COGENT EDUCATION
2024, VOL. 11, NO. 1, 2386892
https://doi.org/10.1080/2331186X.2024.2386892

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HIGHER EDUCATION | RESEARCH ARTICLE

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# An exploratory study of artificial intelligence adoption in higher education

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**ABSTRACT**

Higher education has seen substantial changes with the growing integration of computer-based intelligence technologies into the learning process. Nevertheless, the acceptance of computer-based intelligence in advanced educational settings is still faced with various difficulties, including perceived dangers, implementation assumptions, and exertion assumptions. This exploration plans to determine the relationship between risk policies, implementation assumptions, and effort assumptions with social expectations regarding the acceptance of computer-based intelligence innovations in advanced educational organizations in North Sulawesi, Indonesia. Moreover, this exploration also tests the role of social goals as a mediator variable connecting these elements. As a research method, a survey was conducted using a survey of students and academic staff from various universities in North Sulawesi with a sample size of 330 people with different educational backgrounds. The research results show that risk perception, performance expectations, and effort expectations have a large influence on behavioral intentions to adopt artificial intelligence (AI) in higher education. In addition, this study found that behavioral intention acts as a moderator that moderates the relationship between perceived risks, performance expectations; while effort expectations through behavioral intentions do not have a significant influence on AI adoption. These results provide valuable insights for higher education institutions in planning AI adoption strategies, with a focus on managing perceived risk, increasing performance expectations, and reducing effort expectations. In addition, this research also highlights the large role of recognizing behavioral intentions in the process of adopting AI technology in higher education, so that it can increase the effectiveness of its implementation.

**PUBLIC INTEREST STATEMENT**

This research highlights the role of technological innovation, particularly artificial intelligence, in the context of higher education. The focus is on how colleges adopt these technologies and how individual behavioral intentions influence such adoption. This has broad implications and is relevant to the general public. Firstly, this research offers insights into how artificial intelligence can enhance students' learning experience. With intelligent algorithms, learning systems can be tailored to individual needs, providing a more personalized and effective approach to learning. Secondly, the findings of this study also highlight the role of lecturers and academic staff in adopting this technology. By understanding the factors that influence their behavioral intentions, higher education institutions can develop better strategies to support the use of technology in the learning process. In addition, this research is relevant to society as it can open the door to improving the accessibility of higher education. With the right use of technology, quality education can be more accessible to everyone, regardless of geographical or economic boundaries. Overall, this research is not only about academic development, but also about creating a more inclusive, efficient, and innovative future of education for the general public.

**ARTICLE HISTORY**
Received 27 March 2024
Revised 25 July 2024
Accepted 28 July 2024

**KEYWORDS**
Artificial intelligence; higher education; behavioral intention

**SUBJECTS**
Artificial Intelligence; Sustainability Education, Training & Leadership; Higher Education

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## 1. Introduction

The transformation of technology in higher education has opened up a range of new opportunities and challenges, the increased access and flexibility of technology also requires institutions to adapt to change and ensure that its use supports sustainable educational goals. The expansion of technology in education circumstances began with the first computers (Renner et al., 2020). Since that time, educators have employed computers for a multitude of functions, including but not limited to e-learning, accessing digital materials, communication and teamwork, educational data analysis, administrative tasks, and ensuring precision in research and scholarly endeavors. One of the most prominent in current technological developments, especially in the field of higher education, is the presence of artificial intelligence (AI) which is integrated into higher education (Slimi & Carballido, 2023). Artificial intelligence (AI) innovation is going through monstrous advancement from one year to another. Its presence with new elements, capabilities, and appearances is progressively influencing numerous parts of human existence and become an essential piece of the development and improvement of instructive innovation (Luger & Stubblefield, 1993). This has explicit implications for human work life in the future. The incorporation and acceptance of Artificial Intelligence (AI) in higher education have been duly acknowledged in the advancement of higher education in Indonesia, particularly within North Sulawesi, a prominent hub for higher education. Presently, diverse endeavors and actions have been initiated to harness the capabilities of AI within the higher education realm in North Sulawesi. AI has been employed to streamline learning processes, enhance research endeavors, and manage campus administration effectively. One prominent example is the use of AI as Chat GPT, Quillbot, Gramarlly etc. that provide assistance to students, educators, and academic staff in completing their academic tasks. The emergence of AI brings its own challenges for higher education (Duong et al., 2023); one of the main challenges is its influence on the way of thinking of lecturers, students, and overall university policies (Kooli, 2023); as they rely increasingly on automated systems to fulfill their tasks.

Implementing AI technology in higher education comes with both advantages and disadvantages concerning strategies for AI utilization, so having a thorough understanding of the benefits and risks is crucial. Instructive foundations should adopt a decent strategy that boosts the advantages of artificial intelligence while remembering issues of morals, security, and nature of learning (Ibrahim et al., 2023). According to Duong et al. (2023) the utilization of the computer based intelligence bot for tasks has been named scholarly wrongdoing by eight of the 24 colleges in the renowned UK Russell Gathering, including Oxford and Cambridge. In the interim, numerous different colleges all over the planet are hurrying to analyze their counterfeiting approaches, referring to scholarly honesty issues. However, research by Kasneci et al. (2023) contend that generative artificial intelligence can possibly change training and further develop understudies' growth opportunities. As per a few specialists, generative computer based intelligence may be utilized to convey customized criticism and exhortation to understudies, supporting them in identifying weak spots and adaptively fostering their abilities (Montenegro-Rueda et al., 2023). Another research by Fuchs & Aguilos (2023) stated according to a survey of five EU countries, artificial intelligence performance was equivalent if not superior to student for achievement in many subjects. Public and worldwide associations will proceed to needs the conversation and detailing of legitimate and moral standards through UNESCO's system for man-made intelligence in schooling, which depends on a humanistic methodology and endeavors to safeguard basic freedoms while likewise outfitting people with the abilities and values required for long-term development, as well as compelling human-machine cooperation in living, learning, and working (Lewis et al., 2021). This paradigm prioritizes human control over AI and ensures that AI is used to improve teachers' and students' capacities (Duong et al., 2023). Furthermore, This paradigm requires the development of ethical, clear, not discriminatory, and accessible AI applications (Lakshmi et al., 2023).

The adoption of AI remains a topic of lively discussion within higher education in Indonesia. In addition to the advantages and disadvantages faced by higher education providers in North Sulawesi, this study delves deeper into the benefits of AI in fostering a more tailored, efficient, and analytical learning environment. It also examines challenges such as reliance, privacy concerns, and bias that must be considered in the adoption process. Despite acknowledging several concerns within educational environments, policies regarding artificial intelligence in education tend to be generic and specific due to the lack of substantial evidence of implementing AI technologies. This research contributes to the body of knowledge by addressing a theoretical gap in the literature regarding how students perceive artificial intelligence (AI) during their studies. It examines various factors such as perceived risk, performance expectancy, and effort expectancy, with behavioral intention as a mediating variable, to assess the extent to which AI can be idealized with ethical values and positively impact students, educators, academic staff, and other stakeholders without compromising the scholarly aspects of higher education in North Sulawesi, Indonesia.

## 2. Literature review

Artificial Intelligence (AI) rapidly emerging technology domain that is capable of transforming every aspect of our social interactions. In the field of education, AI has started to generate new teaching and learning solutions that are now undergoing testing in different context. According research by Bali et al. (2022) artificial intelligence (AI) is a framework with human mental elements that can consequently supply information and data to develop keen applications to assist with critical thinking, for example, critical thinking, discourse acknowledgment, and learning. The development of AI adoption in higher education in Indonesia cannot be separated from the participation of stakeholders involved in advancing higher education. Many universities and colleges in Indonesia have started to adopt AI technology in the learning process, research and development, higher education administration and distance education as well as cooperation with industry (Pendy, 2023). Research by Priyahita (2020) viewed as 87% of Indonesian respondents perceived the capacity of artificial intelligence innovation in supporting intelligent picking up, including e-Learning, the impact of artificial intelligence towards expanding the adequacy of e-Learning ideas permits combination into the progression of the schooling system in Indonesia. However, it is crucial to remember that the successful use of AI in higher education involves investment in technological infrastructure, training of teaching staff, and the development of suitable curricula (Triastuti & Hastungkara, 2019), Despite the fact that artificial intelligence is a reality, academic research on its application in higher education is still lacking (Hinojo-Lucena et al., 2019).

As one of the providers of higher education, colleges and universities in North Sulawesi are starting to offer AI programed or courses related to the field of education, industry, startups and innovation, collaboration to help create a strong higher education ecosystem. Government investment and support through the *Merdeka Belajar* program since 2020 gives students the freedom to pursue higher education according to their interests, talents and career goals, by artificial intelligence make improve learning, especially through students' talents, collaborative learning in higher education, and an accessible research environment (Kuleto et al., 2021). The great challenge of higher education lies in the process of designing, developing and applying digital skills for better professionals who are able to understand and develop the technological environment in an artificial intelligence format (Ocaña-Fernández et al., 2019). Despite the challenges, the utilization of AI in higher education in North Sulawesi has great potential to improve the efficiency, quality and accessibility of education. With support from the government, universities and the private sector, as well as efforts to overcome the challenges, AI development in North Sulawesi universities could continue to grow in the next few years.

There are various thoughts and models that make sense of why advancement innovations like AI intelligence are being embraced. These hypotheses and models are established on a comprehension of Data Frameworks (IS), Humanism, and Brain science as they apply to the examination, while different speculations and models are overlooked. (Venkatesh et al., 2011) utilizing indistinguishable information, the UTAUT model made sense of around 60% of the difference related with social aim, while different models and hypotheses made sense of 20% to 20% of the change related with conduct aim. As a result, the UTAUT model (Venkatesh et al., 2016) is thought to be effective for predicting people' willingness to accept new technology such as AI. Many researchers have used this model with various modifications, such as eliminating some elements and integrating other constructs based on the research setting, and have had positive findings (Im et al., 2010).

### *2.1. Perceived risk*

Perceived risk is a key component that can influence the adoption of artificial intelligence (AI) technology in a university environment. Based on Cocosila et al. (2009) perceived risk is incorporated as a precursor of motivational factors, and the impression of real or virtual obstacles might have a detrimental influence on technology adoption, and was discovered to have a considerable impact on AI adoption (Salloum et al., 2019). However, many negative elements of this technical advancement are being neglected by artificial intelligence users. Apart from providing several benefits, this phenomenon may also bring substantial risks to people, such as reduced employment prospects and higher unemployment rates (Alzaabi & Shuhaiber, 2022). On the other hand, users' risk perception of technology dominates their knowledge and behavioral control, so perceived expertise and behavioral control do not directly impact their intention to trust the technology (Ho et al., 2017), and decreased these risk concerns (Featherman & Pavlou, 2003). As a result, this study formulates the following hypothesis:

H1: Perceived risk has a negative impact on the adoption of artificial intelligence in higher education.

H2: Perceived risk has a negative impact on behavioral intention to adopt artificial intelligence in higher education.

### *2.2. Performance expectancy*

Performance expectation is a new framework model that is an embodiment of the TAM concept's primary model, and it is theoretically significant for anticipating actors' intents to embrace technology (Riad Jaradat et al., 2020). People must be encouraged to use and recognize a specific innovation when they understand how employing the innovation would add value to their daily lives (Raffaghelli et al., 2022). While previous evidence suggests that technology performance expectations (PE) indirectly influence AI usage confidence, it is unclear how this happens (Figueroa-Armijos et al., 2022), on the contrary with (Andrews et al., 2021) stated that performance expectancy (PE) and attitudes towards using AI and related technologies have a significant influence on academic performance. Therefore, this leads to the following hypothesis:

H3: Performance expectancy has a positive impact on the adoption of artificial intelligence in higher education.

H4: Performance expectancy has a positive impact on behavioral intention to adopt artificial intelligence in higher education.

### *2.3. Effort expectancy*

EE is a critical determinant of innovation acknowledgment, alluding to the apparent usability related with the framework (Hasan Emon et al., 2023). If the technology is user-friendly, EE will be low and the technology will be easy to adopt (Alzahrani, 2023),this includes factors such as difficulty of use, complexity of the technology, system complexity, and the level of skill required to interact with the AI technology (Ragheb et al., 2022). It is critical to figure out some kind of harmony between usability (*Effort Expectancy*) and the advantages presented by computer based intelligence innovation. According to research by Lin et al. (2022) in terms of EE, users don't want to spend too much effort and time learning a new system, It can be concluded that when users find it easy to use AI to get work done, it helps users get things done faster (Mohd Rahim et al., 2022). In addition, individual user behavioral characteristics influence technology adoption leading to the formulation of the following hypotheses:

H5: Effort expectancy has a positive impact on the adoption of artificial intelligence in higher education.

H6: Effort expectancy has a positive impact on behavioral intention to adopt artificial intelligence in higher Education.

### 2.4. Behavioral intention

Moderating variables are an important research issue in the study of technological acceptability (Chen & Huang, 2016). The primary motivation for investigating consumer acceptability, adoption, and use of developing technology is adoption behavior (Schießl et al., 2023). Summarized the relationship between behavioral intentions and technology adoption in terms of UTAUT theory, and observed that technology adoption is influenced by perceived usefulness after use which directly affects behavior (Ching-Ter et al., 2017). Behavioral intention to use in this study is defined in a somewhat similar way to previous research as an individual to use artificial intelligence technology (Humida et al., 2021). Behavioral intention functions as a moderating variable in this research, successfully influencing conduct in favor of the activity to which one's goal becomes apparent (Duong et al., 2023), from this important standpoint, the following hypothesis is formulated.

H7: Behavioral intention has a positive impact to adopt artificial intelligence in higher education.

### 2.5. Adoption artificial intelligence (AI) in higher education

Regarding personalized educational processes in some ways the application of artificial intelligence might be regarded a suitable option, since automated aid provides fresh and exciting perspectives on the dynamism of learning (Bali et al., 2022), as virtual interactions governed by AI parameters facilitate the learning process (Chatterjee & Bhattacharjee, 2020). This is on the grounds that the help systems will be accessible when required, no matter what the client's reality (Pendy, 2023). The preceding causes us to reconsider the teaching-learning process, as the impact of adaptive educational scenarios has a significant impact on traditional learning. As new and improved AI-based apps are produced, it is expected that the new curriculum will be versatile and adaptable to new and stingy methods of perceiving educational activities in this century (Ocaña-Fernández et al., 2019). As a result, the subsequent hypotheses (Figure 1) are identified:

## 3. Methodology

A quantitative research design, descriptive statistics, and correlation analysis are used to discover the relationship between research variables. The statistical analysis of the data was supported by the SPSS and PLS software tools. SPSS was used for basic demographic analysis, and PLS was used to construct the measurement model and structure. These models' dependability and construct validity were

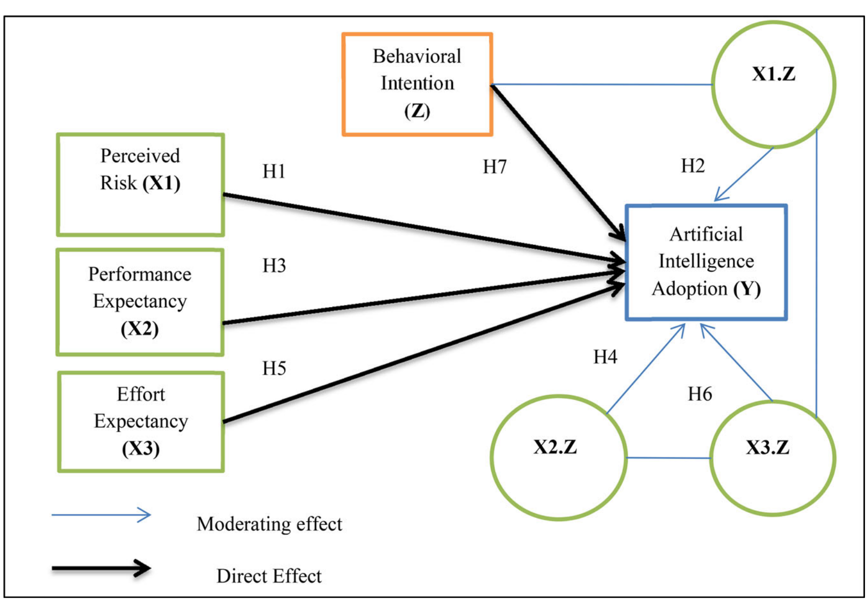


Figure 1. Research frame work.

evaluated, and structural models were used to test the hypothesized relationships between variables. Prior to beginning the method advocated conducting a literature review and documentation study to contextualize the problem statement and identify research gaps. To appropriately capture the construct domain, all variables in the model were measured using various items produced by other researchers. The items were assessed on a five-point Likert scale, with 1 being strongly disagree, 2 being disagree, 3 being neutral, 4 being agree, and 5 being very agreeable. To guarantee content legitimacy and bias, the survey utilized a five-point Likert scale to gather information on the factors of the review model, which was considerably gotten from before research alongside 21 inquiries as explanations for the most part connected with different parts of computer based intelligence innovation for the advanced education area. The researcher selected several leading universities across North Sulawesi located in Manado City, Minahasa Regency, North Minahasa and Mobagu City. We contacted students, teaching staff (lecturers) and administrative staff from these universities and sent questionnaires via email within a period of 90 days (December 2023-February 2024) with a total of 500 questionnaires sent, but we only received 330 questionnaires due to effectiveness bias. The data was statistically analyzed by the authors of this study using SPSS and PLS. SPSS was utilized for preliminary demographic analysis, and PLS was used for measurement model and structural model analyses (Wong, 2019), as shown by Table 1.

## 4. Result

Researchers used Smart-PLS to test the measurement model's convergent validity, discriminant validity, and construct reliability. Purwanto & Sudargini (2021) investigated convergent validity using the extracted average variance (AVE). According to Fornell & Larcker (1981) research, the loading value should be less than 0.50, the CR value less than 0.70, and the AVE value less than 0.50. The measurement model's results are shown in Figure 2, Tables 2–4, correspondingly.

As part of the measurement model evaluation, the reliability of the individual items used to measure each latent construct, as well as the internal consistency reliability (also referred to as construct reliability), discriminant validity, and convergent validity for each construct are evaluated. In this study, the PLS approach was used to determine the reliability of each item and to evaluate different types of measurement models. The current study was found to be reliable and achieved convergent validity, as shown in Tables 2 and 3. This is due to the fact that all loading, alpha CR and AVE values meet the requirements.

According to research findings conducted by Fornell & Larcker (1981), to attain construct discriminant validity, the correlation of a certain variable with other variables must be less than the square root of the AVE. This is thought to be necessary in order to attain the desired level of discriminant validity. Furthermore, in most circumstances, the HTMT ratio is substantially lower than 0.70. Table 4 shows that the research reported here has reached the required degree of discriminant validity.

**Table 1.** Demographics of respondent profile.

| Demographics variable | Categories | Frequency | N = 330 (in Percentages) |
|---|---|---|---|
| Gender | Male | 211 | 63.9 |
| | Female | 119 | 36.1 |
| Age | 17-22 | 117 | 35.5 |
| | 22-27 | 34 | 10.3 |
| | 27-32 | 37 | 11.2 |
| | 32-45 | 90 | 27.3 |
| | 45-50 | 28 | 8.5 |
| | Above 50 | 24 | 7.3 |
| Education Level | Bachelor Degree | 184 | 55.8 |
| | Master | 77 | 23.3 |
| | Doctor | 49 | 14.8 |
| | Full Professor | 20 | 6.1 |
| Occupation | Student | 174 | 52.7 |
| | Lectures | 88 | 26.7 |
| | Academic Staff | 55 | 16.7 |
| | Mentoring Staff | 13 | 3.9 |

*Source*: Author's SPSS 28.

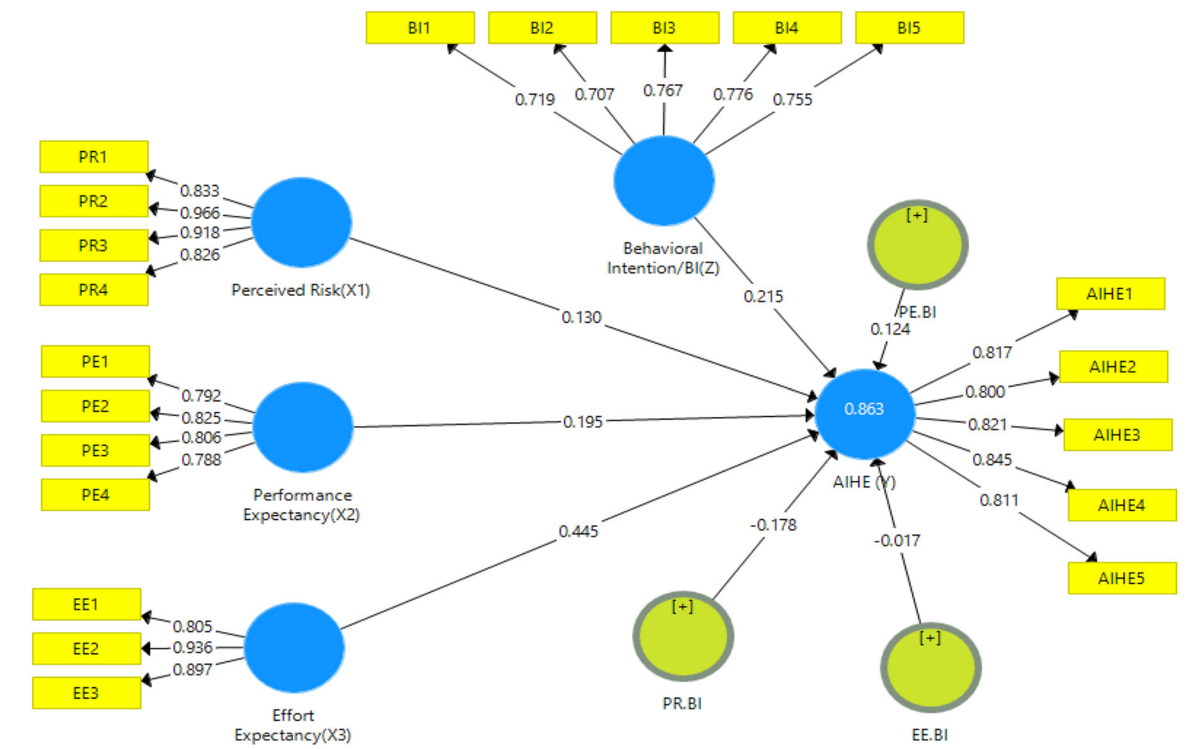


**Figure 2.** Measurement table assessments.

**Table 2.** Outer loadings.

| | AIHE (Y) | Behavioral Intention/BI (Z) | EE.BI | Effort Expectancy (X3) | PE. BI | PR. BI | Perceived Risk (X1) | Performance Expectancy (X2) |
|---|---|---|---|---|---|---|---|---|
| AIHE1 | 0.817 | | | | | | | |
| AIHE2 | 0.800 | | | | | | | |
| AIHE3 | 0.821 | | | | | | | |
| AIHE4 | 0.845 | | | | | | | |
| AIHE5 | 0.811 | | | | | | | |
| BI1 | | 0.719 | | | | | | |
| BI2 | | 0.707 | | | | | | |
| BI3 | | 0.767 | | | | | | |
| BI4 | | 0.776 | | | | | | |
| BI5 | | 0.755 | | | | | | |
| EE1 | | | | 0.805 | | | | |
| EE2 | | | | 0.936 | | | | |
| EE3 | | | | 0.897 | | | | |
| Effort Expectancy(X3) * Behavioral Intention/ BI (Z) | | | 1.213 | | | | | |
| PE1 | | | | | | | | 0.792 |
| PE2 | | | | | | | | 0.825 |
| PE3 | | | | | | | | 0.806 |
| PE4 | | | | | | | | 0.788 |
| PR1 | | | | | | | 0.833 | |
| PR2 | | | | | | | 0.966 | |
| PR3 | | | | | | | 0.918 | |
| PR4 | | | | | | | 0.826 | |
| Perceived Risk(X1) * Behavioral Intention/BI(Z) | | | | | | 0.975 | | |
| Performance Expectancy(X2) * Behavioral Intention/BI(Z) | | | | | 1.093 | | | |

*Source*: Author's Smart PLS 3.

PLS-SEM was utilized to approve the applied model of this examination. To test immediate and aberrant speculations, the bootstrapping approach was used. The outcome showed in Figure 3. Bootstrapping results in SMART PLS provide standard error estimates for each path coefficient. Standard

**Table 3.** Convergent validity, composite reliability, and AVE.

| | Cronbach's Alpha | rho_A | Composite Reliability | Average Variance Extracted (AVE) |
|---|---|---|---|---|
| AIHE (Y) | 0.877 | 0.878 | 0.911 | 0.671 |
| Behavioral Intention/BI(Z) | 0.800 | 0.803 | 0.862 | 0.555 |
| EE.BI | 1.000 | 1.000 | 1.000 | 1.000 |
| Effort Expectancy(X3) | 0.854 | 0.858 | 0.912 | 0.776 |
| PE.BI | 1.000 | 1.000 | 1.000 | 1.000 |
| PR.BI | 1.000 | 1.000 | 1.000 | 1.000 |
| Perceived Risk(X1) | 0.908 | 0.912 | 0.937 | 0.788 |
| Performance Expectancy(X2) | 0.818 | 0.821 | 0.879 | 0.645 |

*Source*: Author's Smart PLS 3.

**Table 4.** Fornell-larcker criterion.

| | AIHE (Y) | Behavioral Intention/BI(Z) | EE.BI | Effort Expectancy(X3) | PE.BI | PR.BI | Perceived Risk (X1) | Performance Expectancy (X2) |
|---|---|---|---|---|---|---|---|---|
| AIHE (Y) | 0.819 | | | | | | | |
| Behavioral Intention/BI(Z) | 0.881 | 0.745 | | | | | | |
| EE.BI | −0.406 | −0.355 | 1.000 | | | | | |
| Effort Expectancy(X3) | 0.878 | 0.889 | −0.474 | 0.881 | | | | |
| PE.BI | −0.323 | −0.235 | 0.629 | −0.264 | 1.000 | | | |
| PR.BI | −0.378 | −0.267 | 0.615 | −0.293 | 0.864 | 1.000 | | |
| Perceived Risk(X1) | 0.763 | 0.742 | −0.235 | 0.635 | −0.324 | −0.386 | 0.888 | |
| Performance Expectancy(X2) | 0.787 | 0.779 | −0.238 | 0.692 | −0.438 | −0.363 | 0.833 | 0.803 |

*Source*: Author's Smart PLS 3.

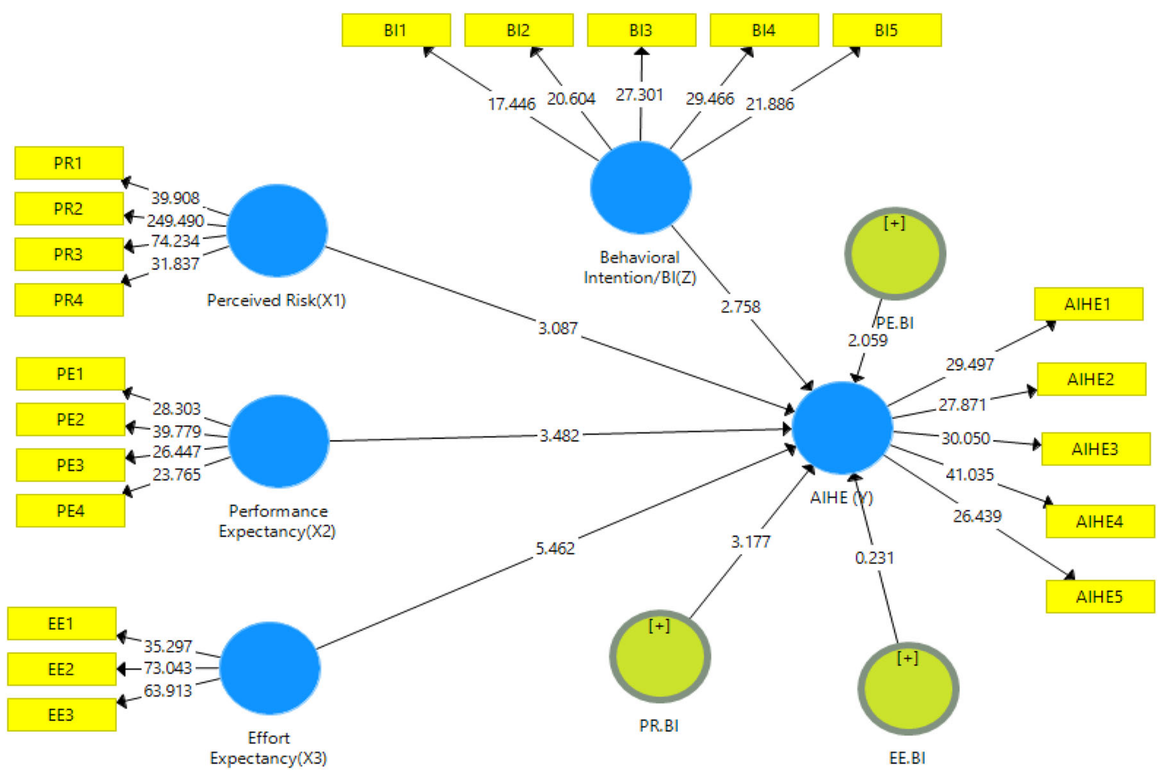


**Figure 3.** Bootstrapping model.

error estimates the degree to which your assessed way coefficients could vary assuming examples were drawn over and again. Bootstrapping produces certainty stretches for every way coefficient to test the speculation in the review. In the event that the way coefficient esteem is positive, the impact of the exogenous variable on the endogenous variable is in a similar heading, as well as the other way around, with a p-value $< 0.05$. The more modest the p-value, the more grounded the proof of a huge connection between the factors being connected. *P-value* estimates the degree of measurable meaning of the way coefficient. A certainty stretch shows the scope of values that most probable contain the genuine

**Table 5.** Direct relationship.

| | Original Sample (O) | Sample Mean (M) | Standard Deviation (STDEV) | T Statistics (\|O/STDEV\|) | *P*-values | Remarks |
|---|---|---|---|---|---|---|
| Behavioral Intention/BI (Z) -> AIHE (Y) | 0.215 | 0.221 | 0.078 | 2.758 | 0.006 | Supported |
| EE.BI -> AIHE (Y) | −0.017 | 0.012 | 0.073 | 0.231 | 0.818 | Not supported |
| Effort Expectancy(X3) -> AIHE (Y) | 0.445 | 0.448 | 0.081 | 5.462 | 0.000 | Supported |
| PE.BI -> AIHE (Y) | 0.124 | 0.106 | 0.060 | 2.059 | 0.040 | Supported |
| PR.BI -> AIHE (Y) | −0.178 | −0.191 | 0.056 | 3.177 | 0.002 | Supported |
| Perceived Risk(X1) -> AIHE (Y) | 0.130 | 0.134 | 0.042 | 3.087 | 0.002 | Supported |
| Performance Expectancy(X2) -> AIHE (Y) | 0.195 | 0.182 | 0.056 | 3.482 | 0.001 | Supported |

*Source*: Author's Smart PLS 3.

population boundary. This confidence interval is useful for assessing the extent to which the path coefficient is reliable. In Figure 3 the Bootstrapping results show that the p-value for each path coefficient is positive with PR = 3.087; PE = 3.482, EE = 5.463, BI = 2.758, while the value for the moderator variable is PR.BI = 3.177; PE.BI = 2.059; EE.BI = 0.231. Among samples from research with students, lecturers, administrative staff, and expert staff at the university level, we conducted the statistical analysis of the correlation between PR, PE, EE, and the average BI of a set of values is the sample mean, or M.

The standard deviation, as shown in Table 5, is a statistical measure that provides a numerical value for the distribution of data around the mean. The T statistic (also known as the O/STDEV statistic) tests whether the observed sample mean and the hypothetical sample mean are similar. This metric shows how much the actual sample mean differs from the estimated mean. The T-statistic measures how closely two variables are related. The p-value expresses the statistical significance of the t-statistic. If the p-value is less than 0.05, there is experimental evidence of a significant relationship between the components. The t-statistics on AI adoption for PR, EE, and BI are all statistically significant ($p < 0.05$), demonstrating a relationship between the variables; however, the correlation of EE with the variable BI as a moderator does not significantly affect AI adoption ($p = 0.818$).

Outer Loading Relationship (OLR) is a concept in path analysis that measures the link between latent variables or constructs and their indicators in a structural mode. In Table 6, it can be concluded that the relationship between latent variables or constructs and their indicators (observed variables or manifest variables) is positive with OLR values ranging from -1 to 1. Positive values indicate a positive relationship between the construct and its indicators, while negative values indicate a negative relationship. Overall, the relationship between the variables PR, PE, EE and BI as moderator variables in adopting artificial intelligence is positive.

## 5. Discussion

The study found a negative association between perceived risk (PE) and adoption of artificial intelligence (AI) in North Sulawesi higher education settings. That is, the greater the perceived risk by higher education institutions or decision makers, the less probable AI will be deployed for learning in higher education. In this context, perceived risks may include financial risks, data security concerns, and other hazards associated with the installation and usage of AI technology in education. Factors such as lack of understanding of the benefits of AI, investment uncertainty, and fear of a paradigm shift in education may also influence higher risk perceptions. However, behavioral intention could act as a moderator variable in this relationship. This means that the negative relationship between perceived risk and behavioral intention weakens when other factors, such as belief in the benefits of AI, organizational support, or positive knowledge about this technology, increase with perceived risk. This indicates that when parties involved in higher education in North Sulawesi have a better understanding of the potential benefits of AI, strong organizational support, and positive beliefs, they are more likely to still intend to adopt this technology, even in the face of high perceived risk. Therefore, it is important for parties involved in higher education in North Sulawesi to address and mitigate perceived concerns through effective teaching, training, and communication about the potential benefits of AI in improving education quality, increasing efficiency, and preparing students for the future. There is a significant positive relationship between performance expectancy and AI adoption in the context of higher education in North Sulawesi. That is, the higher the performance expectancy or perceived benefits associated with the use of AI, the

**Table 6.** Outer loading relationship.

| | Original Sample (O) | Sample Mean (M) | Standard Deviation (STDEV | T Statistics (\|O/STDEV\|) | *P*-values |
|---|---|---|---|---|---|
| AIHE1 <- AIHE (Y) | 0.817 | 0.818 | 0.028 | 29.497 | 0.000 |
| AIHE2 <- AIHE (Y) | 0.800 | 0.801 | 0.029 | 27.871 | 0.000 |
| AIHE3 <- AIHE (Y) | 0.821 | 0.823 | 0.027 | 30.050 | 0.000 |
| AIHE4 <- AIHE (Y) | 0.845 | 0.843 | 0.021 | 41.035 | 0.000 |
| AIHE5 <- AIHE (Y) | 0.811 | 0.811 | 0.031 | 26.439 | 0.000 |
| BI1 <- Behavioral Intention/ BI (Z) | 0.719 | 0.720 | 0.041 | 17.446 | 0.000 |
| BI2 <- Behavioral Intention/BI (Z) | 0.707 | 0.706 | 0.034 | 20.604 | 0.000 |
| BI3 <- Behavioral Intention/BI (Z) | 0.767 | 0.770 | 0.028 | 27.301 | 0.000 |
| BI4 <- Behavioral Intention/BI (Z) | 0.776 | 0.777 | 0.026 | 29.466 | 0.000 |
| BI5 <- Behavioral Intention/BI (Z) | 0.755 | 0.753 | 0.034 | 21.886 | 0.000 |
| EE1 <- Effort Expectancy(X3) | 0.805 | 0.806 | 0.023 | 35.297 | 0.000 |
| EE2 <- Effort Expectancy(X3) | 0.936 | 0.936 | 0.013 | 73.043 | 0.000 |
| EE3 <- Effort Expectancy(X3) | 0.897 | 0.897 | 0.014 | 63.913 | 0.000 |
| Effort Expectancy(X3) * Behavioral Intention/BI(Z) <- EE.BI | 1.213 | 1.204 | 0.093 | 13.027 | 0.000 |
| PE1 <- Performance Expectancy(X2) | 0.792 | 0.791 | 0.028 | 28.303 | 0.000 |
| PE2 <- Performance Expectancy(X2) | 0.825 | 0.825 | 0.021 | 39.779 | 0.000 |
| PE3 <- Performance Expectancy(X2) | 0.806 | 0.803 | 0.030 | 26.447 | 0.000 |
| PE4 <- Performance Expectancy(X2) | 0.788 | 0.783 | 0.033 | 23.765 | 0.000 |
| PR1 <- Perceived Risk(X1) | 0.833 | 0.834 | 0.021 | 39.908 | 0.000 |
| PR2 <- Perceived Risk(X1) | 0.966 | 0.966 | 0.004 | 249.490 | 0.000 |
| PR3 <- Perceived Risk(X1) | 0.918 | 0.917 | 0.012 | 74.234 | 0.000 |
| PR4 <- Perceived Risk(X1) | 0.826 | 0.827 | 0.026 | 31.837 | 0.000 |
| Perceived Risk(X1) * Behavioral Intention/BI(Z) <- PR.BI | 0.975 | 0.976 | 0.055 | 17.609 | 0.000 |
| Performance Expectancy(X2) * Behavioral Intention/BI(Z) <- PE.BI | 1.093 | 1.090 | 0.076 | 14.304 | 0.000 |

*Source*: Author's Smart PLS 3.

greater the likelihood of AI technology adoption within higher education institutions in the area. Factors that can influence performance expectancy include expectations for increased efficiency in the education process, improved quality of learning, administration and the ability of AI to provide better solutions to educational challenges.

Better knowledge of AI technology and positive experiences using it may also increase performance expectancy. However, behavioral intention may act as a moderator variable in this relationship. This means that other factors, such as perceived risk, organizational support, or technical barriers, may influence the extent to which the positive relationship between performance expectancy and behavioral intention is realized. For example, while high performance expectations may increase the intention to adopt AI, if the perceived risk is high or there is a lack of organizational support, the positive effect may be mitigated. Therefore, to promote the adoption of AI in higher education in North Sulawesi, it is important to identify and consider factors other than performance expectancy that may influence behavioral intention.

Factors that can influence effort expectation include an easy-to-use interface, the amount of training required, and the suitability of the AI technology to the user's needs. Intuitive and effortless use of AI, as well as good technical support, can increase the adoption of AI in higher education. Therefore, it is important to develop and implement AI solutions that are simple and easy to use in the context of higher education in North Sulawesi. The study shows that there is a negative relationship between effort expectancy and behavioral intention to adopt AI in higher education in North Sulawesi. This means that the higher the perception of the level of effort required to use AI technology, the lower the likelihood of individuals or higher education institutions having the intention to adopt AI in the education process. However, behavioral intention can act as a moderator variable in this relationship. This means that other factors, such as performance expectancy, perceived risk, or organizational support, can moderate the negative relationship between effort expectancy and behavioral intention. If performance expectancy is high or there is strong organizational support, then the negative effect of effort expectancy on behavioral intention can be weakened.

The Result highlights that:

- Perceived risk (PR) has a negative impact on the adoption of artificial intelligence in higher education, H1 is accepted.
- Perceived risk (PR) has a negative impact on behavioral intention to adopt artificial intelligence in higher education, H2 is accepted.
- Performance expectancy (PE) has a positive impact on the adoption of artificial intelligence in higher education, H3 is accepted.
- Performance expectancy (PE) has a positive impact on behavioral intention to adopt artificial intelligence in higher education, H4 is accepted.
- Effort expectancy (EE) has a positive impact on the adoption of artificial intelligence in higher education, H5 is accepted.
- Effort expectancy (EE) has a negative impact on Behavioral Intention to adopt Artificial Intelligence in Higher Education (AIHE), H6 is rejected.
- Behavioral intention has a positive and significant effect on adopt artificial intelligence in higher education, H7 is accepted.

## 6. Conclusions

The presence of simulated artificial intelligence (AI) innovation is a forward leap in the domain of instructive innovation to assist understudies with concentrating on more really. The judicious and controlled application of technology has the potential to accelerate education. The improvement of artificial intelligence technology can assist with imparting in understudies a feeling of freedom, educators are not burdened with such areas of strength for a; all things considered, their obligations are restricted to providing edification with critical terms. Every use of technology for instructors is based on continuing to priorities the essence of education, namely regulating students' morals and behavior. For students, educational technology can assist them in controlling and monitoring their own learning, allowing them to live and work successfully in the future. Adoption of artificial intelligence solutions has expanded teaching, learning, and administrative work prospects in North Sulawesi's higher education institutions. The concept of using AI is still in its early stages. We examined the expected utilizations of simulated artificial intelligence (AI) in advanced education and fostered a model that distinguishes the qualities that will help and speed up the reception of simulated AI in higher education. Artificial intelligence will give critical advantages to advanced education establishments. It is critical to remember that education is fundamentally a human-centered endeavor. It is fundamentally unaffected by technical solutions. Education is regarded as a human-centered concern. The reliance on technology in education will not yield the desired results. Regardless of the most recent technological breakthroughs, humans are scheduled to discover the problem. Criticism will be present to identify potential hazards. To stimulate innovation, people will ask a lot of questions concerning higher education issues. Humans should be able to enhance all of this, and technological answers can be developed. In this situation, AI will or may play a significant role. As a result, the rapid growth of AI is predicted to give an undeniable remedy for individuals pursuing higher education and riding the wheel of reality. Identify human endeavor-related difficulties and issues in higher education. AI input could provide quick and accurate results. In this light, the application of AI is crucial in addition to developing human skills and talents.

## 7. Research implication

In this study, we rely on the UTAUT model (Venkatesh et al., 2016). This model is designed to contain three exogenous (PR, PE, EE), one variable endogen (AIHE) and BI as moderator variables. So far, no explicit research on the application of AI in higher education in the Indonesian environment, particularly in North Sulawesi, has been developed. In this context, the proposed theoretical model is thought to be capable of providing theoretical information to stakeholders concerned with the implementation of AI in universities in North Sulawesi. As an exogenous variable, we considered the Perceived Risk (PR) construct. It is stated that this has improved the overall performance of the proposed theoretical model. Stakeholder trust in the implementation of AI is regarded as critical. Again, neither the UTAUT model nor its expansions take into account the impact of EE on AI adoption. It is stated that using BI as a moderator variable increased the performance of our theoretical model because its explanatory power reached 70%. The following are some of the potential consequences of implementing AI in higher education in North Sulawesi: increased educational accessibility, personalized learning, administrative efficiency, improved teaching quality, advances in research and innovation, ethical and privacy challenges, new training and skills, internet access and technology infrastructure. It is critical to stress that the impact of AI adoption in higher education will be strongly dependent on proper implementation, collaboration, and constant monitoring in order to minimize negative effects and maximize advantages for education and development in North Sulawesi.

## Disclosure statement

The Research Team states that in the process of collecting data and writing articles, it has no personal, financial, or other interests that could influence the team's ability to make specific objective, fair, or neutral decisions or actions so that transparency and appropriate management to maintain integrity and public trust for the entire research process.

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