively distinguishing between different constructs. Therefore, it can be concluded that the measurement instruments used in this research are valid.

2) *Latent Variables*

Latent variable correlation is part of the steps used to assess discriminant validity, examining the degree of association between variables in the model. High correlations between variables may indicate issues with discriminant validity and multicollinearity. The estimation output is presented in Table 4.4 as follows:

Table 4. 4 Latent Variable Results

Variables	Actual Use	Attitude Toward Use	Behavioral Intention	Perceived Ease of Use	Perceived Usefulness	AVE	$\sqrt{AVE}$	Information
Actual Use	1.000	0.792	0.749	0.742	0.765	0.811	0.901	Valid
Attitude Toward Use	0.792	1.000	0.827	0.809	0.834	0.790	**0.889**	Valid
Behavioral Intention	0.749	0.827	1.000	0.770	0.753	0.775	0.880	Valid
Perceived Ease of Use	0.742	0.809	0.770	1.000	0.821	0.725	0.851	Valid
Perceived Usefulness	0.765	0.834	0.753	0.821	1.000	0.779	0.883	Valid

The value of the latent variable correlation can be assessed by comparing it with the square root of the AVE. The square root of the AVE should be greater than the correlation between latent variables in the same row/column. If the result is greater, discriminant validity is considered satisfied. Based on the test results, it shows that:

Based on the latent variable correlation results, the square root of the Average Variance Extracted (√AVE) for each construct is greater than its correlations with other constructs, indicating that the Fornell–Larcker criterion for discriminant validity is fulfilled. Specifically, AU has a √AVE of 0.901, exceeding all its correlation values (0.765, 0.742, 0.749, 0.792). ATU records a √AVE of 0.889, higher than its correlations (0.834, 0.809, 0.827, 0.792). BI has a √AVE of 0.880, greater than its correlations (0.753, 0.770, 0.827, 0.749). PEU shows a √AVE of 0.851, surpassing its correlations (0.821, 0.770, 0.809, 0.742). Finally, PU has a √AVE of 0.883, which is also higher than its correlations (0.821, 0.753, 0.834, 0.765). These findings confirm that all constructs meet the discriminant validity requirement.

3) Fornell *Larcker*

The Fornell–Larcker criterion is effectively used to examine whether the constructs in a PLS model demonstrate

good discriminant validity. If the √AVE is greater than the correlation values in the same row, the result is considered Valid; whereas if the √AVE is not greater than the correlation values in the same row, the result is considered Not Valid. This indicates that the measurement model is valid in distinguishing between different constructs.

Table 4. 5 Fornell Larcker Results

Variables	Actual Use	Attitude Toward Use	Behavioral Intention	Perceived Ease of Use	Perceived Usefulness	Remarks
Actual Use	0.900					Valid
Attitude Toward Use	0.792	0.889				Valid
Behavioral Intention	0.749	0.827	0.880			Valid
Perceived Ease of Use	0.742	0.809	0.770	0.852		Valid
Perceived Usefulness	0.765	0.834	0.753	0.821	0.883	Valid

Based on Table 4. 5, the results can be interpreted as follows:

1) For AU, the √AVE value is 0.900, while its correlations with other variables—ATU (0.792), BI (0.749), PEU (0.742), and PU (0.765)—are all smaller than 0.900. Therefore, AU is considered valid.
2) For ATU, the √AVE value is 0.889, while its correlations with AU (0.792), BI (0.827), PEU (0.809), and PU (0.834) are all smaller than 0.889. Therefore, ATU is considered valid.

3) For BI, the √AVE value is 0.880, while its correlations with AU (0.749), ATU (0.827), PEU (0.770), and PU (0.753) are all smaller than 0.880. Therefore, BI is considered valid.
4) For PEU, the √AVE value is 0.852, while its correlations with AU (0.742), ATU (0.809), BI (0.770), and PU (0.821) are all smaller than 0.852. Therefore, PEU is considered valid.
5) For PU, the √AVE value is 0.883, while its correlations with AU (0.765), ATU (0.834), BI (0.753), and PEU (0.821) are all smaller than 0.883. Therefore, PU is considered valid.

c) Construct Reliability

Construct reliability can be analyzed using two common measures: Cronbach's alpha and composite reliability. Both are used to evaluate the internal consistency of indicators within a construct, ensuring that the items reliably measure the same underlying variable. Values above 0.70 are generally considered acceptable, and according to Hair et al. (2019), this threshold reflects satisfactory reliability and measurement consistency.

I. Cronbach's Alpha

Cronbach's alpha is an important indicator for testing the reliability of variables in a PLS-SEM model. A high Cronbach's alpha value indicates that the construct is well-measured and consistent, which

supports measurement validity in PLS analysis. Low values, according to Hair et al. (2019), can indicate that the items do not share sufficient common variance, which may result from weak inter-item correlations or poorly formulated statements, and therefore require revision or replacement.

Table 4. 6 Cronbach's Alpha Results

Variables	Cronbach's alpha	Information
Actual Use	0.883	Reliable
Attitude Toward Use	0.867	Reliable
Behavioral Intention	0.855	Reliable
Perceived Ease of Use	0.810	Reliable
Perceived Usefulness	0.858	Reliable

The results presented in Table 4.6 indicates that the Cronbach's alpha value for the AU variable is 0.883, for ATU is 0.867, for BI is 0.855, for PEU is 0.810, and for PU is 0.858. All of these Cronbach's alpha values are greater than or equal to the threshold of 0.70, which is widely considered the minimum acceptable standard for internal consistency. This finding suggests that all variables in the study demonstrate a high level of reliability, meaning that the measurement items for each construct are consistent and dependable in capturing the intended concepts.

II. Composite Reliability

Composite reliability is used to assess the internal consistency of the indicators that make up a latent variable. In SmartPLS, composite

reliability serves as a primary measure for evaluating reliability. A composite reliability value of 0.70 or higher is generally considered to meet the standard for research, indicating that the set of indicators consistently represents the intended construct.

Table 4. 7 Composite Reliability Results

Variables	Composite reliability	Information
Actual Use	0.928	Reliable
Attitude Toward Use	0.918	Reliable
Behavioral Intention	0.912	Reliable
Perceived Ease of Use	0.888	Reliable
Perceived Usefulness	0.914	Reliable

The analysis results from Table 4.7 shows that the composite reliability value for the AU variable is 0.928, for ATU is 0.918, for BI is 0.912, for PEU is 0.888, and for PU is 0.914. All of these composite reliability values are equal to or greater than 0.70, indicating that each variable demonstrates strong reliability. This means that the indicators within each construct consistently measure the intended concept with a high degree of internal consistency.

2. Inner Model

The inner model in PLS-SEM describes the relationships between latent variables and is evaluated to determine the strength and significance of these relationships. The evaluation covers three main aspects: R-square, the significance of the relationship (hypothesis testing), and effect size.

1. R Square (R^2)

In PLS-SEM, R Square measures the extent to which the latent independent variables in the model can explain the variability of the latent dependent variables. The R^2 value reflects the overall predictive strength of the model, ranging from 0 to 1, with higher values indicating a greater ability of the model to explain variance. The R^2 test results for this model are presented in Table 4.8

Table 4. 8 R-Square Table

Dependent Variables	R-square	R-square adjusted
Actual Use	0.561	0.559
Attitude Toward Use	0.743	0.740
Behavioral Intention	0.684	0.682
Perceived Usefulness	0.674	0.672

Based on the analysis results, the R-Square (R^2) value for the AU variable is 0.561, indicating that 56.1% of the variance in this variable is explained by the independent variables in the model, while the remaining 43.9% is influenced by other factors outside the model. According to Hair et al. (2019), this value falls into the moderate category. The ATU variable has an R-Square (R^2) value of 0.743, meaning that 74.3% of its variance is explained by the independent variables, with the remaining 25.7% influenced by external factors. This value is classified as substantial, indicating a very strong predictive capability of the model. The BI variable records an R-Square (R^2) value of 0.684, suggesting that 68.4% of its variance is accounted for by the

independent variables, while 31.6% is affected by factors beyond the model. This is also categorized as substantial. Furthermore, the PU variable has an R-Square (R^2) value of 0.674, showing that 67.4% of its variance is explained by the model's independent variables, with the remaining 32.6% influenced by external factors. Based on Hair et al.'s (2019) criteria, this too falls into the substantial category. Overall, these results demonstrate that the research model possesses a good to very good ability to explain the dependent variables under investigation. The PLS-SEM Algorithm output for R-Square (R^2) is illustrated in the following figure.

2. Significance (Hypothesis Testing)

Significance testing in PLS-SEM is conducted to determine whether the relationships between latent variables in the model can be considered statistically significant. This process typically employs the bootstrapping technique, in which the data are resampled to calculate the path coefficients and their standard errors. The results are reported in terms of t-statistics or p-values. A relationship is deemed significant if the p-value is smaller than the predetermined significance level (0.05 in this study). Significant path coefficients indicate that the relationship between the independent and dependent latent variables has strong statistical support, meaning the proposed hypotheses can be accepted. The following section presents the bootstrapping results for both direct and indirect effects in the research model.

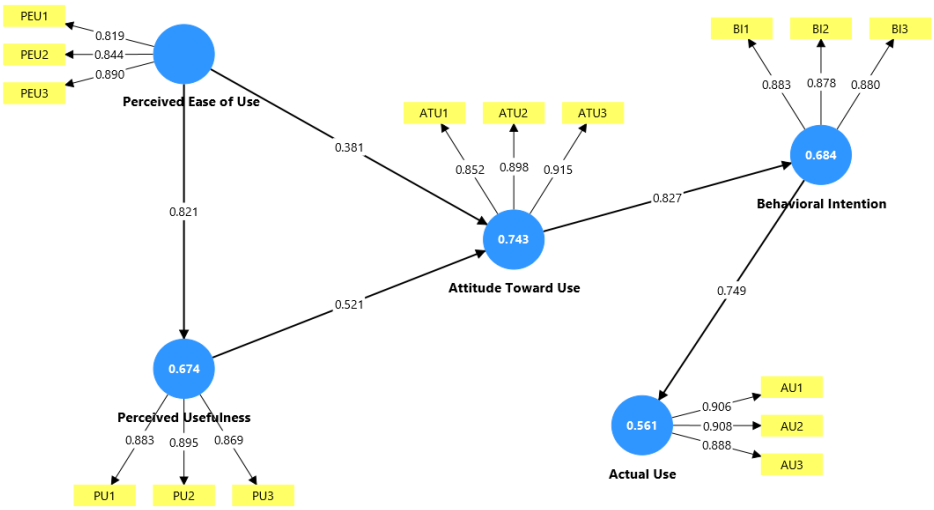


Figure 4. 5 Bootstraping Diagram's Result

1) Bootstrapping Results for *(Direct Effects)*

The bootstrapping results for the direct effects are presented in Table below.

Table 4. 9 Direct Effect Results

Path Coefficient	Original Sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics	P values	Remark
ATU → BI	0.827	0.827	0.030	27.819	0.000	Supported
BI → AU	0.749	0.751	0.041	18.460	0.000	Supported
PEU → ATU	0.381	0.378	0.095	4.036	0.000	Supported
PEU → PU	0.821	0.822	0.028	28.982	0.000	Supported
PU → ATU	0.521	0.525	0.093	5.600	0.000	Supported

Based on the results presented in Table 4.9, According to Hair et al. (2019), a path coefficient is regarded as statistically significant when the t-statistic exceeds 1.96 at the 95%

confidence level, whereas values below this threshold indicate a nonsignificant relationship. Hence, this criterion is employed to decide whether the proposed hypotheses can be accepted or rejected. The relationships among the latent variables can be explained as follows:

- **H1: Effect of Perceived Ease of Use (PEU) on Perceived Usefulness (PU)**

  The first hypothesis (H1) shows a positive path coefficient of 0.821, with a T-statistic of 28.982 (> 1.96) and a P-value of 0.000 (< 0.05). This indicates that PEU has a positive and significant effect on PU. In other words, the easier a technology is perceived to be, the greater its perceived usefulness. Therefore, H1 is supported.

- **H2: Effect of Perceived Ease of Use (PEU) on Attitude Toward Use (ATU)**

  The second hypothesis (H2) records a positive path coefficient of 0.381, with a T-statistic of 4.036 (> 1.96) and a P-value of 0.000 (< 0.05). This finding demonstrates that PEU positively and significantly influences ATU. This means that the easier the technology is to use, the more favorable the user's attitude toward using it. Thus, H2 is supported.

- **H3: Effect of Perceived Usefulness (PU) on Attitude Toward Use (ATU)**

  The third hypothesis (H3) reveals a positive path coefficient of 0.521, with a T-statistic of 5.600 (> 1.96) and a P-value of 0.000 (< 0.05). These results confirm that PU has a positive and significant effect on ATU, suggesting that higher perceived usefulness leads to a more favorable attitude toward using the technology. Hence, H3 is supported.

- **H4: Effect of Attitude Toward Use (ATU) on Behavioral Intention (BI)**

  The fourth hypothesis (H4) yields a positive path coefficient of 0.827, with a T-statistic of 27.819 (> 1.96) and a P-value of 0.000 (< 0.05). This indicates that ATU significantly and positively impacts BI. In other words, a more positive attitude toward technology usage increases the intention to use it. Therefore, H4 is supported.

- **H5: Effect of Behavioral Intention (BI) on Actual Use (AU)**

  The fifth hypothesis (H5) produces a positive path coefficient of 0.749, with a T-statistic of 18.460 (> 1.96) and a P-value of 0.000 (< 0.05). This confirms that BI has a positive and significant effect on AU, meaning that a

stronger behavioral intention to use technology increases the likelihood of its actual usage. Accordingly, H5 is supported.

2) Bootstrapping result for *(indirect effects)*

The bootstrapping results for the indirect effects are presented in Table 4.10 as follows:

Table 4. 10 Indirect Effects Result

Path Coefficient	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics	P values	Remarks
Perceived Ease of Use -> Attitude Toward Use -> Behavioral Intention -> Actual Use	0.236	0.236	0.065	3.611	0.000	Supported
Perceived Ease of Use -> Attitude Toward Use -> Behavioral Intention	0.315	0.313	0.081	3.908	0.000	Supported
Perceived Usefulness -> Attitude Toward Use -> Behavioral Intention -> Actual Use	0.323	0.326	0.061	5.251	0.000	Supported
Perceived Usefulness -> Attitude Toward Use -> Behavioral Intention	0.431	0.434	0.078	5.543	0.000	Supported
Perceived Ease of Use -> Perceived Usefulness -> Attitude Toward Use -> Behavioral Intention	0.354	0.356	0.065	5.429	0.000	Supported
Perceived Ease of Use -> Perceived Usefulness -> Attitude Toward Use -> Behavioral Intention -> Actual Use	0.265	0.268	0.053	5.037	0.000	Supported
Attitude Toward Use -> Behavioral Intention -> Actual Use	0.619	0.622	0.051	12.174	0.000	Supported

Path Coefficient	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics	P values	Remarks
Perceived Ease of Use -> Perceived Usefulness -> Attitude Toward Use	0.428	0.431	0.076	5.590	0.000	Supported

3. Effect Size

In addition to examining the significance of relationships among latent variables, the effect size (f^2) analysis was conducted to assess the magnitude of each independent variable's contribution to the dependent variable. The f^2 value indicates whether the influence of a variable on another within the model is large, medium, or small. The calculated f^2 values for each relationship between variables are presented below.

Table 4. 11 The Calculated of f^2 Values

Variables	Actual Use	Attitude Toward Use	Behavioral Intention	Perceived Ease of Use
Actual Use				
Attitude Toward Use			2.164	
Behavioral Intention	1.277			
Perceived Ease of Use		0.185		
Perceived Usefulness		0.345		2.065

The effect size (f^2) analysis was employed to measure the extent of the influence of independent variables on dependent variables within the research model. The interpretation criteria for f^2 values follow the guidelines of Hair et al. (2019), as presented in the table below.

Table 4. 12 Interpretation Criteria of f^2 Values

F^2 Value	Effect Category
$0.02 \leq f^2 < 0.15$	Small
$0.15 \leq f^2 < 0.35$	Medium
$f^2 \geq 0.35$	Large

Based on the results presented in Table 4.12, the discussion of the effect size among the latent variables is as follows:

1. **Actual Use on Behavioral Intention**

   The f^2 value for this path is 1.277, which falls into the large category. This indicates that Actual Use has a very strong influence in enhancing Behavioral Intention. In other words, high actual usage can significantly drive users' behavioral intention to continue using the system.

2. **Attitude Toward Use on Behavioral Intention**

   The f^2 value for this path is 2.164, also classified as large. This means that attitude toward use makes a highly significant contribution to increasing Behavioral Intention. A positive user attitude toward the system is an important factor influencing their intention to continue using it.

3. **Perceived Ease of Use on Attitude Toward Use**

   The f^2 value for this path is 0.185, which is in the medium category. This suggests that perceived ease of use plays a reasonably important role in shaping attitude toward use. Although its influence is not as great as other variables, the

perceived ease of use remains a factor to consider for improving users' positive attitudes.

4. **Perceived Usefulness on Attitude Toward Use**

   The f^2 value for this path is 0.345, also classified as medium. This shows that perceived usefulness makes a considerable contribution to shaping a positive attitude toward use. The greater the benefits perceived by users, the more positive their attitude toward the system.

Based on the effect size (f^2) analysis, the path with the greatest influence on other variables is Attitude Toward Use on Behavioral Intention, with a value of 2.164, followed by Actual Use on Behavioral Intention, with a value of 1.277. Meanwhile, Perceived Ease of Use and Perceived Usefulness have a medium effect on Attitude Toward Use. These findings confirm that users' positive attitudes and the level of actual use are key factors in shaping the behavioral intention to use the system.

4.2 Discussion

The findings of this research provide strong empirical support for the Technology Acceptance Model (TAM) in explaining students' adoption of Artificial Intelligence (AI) tools in higher education. Using PLS-SEM analysis, the study confirmed that the five main constructs Perceived Ease of Use (PEU), Perceived Usefulness (PU), Attitude Toward Use (ATU), Behavioral Intention (BI), and Actual Use (AU) are significantly interrelated, forming a coherent

pathway from initial perceptions to actual behavioral outcomes. This result underscores the relevance of TAM in predicting technology adoption behavior in the context of emerging educational technologies in Indonesia.

Furthermore, this study emphasized the strong and significant effect is the strong and significant effect of PEU on PU ($\beta = 0.601$, $p < 0.001$, $f^2 = 0.568$). Students who find AI tools such as ChatGPT, Grammarly, or DeepSeek intuitive and user-friendly tend to view them as more beneficial for their academic tasks. This aligns with Davis & Granić (2024), who emphasized that ease of use not only reduces cognitive load but also increases perceived value. In practice, when students can operate AI tools without complex instructions or steep learning curves, they can focus more on learning outcomes rather than the mechanics of the technology itself. Similar results were reported by Mahmudi et al. (2023), who found that in distance learning environments, usability was a decisive factor for sustained AI tool adoption. Thus, the evidence confirms that ease of use acts as a foundational driver of perceived usefulness, highlighting its critical role in shaping students' positive attitudes toward AI integration in higher education.

The second key relationship, PEU → ATU ($\beta = 0.344$, $p < 0.001$, $f^2 = 0.195$), further reinforces the role of usability. A straightforward interface and responsive system foster positive emotional reactions, making students more receptive to AI integration in their study routines. This finding reflects Wang et al. (2023), who observed that ease of interaction encourages favorable attitudes toward digital tools, especially when paired with supportive institutional environments. In the Indonesian context, where digital literacy levels may vary significantly, this

relationship suggests that investing in usability is essential to building positive perceptions.

Equally important is the substantial effect of PU on ATU ($\beta = 0.524$, $p < 0.001$, $f^2 = 0.400$). Students who believe that AI tools enhance their learning performance by improving writing quality, speeding up assignments, or providing better comprehension of materials are more likely to develop favorable attitudes toward them. This supports the TAM proposition that perceived usefulness is a primary driver of acceptance. The finding resonates with Herawati et al. (2024), who documented those clear academic benefits strongly influence openness to integrating technology into learning processes. In this study, this effect also reflects students' growing reliance on AI tools not just for routine tasks, but also for complex academic challenges such as research synthesis and thesis writing.

The transition from attitudes to intentions is captured by the strong link ATU → BI ($\beta = 0.699$, $p < 0.001$, $f^2 = 0.703$). This relationship indicates that once students develop a positive disposition toward AI, they are highly likely to commit to its future use. The effect size here is notably large, highlighting the centrality of attitudes in predicting behavioral intentions. This aligns with Sîrghi et al. (2024), who reported that favorable perceptions were directly associated with consistent intentions to adopt educational technologies. In conclusion, attitudes serve as a pivotal bridge between students' evaluations of AI and their actual commitment, underscoring the importance of fostering positive experiences to ensure long-term adoption.

The final link in the TAM sequence, BI → AU, is particularly strong in this study ($\beta = 0.763$, $p < 0.001$, $f^2 = 1.382$). This shows that behavioral intention is not just a theoretical predictor but translates effectively into actual usage behavior. Students who plan to use AI tools are indeed implementing them regularly in their academic tasks ranging from grammar checking and paraphrasing to data analysis and idea generation (Msambwa et al., 2025). The strength of this path confirms that fostering intention is critical for ensuring long-term adoption.

From a predictive perspective, the R^2 values indicate the model explains a substantial portion of the variance in key constructs: PU ($R^2 = 0.361$), ATU ($R^2 = 0.621$), BI ($R^2 = 0.489$), and AU ($R^2 = 0.582$). These values exceed the threshold of 0.25 suggested by Hair et al. (2019), with ATU and AU reaching moderate-to-substantial predictive levels. This indicates the model captures the dynamics of AI adoption effectively within the sampled population.

When compared with previous studies, these findings are broadly consistent with global patterns but reveal distinctive local features. Internationally, Aldossary et al. (2024) found high readiness levels among Saudi students, driven by institutional infrastructure and awareness campaigns. In contrast, this study's Indonesian sample points to more grounded challenges, such as limited access to premium AI features due to subscription costs, and skepticism toward AI accuracy without human verification. These constraints, while not diminishing students' interest in adopting AI for learning, highlight the importance of contextual factors such as affordability, technological accessibility, and trust in system reliability. Unlike the contexts reported in developed settings, where infrastructure and

institutional support reduce barriers to adoption, the Indonesian case underscores the need for policies and educational strategies that address cost-related limitations and build confidence in AI-assisted learning. This suggests that while global trends indicate a generally positive attitude toward AI integration, localized interventions remain crucial to ensure equitable and effective use in diverse educational environments.

CHAPTER V

CONCLUSION AND RECOMMENDATION

5.1 Conclusion

This study explored the role of AI in higher education through the Technology Acceptance Model (TAM). The analysis confirmed that all proposed relationships—PEU → PU, PEU → ATU, PU → ATU, ATU → BI, and BI → AU were statistically significant. The results highlight that Perceived Ease of Use (PEU) is a fundamental factor, as students who find AI tools simple and intuitive also perceive them as more useful and develop positive attitudes toward their use. Perceived Usefulness (PU) further strengthens these attitudes by demonstrating clear academic benefits, such as improved writing quality, efficiency in completing tasks, and enhanced comprehension. Positive Attitudes (ATU) then translate into strong Behavioral Intentions (BI), which consistently predict Actual Use (AU) of AI tools for various academic purposes.

From a predictive standpoint, the model shows moderate to substantial explanatory power, indicating that TAM effectively captures the drivers of AI adoption in this context. The findings also align with global studies but reveal unique challenges for Indonesian students, including limited access to premium AI features, concerns about accuracy, and the need for critical evaluation of AI-generated outputs.

Overall, this study concluded that AI adoption in higher education follows a sequential process: ease of use leads to perceived usefulness, which fosters positive attitudes, and these attitudes shape behavioral intentions that ultimately result in

actual usage. While the adoption level is promising, sustainable integration requires supportive institutional policies, targeted training, and mechanisms to ensure accessibility, accuracy, and ethical use of AI tools in the academic environment. In addition, the results emphasize the importance of preparing students not only as passive users of AI but also as critical thinkers who can evaluate and responsibly apply AI-generated outputs. This dual approach will help ensure that the integration of AI in higher education enhances learning outcomes while maintaining academic integrity and equity.

5.2 Recommendation

In light of the findings and discussions, this study puts forward several recommendations to support the effective integration of AI in higher education. These suggestions are intended to guide different stakeholders in addressing current challenges, optimizing opportunities, and ensuring that the use of AI contributes meaningfully to the learning process. The recommendations are outlined as follows:

1. For Higher Education Institutions
    a. Provide institutional access to premium AI tools to eliminate cost barriers for students.
    b. Organize regular workshops and training to improve digital literacy and AI tool proficiency.
    c. Integrate AI-based activities into course curricula, ensuring that usage is purposeful and aligned with learning objectives.

2. For Lecturers and Educators
    a. Demonstrate practical applications of AI tools in academic work, showing clear benefits for learning outcomes.
    b. Encourage students to critically evaluate AI outputs to maintain accuracy, originality, and ethical use.
    c. Share case studies and peer experiences to promote positive perceptions and trust in AI-assisted learning.
3. For Students
    a. Use AI tools strategically to enhance, not replace, personal academic effort and critical thinking.
    b. Develop the habit of verifying AI-generated content to ensure credibility and reliability.
    c. Exchange tips, resources, and best practices with peers to maximize the benefits of AI adoption.
4. For Future Researchers
    a. Expand the TAM framework by including variables such as trust, perceived risk, or prior experience with AI.
    b. Conduct longitudinal studies to observe changes in perceptions and usage patterns over time.
    c. Explore demographic factors such as gender, discipline, and academic level to design more targeted AI adoption strategies.

REFERENCES

Afrin, N. A. A. (2023). Artificial Intelligences (AI) In Education. *Tuijin Jishu/Journal of Propulsion Technology*, *44*(3), 936–942. https://doi.org/10.52783/tjjpt.v44.i3.395

Aidah Novianti Putri, & Moh. Abdul Kholiq Hasan. (2022). Penerapan Kecerdasan Buatan sebagai Media Pembelajaran Bahasa Arab di Era Society 5.0. *Tarling : Journal of Language Education*, *7*(1), 69–80. https://doi.org/10.24090/tarling.v7i1.8501

Aldossary, A. S., Aljindi, A. A., & Alamri, J. M. (2024). The role of generative AI in education: Perceptions of Saudi students. *Contemporary Educational Technology*, *16*(4). https://doi.org/10.30935/cedtech/15496

Allen, J., Galescu, L., Teng, C. M., & Perera, I. (2020). Conversational agents for complex collaborative tasks. *AI Magazine*, *41*(4), 54–78. https://doi.org/10.1609/aimag.v41i4.7384

Alneyadi, S., Wardat, Y., Alshannag, Q., & Abu-Al-Aish, A. (2023). The effect of using smart e-learning app on the academic achievement of eighth-grade students. *Eurasia Journal of Mathematics, Science and Technology Education*, *19*(4). https://doi.org/10.29333/EJMSTE/13067

Alqahtani, T., Badreldin, H. A., Alrashed, M., Alshaya, A. I., Alghamdi, S. S., bin Saleh, K., Alowais, S. A., Alshaya, O. A., Rahman, I., Al Yami, M. S., & Albekairy, A. M. (2023). The emergent role of artificial intelligence, natural learning processing, and large language models in higher education and research. *Research in Social and Administrative Pharmacy*, *19*(8), 1236–1242. https://doi.org/10.1016/j.sapharm.2023.05.016

Bhutoria, A. (2022). Personalized education and Artificial Intelligence in the United States, China, and India: A systematic review using a Human-In-The-Loop model. *Computers and Education: Artificial Intelligence*, *3*(April), 100068. https://doi.org/10.1016/j.caeai.2022.100068

Buabbas, A. J., Miskin, B., Alnaqi, A. A., Ayed, A. K., Shehab, A. A., Syed-Abdul, S., & Uddin, M. (2023). Investigating Students' Perceptions towards Artificial Intelligence in Medical Education. *Healthcare (Switzerland)*, *11*(9), 1–16. https://doi.org/10.3390/healthcare11091298

Caldarini, G., Jaf, S., & McGarry, K. (2022). A Literature Survey of Recent Advances in Chatbots. *Information (Switzerland)*, *13*(1), 1–24. https://doi.org/10.3390/info13010041

Chan, C. K. Y., & Colloton, T. (2024). Generative AI in Higher Education: The ChatGPT Effect. In *Generative AI in Higher Education: The ChatGPT Effect*. https://doi.org/10.4324/9781003459026

Chan, C. K. Y., & Hu, W. (2023). Students' voices on generative AI: perceptions, benefits, and challenges in higher education. *International Journal of Educational Technology in Higher Education*, *20*(1). https://doi.org/10.1186/s41239-023-00411-8

Chukwuere, J. E. (2024). The Future of Generative AI Chatbots in Higher Education. *Journal of Emerging Technologies*, *4*(1), 1–14.

Creswell, J. W., & Creswell, J. D. (2023). Research Design, Qualitative, Quantitative and Mixed Methods Approaches. In *SAGE Publications,Inc.: Vol. Sixth Edit* (Issue 1).

Davar, N. F., Dewan, M. A. A., & Zhang, X. (2025). AI Chatbots in Education: Challenges and Opportunities. *Information (Switzerland)*, *16*(3). https://doi.org/10.3390/info16030235

Davis, F. D., & Granić, A. (2024). The Technology Acceptance Model: 30 Years of TAM. In *Technology* (Vol. 1, Issue 1). https://link.springer.com/10.1007/978-3-030-45274-2

Delcker, J., Heil, J., Ifenthaler, D., Seufert, S., & Spirgi, L. (2024). First-year students AI-competence as a predictor for intended and de facto use of AI-tools for supporting learning processes in higher education. *International Journal of Educational Technology in Higher Education*, *21*(1). https://doi.org/10.1186/s41239-024-00452-7

Fiandini, M., Nandiyanto, A. B. D., Al Husaeni, D. F., Al Husaeni, D. N., & Mushiban, M. (2023). How to Calculate Statistics for Significant Difference Test Using SPSS: Understanding Students Comprehension on the Concept of Steam Engines as Power Plant. *Indonesian Journal of Science and Technology*, *9*(1), 45–108. https://doi.org/10.17509/ijost.v9i1.64035

Garcia, M. B. (2025). Teachers in the metaverse: the influence of avatar appearance and behavioral realism on perceptions of instructor credibility and teaching effectiveness. *Interactive Learning Environments*. https://doi.org/10.1080/10494820.2025.2462144

Glickman, M., & Zhang, Y. (2024). AI and Generative AI for Research Discovery and Summarization. *Harvard Data Science Review*, *6*(2), 1–34. https://doi.org/10.1162/99608f92.7f9220ff

Görgülü, D. (2025). A case study on the perception of artificial intelligence by gifted students in Turkey. *Journal of Digital Educational Technology*, *5*(1), 1–

10. https://doi.org/https://doi.org/10.30935/jdet/15809

Grenander, M., Belfer, R., Kochmar, E., Serban, I. V., St-Hilaire, F., & Cheung, J. C. K. (2021). Deep Discourse Analysis for Generating Personalized Feedback in Intelligent Tutor Systems. *35th AAAI Conference on Artificial Intelligence, AAAI 2021*, *17B*, 15534–15544. https://doi.org/10.1609/aaai.v35i17.17829

Guo, S., Binti, H., Halim, A., Rashid, M., & Mohd, B. (2025). Leveraging AI-enabled mobile learning platforms to enhance the effectiveness of English teaching in universities. *Malaysian Journal of Social Sciences and Humanities (MJSSH)*, *9*(12), 1–10.

Hahn, M. G., Navarro, S. M. B., De La Fuente Valentin, L., & Burgos, D. (2021). A systematic review of the effects of automatic scoring and automatic feedback in educational settings. *IEEE Access*, *9*, 108190–108198. https://doi.org/10.1109/ACCESS.2021.3100890

Hair, Joseph F.; Hult, G. Tomas M.; Ringle, Christian M.; Sarstedt, M. (2019). Multivariate Data Analysis (Eight Edition). In *SAGE Publications, Inc.* (Vol. 19, Issue 3). https://doi.org/10.5117/2006.019.003.007

Hair, J., & Alamer, A. (2022). Partial Least Squares Structural Equation Modeling (PLS-SEM) in second language and education research: Guidelines using an applied example. *Research Methods in Applied Linguistics*, *1*(3), 100027. https://doi.org/10.1016/j.rmal.2022.100027

Herawati, A. A., Yusuf, S., Ilfiandra, I., Taufik, A., & Ya Habibi, A. S. (2024). Exploring the Role of Artificial Intelligence in Education, Students Preferences and Perceptions. *AL-ISHLAH: Jurnal Pendidikan*, *16*(2), 1029–1040. https://doi.org/10.35445/alishlah.v16i2.4784

Juma, H., & Patel, G. S. (2023). AI-Assisted Learning in Higher Education : Exploring the Pedagogical Potential of ChatGPT. *Scientific Reports*, 303–311. https://doi.org/https://doi.org/10.1234/ijet.2024.0101

Jupalli, T. K., Reddy, M. S. T., & Kondaveeti, H. K. (2022). Artificial intelligence in higher education. In *Mobile and Sensor-Based Technologies in Higher Education*. https://doi.org/10.4018/978-1-6684-5400-8.ch001

Katz, A., Shakir, U., & Chambers, B. (2023). The Utility of Large Language Models and Generative AI for Education Research. *ArXiv*. http://arxiv.org/abs/2305.18125

Khosravi, H., Sadiq, S., & Amer-Yahia, S. (2023). Data management of AI-powered education technologies: Challenges and opportunities. *Journal of Learning Letters*, *1*, 1–11. https://doi.org/10.59453/xlud7002

Klimova, B., & Pikhart, M. (2025). Exploring the effects of artificial intelligence

on student and academic well-being in higher education: a mini-review. *Frontiers in Psychology*, *16*(February), 1–5. https://doi.org/10.3389/fpsyg.2025.1498132

Kline, R. B. (2015). Principles and Practice of Structural Equation Modeling. In *Canadian Graduate Journal of Sociology and Criminology* (Vol. 1, Issue 1). https://doi.org/10.15353/cgjsc-rcessc.v1i1.25

Kuphanga, D. (2024). Questionnaires in Research: Their Role, Advantages, and Main Aspects. *ActionAid International*, *March*, 1–8. https://doi.org/10.13140/RG.2.2.15334.64325

Lee, A. V. Y. (2020). Artificial intelligence in education (AIEd). *ICCE 2020 - 28th International Conference on Computers in Education, Proceedings*, *2*(1), 749–751.

Loock, R., & Léchauguette, S. (2021). Machine translation literacy and undergraduate students in applied languages: Report on an exploratory study. *Revista Tradumatica*, *19*, 204–225. https://doi.org/10.5565/rev/tradumatica.281

Mahmudi, A. A., Fionasari, R., Mardikawati, B., & Judijanto, L. (2023). Integration of Artificial Intelligence Technology in Distance Learning in Higher Education. *Journal of Social Science Utilizing Technology*, *1*(4), 190–201. https://doi.org/10.70177/jssut.v1i4.661

Mayasari, N., Dewantara, R., & Yuanti, Y. (2023). Pengaruh Kecerdasan Buatan dan Teknologi Pendidikan terhadap Peningkatan Efektivitas Proses Pembelajaran Mahasiswa di Jawa Timur. *Jurnal Pendidikan West Science*, *01*(12), 851–858. https://doi.org/https://doi.org/10.58812/jpdws.v1i12.863

Msambwa, M., Wen, Z., & Kangwa, D. (2025). The impact of ai on the personal and collaborative learning environments in higher education. *European Journal of Education*, *60*(1). https://doi.org/10.1111/ejed.12909

Muldner, K., Luckin, R., Eds, E. M., & Goebel, R. (2020). *Series Editors*. https://doi.org/10.1007/978-3-030-52237-7

Nguyen, N. D. (2023). Exploring the role of AI in education. *London Journal of Social Sciences*, *6*, 84–95. https://doi.org/10.31039/ljss.2023.6.108

Nurtanto, M., Nawanksari, S., Sutrisno, V. L. P., Syahrudin, H., Kholifah, N., Rohmantoro, D., Utami, I. S., Mutohhari, F., & Hamid, M. A. (2025). Determinants of behavioral intentions and their impact on student performance in the use of AI technology in higher education in Indonesia: A SEM-PLS analysis based on TPB, UTAUT, and TAM frameworks. *Social Sciences and Humanities Open*, *11*(June), 101638.

https://doi.org/10.1016/j.ssaho.2025.101638

Oyebola Olusola Ayeni, Nancy Mohd Al Hamad, Onyebuchi Nneamaka Chisom, Blessing Osawaru, & Ololade Elizabeth Adewusi. (2024). AI in education: A review of personalized learning and educational technology. *GSC Advanced Research and Reviews*, *18*(2), 261–271. https://doi.org/10.30574/gscarr.2024.18.2.0062

Saito, N. (2024). The Comparative Analysis of National Policies for Research and Education Regarding Usage of Generative AI in Japan , the USA and the UK The Comparative Analysis of National Policies for Research and Education Regarding Usage of Generative AI in Japan , th. *EconStor Preprint*. https://doi.org/https://www.econstor.eu/handle/10419/302516

Sánchez-Vera, F., Reyes, I. P., & Cedeño, B. E. (2024). Impact of Artificial Intelligence on Academic Integrity : Perspectives of Faculty Members in Spain. *Octaedro*, 13–30. https://doi.org/https://doi.org/10.36006/09643-1-01

Sîrghi, N., Voicu, M. C., Noja, G. G., & Socoliuc, O. R. (2024). Challenges of Artificial Intelligence on the Learning Process in Higher Education. *Amfiteatru Economic*, *26*(65), 53–70. https://doi.org/10.24818/EA/2024/65/53

Sugiyono. (2021). *Metode Penelitian Pendidikan (Kuantitatif,Kualitatif,Kombinasi,R&D dan Penelitian Pendidikan)* (3rd ed.). ALFABETA.

TAŞÇI, G., & DURMUŞÇELEBİ, M. (2020). Eğitimde Yeni Bir Paradigma: "Yükseköğretimde Yapay Zekâ." *OPUS Uluslararası Toplum Araştırmaları Dergisi*, *16*(29), 2346–2370. https://doi.org/10.26466/opus.747634

Vuorikari, R., Kluzer, S., & Punie, Y. (2022). DigComp 2.2. The Digital Competence Framework for Citizens. With new examples of knowledge, skills and attitudes. In *Publications Office of the European Union* (Issue KJ-NA-31006-EN-N (online),KJ-NA-31006-EN-C (print)). https://doi.org/10.2760/115376

Wang, F., King, R. B., Chai, C. S., & Zhou, Y. (2023). University students ' intentions to learn artificial intelligence : the roles of supportive environments and expectancy – value beliefs. *International Journal of Educational Technology in Higher Education*. https://doi.org/10.1186/s41239-023-00417-2

Wang, T., Lund, B. D., Marengo, A., Pagano, A., Mannuru, N. R., Teel, Z. A., & Pange, J. (2023). Exploring the Potential Impact of Artificial Intelligence (AI) on International Students in Higher Education: Generative AI, Chatbots, Analytics, and International Student Success. *Applied Sciences (Switzerland)*, *13*(11). https://doi.org/10.3390/app13116716

Wong, K. K.-K. (2019). Partial Least Squares Structural Equation Modeling (PLS-SEM) Techniques Using SmartPLS. In *Marketing Bulletin* (Vol. 24, Issue 1). Marketing Bulletin.

Woo, D. J., Blood, P., School, S., Kong, H., Susanto, H., Yeung, C. H., Guo, K., Ka, A., Fung, Y., & Ping, H. (2024). Exploring AI-Generated text in student writing: How does AI help? *Language Learning & Technology*, *28*(2), 183–209. https://hdl.handle.net/10125/73577

Xu, Z. (2025). *Patterns and Purposes: A Cross-Journal Analysis of AI Tool Usage in Academic Writing*. 1–21. http://arxiv.org/abs/2502.00632

Yu, S., & Lu, Y. (2021). An Introduction to Artificial Intelligence in Education. In *Bridging Human and Machine: Future Education with Intelligence*. https://doi.org/10.1007/978-981-16-2770-5

Yun, H. S., Taliaronak, V., Kirtay, M., Chevelère, J., Hübert, H., Hafner, V. V., Pinkwart, N., & Lazarides, R. (2023). *Challenges in Designing Teacher Robots with Motivation Based Gestures*. 1–3. https://doi.org/https://arxiv.org/abs/2302.03942

APPENDICES

Appendix 1 Blueprint Online Questionnaire

Title : The Role of Artificial Intelligence in Education: A Survey Study in Indonesia

Purpose : To examine the role of AI applications in students' learning processes and to identify the factors influencing their intention to adopt AI in higher education.

Blueprint

Theory	Aspects	Indicators	Item Number
Technology Acceptance Model (TAM) (Davis & Granic 2024)	Perceived Ease of Use (PEU)	PEU refers to students' belief that AI tools are simple and intuitive to operate.	1
		PEU is used to examine whether students see AI tools as easy to use and helpful, even without advanced technical skills.	2
		PEU is seen as an early factor that influences students' intention to use AI in learning environments.	3
	Perceived Usefulness (PU)	PU represents the degree to which students believe that AI tools enhance their learning effectiveness or academic performance.	4
		PU significantly improve students' learning productivity.	5
		PU contributes to the credibility of AI as a learning partner rather than a novelty.	6
	Attitude Toward Use (ATU)	ATU refers to students' overall judgment, positive or negative toward the use of AI technologies in their learning process.	7
		ATU includes emotional responses such as enthusiasm, skepticism, or anxiety, as well as openness to future use.	8
		ATU is determining how students evaluate AI not just functionally, but also personally and socially in the learning context.	9
	Behavioral Intention (BI)	BI refers to students' expressed readiness or plan to use AI tools in their academic tasks.	10

Theory	Aspects	Indicators	Item Number
		BI serves as a predictor of actual behavior, indicating how likely students are to continue using AI for learning.	11
		BI includes intentions to use tools regularly and predict the long-term viability of AI adoption.	12
	Actual Use (AU)	AU refers to how frequently and consistently students incorporate AI tools into their academic activities.	13
		AU measures real engagement and usage behavior and is embedded in students' learning strategies.	14
		AU assesses whether student perceptions and intentions translate into habitual use.	15

Appendix 2 Details of the Statements

Variable	Code	Item Statement	Strongly Disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
Perceived Ease of Use (PEU)	PEU1	I believe that AI tools are simple to operate and easy to use for academic purposes.					
	PEU2	I think AI tools are user-friendly and helpful without additional technical skills.					
	PEU3	I ensure that AI tools are easy to use to assist with any of the academic learning assignments.					
Perceived Usefulness (PU)	PU1	I believe AI tools enhance my learning effectiveness and academic performance.					
	PU2	I feel that using AI tools significantly improves my learning productivity.					
	PU3	I consider AI tools credible learning partner, not just a temporary novelty.					
Attitude Toward Use (ATU)	ATU1	I have a positive intention and attitude toward using AI in my learning process.					

Variable	Code	Item Statement	Strongly Disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
	ATU2	I am very enthusiastic about using AI tools for learning.					
	ATU3	I am open to using AI tools in the future because I see it as personally and socially valuable in my studies.					
Behavioral Intention (BI)	BI1	I intend to use AI tools regularly to check my grammar mistakes.					
	BI2	I usually develop my learning ideas with the help of AI tools.					
	BI3	AI tools usually assist me in writing and summarizing my academic sources.					
Actual Use (AU)	AU1	I frequently and consistently use AI tools in my academic activities.					
	AU2	I actively engage with AI tools as part of my learning strategies.					
	AU3	I use AI tools regularly, reflecting my intention and habit in learning.					

Appendix 3. Responses of Online Surveys in Indonesia Universities

No	Perceived Ease of Use			Perceived Usefulness			Attitude Toward Use			Behavioural Intention			Actual Use		
	PEU 1	PEU 2	PEU 3	PU 1	PU 2	PU 3	ATU 1	ATU 2	ATU 3	BI 1	BI 2	BI 3	AU 1	AU 2	AU 3
1	4	2	3	4	4	4	4	4	4	4	4	5	5	5	5
2	5	4	5	4	2	4	5	3	2	4	5	5	2	2	2
3	5	2	5	3	5	5	5	5	5	5	5	3	5	5	3
4	5	4	3	3	2	3	4	4	3	3	3	4	3	3	2
5	4	4	3	2	3	3	4	3	4	4	4	4	3	3	2
6	5	2	3	1	3	4	4	4	4	4	5	4	4	4	4
7	4	4	5	5	5	4	5	5	5	5	4	4	5	5	5
8	5	4	4	4	4	4	3	4	4	5	5	5	2	5	4
9	3	3	3	2	3	3	3	3	4	3	3	4	3	3	3
10	4	4	4	4	3	3	4	4	4	5	5	4	3	3	3
11	5	4	4	4	4	4	4	3	4	5	5	4	4	4	3
12	5	3	5	5	5	5	5	5	4	4	4	3	4	3	4
13	4	4	4	4	5	4	4	4	4	4	4	4	4	4	4
14	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5
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