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# Exploring Generative AI Tools Frequency: Impacts on Attitude, Satisfaction, and Competency in Achieving Higher Education Learning Goals

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**Abstract**

The urgency of using AI in the educational environment as a medium for optimizing student learning personalization in synchronous and asynchronous learning needs to be done to ensure that students experience improved attitudes, motivation, and learning satisfaction, which is reflected in student competencies. This study aimed to investigate the impact of ChatGPT use frequency on students' attitudes, satisfaction levels, and competence in higher education learning goals. The type of research employed was non-experimental quantitative research, specifically ex-post facto research. The sample size was 257 people, which was determined using the criteria of Issac and Michael (1971) and sampling distribution with a proportional random sampling technique. Data collection techniques that utilize questionnaires are effective in obtaining quantitative data. The PLS SEM analysis was used to determine the effect of exogenous latent variables on endogenous latent variables. The study revealed that reliability and satisfaction with ChatGPT positively impact learning outcomes, while the perceived impact on competence does not significantly enhance learning objectives. Increased usage frequency moderates these effects, diminishing the positive influence of perceptions, reliability, and satisfaction and shifting the impact on competence to negative and insignificant. These findings highlight the complexity of integrating ChatGPT into education, suggesting that initial positive perceptions may not be sustained with frequent use.

*Keywords:* ChatGPT; Student's attitudes; Satisfaction Levels; AI Competency; Learning Goals

## 1. Introduction

Artificial Intelligence (AI) has been increasingly integrated into various sectors, including higher education, to improve teaching and learning. The role of AI in influencing attitudes, satisfaction, and competence regarding learning objectives in higher education is a topic of growing interest and importance. Several studies have investigated various aspects of AI in higher education, explaining its impact on learners and educators (Chai et al., 2020; Gupta & Bhaskar, 2020; Roy et al., 2022; Slimi, 2021; Suh & Ahn, 2022). Research by Hajam and Gahir (2024) focused on understanding college students' attitudes towards AI, aiming to identify the factors that influence these attitudes. This study provides valuable insights into how students perceive AI in the context of higher education, which is crucial for designing effective AI integration strategies. Similarly,Slimi ( 2021) investigated the impact of AI implementation in higher education, emphasizing its influence on the quality of education, learning processes, assessments, and future careers. Therefore, understanding these impacts is crucial for optimizing the use of AI in educational settings.

The urgency of using AI in the educational environment as a medium for optimizing student learning personalization in synchronous and asynchronous learning needs to be done to ensure that students experience improved attitudes, motivation, and learning satisfaction, which is reflected in student competencies (Gupta & Bhaskar, 2020; Roy et al., 2022). Research by (Chai et al. (2020) and Wang et al. (2023) highlighted the importance of AI education and

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literacy in shaping students' perceptions and attitudes towards AI, emphasizing the need to incorporate AI-related content into the educational curriculum. Research on ChatGPT in educational settings has concluded that it is a generative artificial intelligence medium that is rapidly gaining global recognition owing to its wide range of potential benefits (Wu et al., 2024; W. Zhang, 2023). However, some studies emphasize the importance of careful integration and consideration of ethical issues when incorporating ChatGPT into education. (P. Zhang, 2023).

ChatGPT can provide creative, interactive, and adaptive learning experiences tailored to students' abilities and performance with technology in shaping their acceptance and use of AI tools, demonstrating its potential to transform higher education (Raman et al., 2023; Salah et al., 2023). Additionally, studies have explored the implications of ChatGPT on learning motivation, memory, and cognitive effects, emphasizing the need for further research to understand its long-term impact on students' learning processes (Ali et al., 2023; Bai, 2023). In addition, research has highlighted the importance of supervision and caution from experts when using the ChatGPT in education to ensure the accuracy and relevance of the information provided to students (Han et al., 2023).

This study investigated the impact of the frequency of ChatGPT use on students' attitudes, satisfaction levels, and competence in higher education learning. These dimensions are specific to this study, beyond the general perspective of the existing ChatGPT research. Several previous studies have described the application of the ChatGPT in various educational contexts, such as learning outcomes, learning motivation, and other general variables (Gilson et al., 2023; Kohnke et al., 2023; Raut & Kumar, 2024). **This study offers a novel approach that contributes to the existing knowledge by providing detailed insights into the specific effects of ChatGPT on students' educational experience. Hence, this study focused on the specific impact of ChatGPT on students' attitudes, satisfaction, and competence in achieving higher education learning objectives.** This study aims to provide actionable insights for educators, policymakers, and technology developers to optimize the integration of ChatGPT in higher education environments.

## 2. Research Method and Materials

The type of study employed was non-experimental quantitative research, specifically ex-post facto research. Ex-post facto research is a type of study in which the independent variables have already occurred, and the researcher begins by observing the dependent variable before searching for a cause (Kerlinger 1986).

The participants in this study were students enrolled in the Department of Informatics and Computer Engineering, Faculty of Engineering, Makassar State University, who had utilised artificial intelligence applications in technological innovation courses. The sample size was 257 people, which was determined using the criteria of Issac & Michael (1971) and sampling distribution with proportional random sampling technique (Isaac & Michael, 1971). Samples are selected based on specific criteria or the objectives of the study. In addition, the sample size is determined by considering the structural equation modeling (SEM) analysis approach, which typically requires a sample size of 100-200 (Ghozali, 2012) or 5-10 times the number of observation parameters (Hair et al., 2006). For small samples with complex models, it is recommended to use SmartPLS software (Santosa, 2018).

Data collection techniques that utilize questionnaires are effective in obtaining quantitative data. These questionnaires are designed to elicit the viewpoints of respondents regarding the use of ChatGPT and its frequency in relation to attitudes, satisfaction, and competence in achieving objectives for higher education learning. The indicators for the questionnaire sheet of the study show on Table 1.

**Table 1.** The indicators for the questionnaire sheet

| No. | Variable | Statement |
|---|---|---|
| 1 | Perception and Attitude towards ChatGPT in Academics (PATA) | 6, 12, 13 |
| 2 | Reliability and Satisfaction (RS) | 3, 11 |
| 3 | Impact on Competencies (IC) | 7 – 9 |
| 4 | Frequency and Usage (FU) | 2, 5, 14 |
| 5 | Effectiveness and Achievement of Learning Goals (EALG) | 1, 4, 10 |

Instrument validity in this study uses construct validity. Construct validity uses confirmatory factor analysis (CFA) with the help of SmartPLS software. Meanwhile, the calculation of reliability uses the rules of construct reliability (CR) and variance extracted (VE). A construct or variable is said to be reliable if it provides a CR value $\geq 0.7$ and VE $\geq 0.5$ (Hair, 2017).

Quantitative data analysis techniques in research using descriptive statistical analysis using IBM SPSS and structural equation modeling (SEM) analysis with the help of SmartPLS software. SEM analysis is used to determine the effect of exogenous latent variables on endogenous latent variables.

The SEM analysis requirements test uses normality tests (univariate normality and multivariate normality) and multicollinearity. Data is declared to meet the assumption of normality if the pvalue of skewness and kurtosis> 0.05. Independent variables are said not to occur multicollinearity if the tolerance value> 0.1 and VIF <10. SEM will produce and analyze measurement models (CFA) and structural models. The analysis was carried out using SmartPLS software.

Five variables were used for model tests: Perceptions and attitudes towards AI in academia, Reliability and satisfaction, effectiveness and achievement of learning objectives, The impact on competence, and frequency and use of AI. The assessment of PLS-SEM model was done in two models: measurement model and structural model. The assessment of PLS-SEM model was done in two models: measurement model and structural model (Hair et al., 2019).

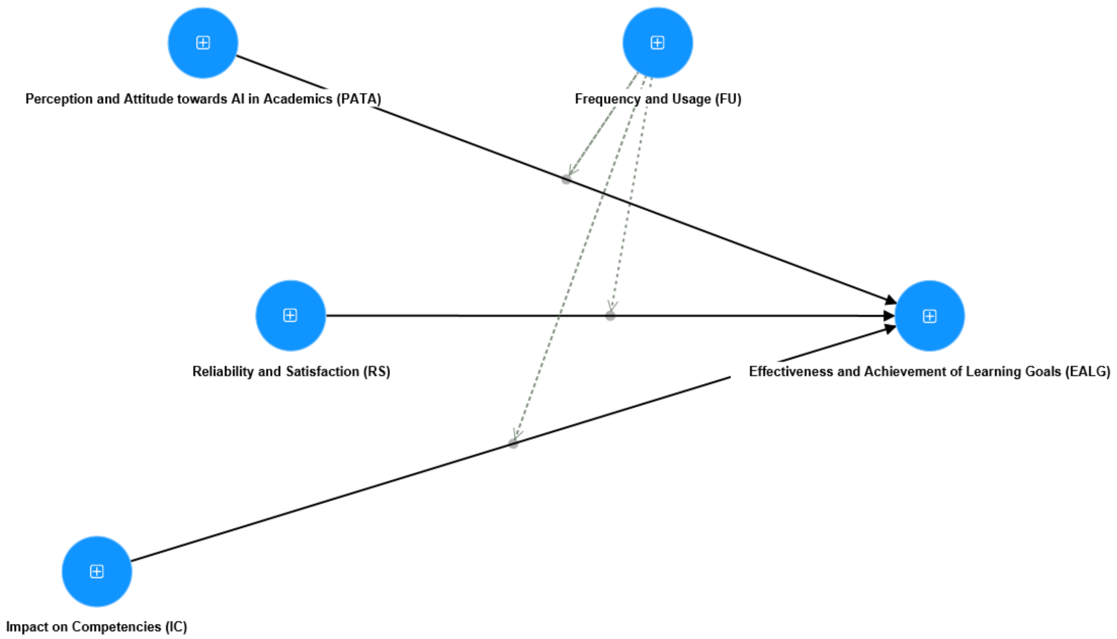


**Figure 1.** Framework of the study

The hypotheses in this study are:

H1: Perceptions and attitudes towards ChatGPT in academia have a positive and significant effect on the effectiveness and achievement of learning objectives.
H2: Reliability and satisfaction have a positive and significant effect on the effectiveness and achievement of learning objectives.
H3: The impact on competence has a positive and significant effect on the effectiveness and achievement of learning objectives
H4: Perceptions and attitudes towards ChatGPT in the academic field have a positive and significant effect on the effectiveness and achievement of learning objectives moderated by the frequency and use of ChatGPT
H5: Reliability and satisfaction have a positive and significant effect on the effectiveness and achievement of learning goals moderated by the frequency and use of the ChatGPT.
H6: Impact on competence has a positive and significant effect on the effectiveness and achievement of learning objectives moderated by the frequency and use of ChatGPT

## 3. Results and Discussion

### *3.1. Descriptive Statistics*

The participants in this study were (undergraduate) students who attended hybrid learning courses during the Covid-19 endemic period in the Department of Informatics and Computer Engineering, Makassar State University, Indonesia. The survey link was saved on the researcher's Google form, and a proportional sampling method was used to further distribute the survey. A total of 257 participants responded regarding their understanding artificial intelligence literacy. As the data were collected via Google Forms and all questions were answered and required, there were no missing data. The respondents consisted of 49% females and 51% males. Students from Informatics and Computer Engineering majors were included.

A descriptive analysis was conducted on the survey items, as shown in Table 2. The standard deviations ranged from -2 to +2, indicating that there was not much deviation from the normal distribution; hence, most of the statistical analyses could be applied to the models in this study (Badri et al., 2016).

**Table 2.** Descriptive Analysis Data

Descriptives

| | Sex | N | Mean | Median | SD | Minimum | Maximum |
|---|---|---|---|---|---|---|---|
| PATA | Male | 131 | 3.42 | 3.33 | 0.674 | 1.33 | 5.00 |
| | Female | 126 | 3.25 | 3.33 | 0.742 | 1.33 | 5.00 |
| RS | Male | 131 | 3.62 | 3.50 | 0.629 | 1.00 | 5.00 |
| | Female | 126 | 3.52 | 3.50 | 0.643 | 2.00 | 5.00 |
| IC | Male | 131 | 3.81 | 3.67 | 0.579 | 2.00 | 5.00 |
| | Female | 126 | 3.71 | 3.67 | 0.614 | 2.00 | 5.00 |
| FU | Male | 131 | 3.44 | 3.33 | 0.709 | 1.67 | 5.00 |
| | Female | 126 | 3.31 | 3.33 | 0.744 | 1.00 | 5.00 |
| EALG | Male | 131 | 3.68 | 3.67 | 0.642 | 1.00 | 5.00 |
| | Female | 126 | 3.48 | 3.33 | 0.743 | 1.00 | 5.00 |
| Age | Male | 131 | 19.34 | 19 | 0.926 | 18 | 21 |
| | Female | 126 | 19.17 | 19.00 | 0.787 | 18 | 21 |

### *3.2. Structural Equation Modelling*

#### *3.2.1. Reflective Measurement Model Analysis*

The results of the reliability and validity of the scale used in Table 3, show that the outer loading value for each construct item/indicator from the student assessment results is above the minimum value of 0.60. Because all results are greater than 0.70, the indicators are proven to be reliable (Hair Jr. et al., 2017). The internal consistency value obtained is above 0.7. This means that the internal consistency value is satisfactory because it is at a value of 0.7-0.9 (Nunnally & Bernstein, 1994). This criterion is also used for Cronbach Alpha, Rho A and composite reliability. Based on the composite reliability and Rho A values of the constructs, all constructs are reliable. In addition, there are 2 construct variables that have a Cronbanch alpha value below 0.7, namely RS and IC in table 3. The Cronbanch alpha value should be above 0.7 (in exploratory research, 0.60 to 0.70 is considered acceptable) (Ketchen, 2013).. Convergent validity is indicated by AVE. The analysis results in Table 3 show that all AVEs are higher than 0.50. The AVE value must be greater than 0.50 to explain more than half of the indicator variance (Hair Jr. et al., 2017).

**Table 3.** Reliability and Validity of the scale used

| Construct | Item | Outlier Loadings | Cronbach's Alpha | rho_A | Composite Reliability | AVE |
|---|---|---|---|---|---|---|
| Perception and Attitude Towards AI in Academics (PATA) | PATA-1 | 0.784 | 0.758 | 0.762 | 0.861 | 0.674 |
| | PATA-2 | 0.794 | | | | |
| | PATA-3 | 0.882 | | | | |
| Reliability and Satisfaction (RS) | RS-1 | 0.824 | 0.676 | 0.718 | 0.858 | 0.752 |
| | RS-2 | 0.908 | | | | |
| Impact on Competencies (IC) | IC-1 | 0.676 | 0.690 | 0.716 | 0.828 | 0.619 |
| | IC-2 | 0.825 | | | | |
| | IC-3 | 0.848 | | | | |
| Frequency and Usage (FU) | FU-1 | 0.799 | 0.732 | 0.732 | 0.849 | 0.652 |
| | FU-2 | 0.846 | | | | |
| | FU-3 | 0.777 | | | | |
| Effectiveness and Achievement of Learning Goals (EALG) | EALG-1 | 0.866 | 0.815 | 0.817 | 0.890 | 0.730 |
| | EALG-2 | 0.866 | | | | |
| | EALG-3 | 0.830 | | | | |

Furthermore, the discriminant validity of the constructs is demonstrated in tables 4 and 5, which use the criteria established by Fornell and Larcker (1981) (Fornell & Larcker, 1981) to assess cross-loading by comparing all item loadings. The Fornell Larcker criterion measures discriminant validity based on AVE, the most widely used validity measurement in PLS-SEM. In order to assess the discriminant validity of the model for reflective structures, AVE must be greater than the squared correlation (Mehmetoglu, 2021). Table 4 below shows the Fornell Larckell Criteria. All constructs in the model have good discriminant validity.

**Table 4.** Fornell Larckell Table (Correlation Between Factors and Root AVE)

| | EALG | FU | IC | PATA | RS |
|---|---|---|---|---|---|
| EALG | **0.854** | | | | |
| FU | 0.710 | **0.808** | | | |
| IC | 0.458 | 0.421 | **0.787** | | |
| PATA | 0.738 | 0.701 | 0.501 | **0.821** | |
| RS | 0.714 | 0.586 | 0.400 | 0.641 | **0.867** |

The table below displays the cross-loadings of all indicators. It is evident that all indicators exhibit the highest loadings on their respective constructs among all other constructs (Barclay et al., 1995; Hair, 2017). Consequently, all items/indicators within a given construct fulfill the criteria for good discriminant validity. Figure 2 below illustrates the outer model.

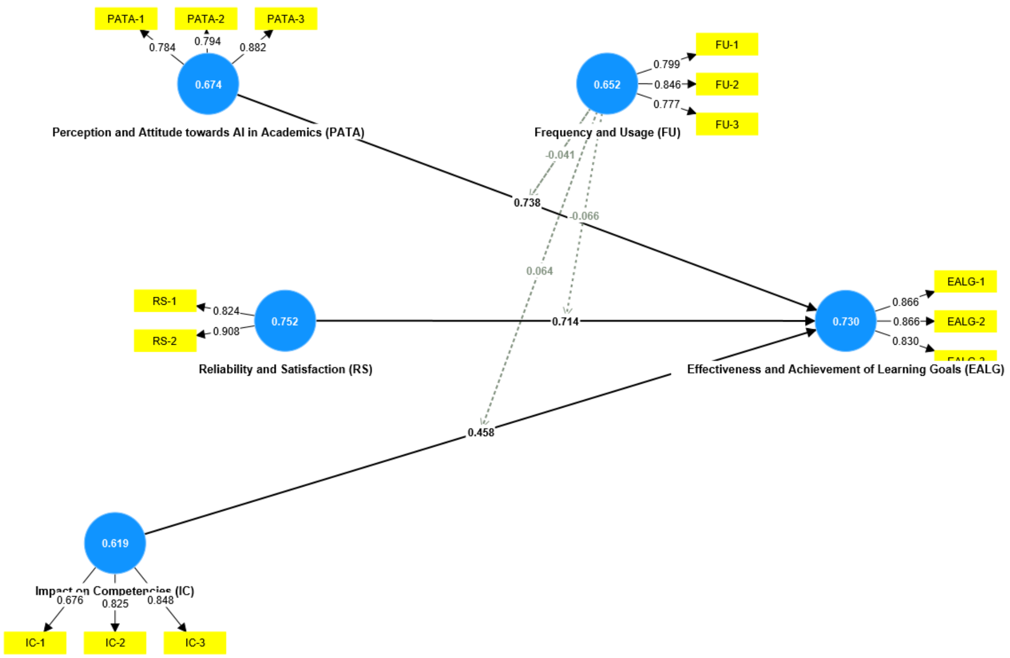


**Figure 2.** Outer Model of the Study

*3.2.2. Structural Model Analysis with Inner Model (Hypothesis Test)*

The PLS estimation results of structural equation modeling, path coefficient values, and item loadings for the research constructs are presented in Figure 3 below:

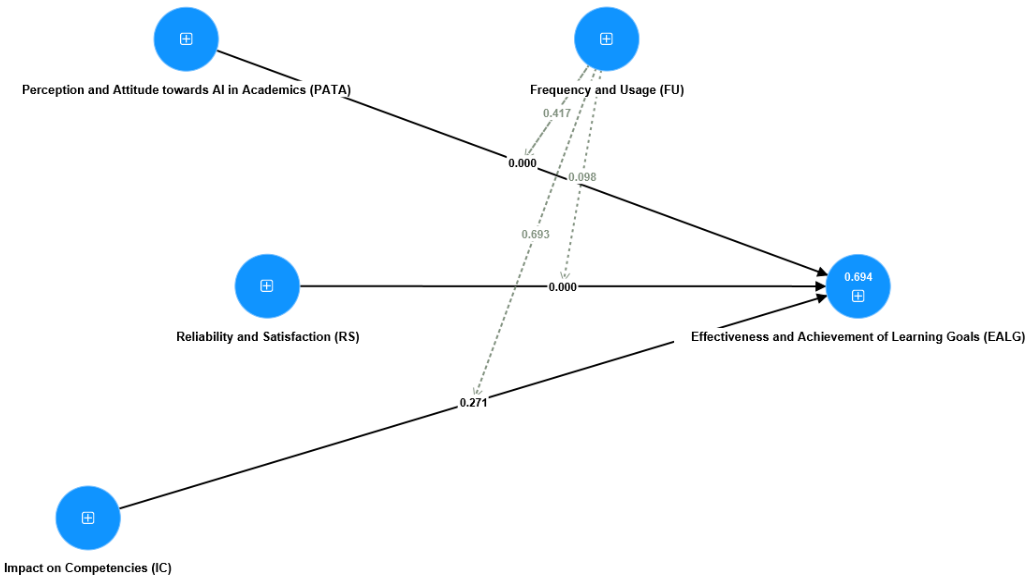


**Figure 1.** PLS Estimation Results

Table 5 shows the designed hypotheses of this study and the results obtained from SEM analysis.

Based on table 5, it is known that the Path Coefficient value (Original Sample) of H1 until H4 has a positive value, which means it has a positive effect. However, H3 and H4 have no significant effect. Furthermore, H5 and H6 have a negative and insignificant effect, which is indicated by the negative original sample or path coefficient value.

**Table 5.** Summary of Hypothesis Test Results

| Path | Hypothesis | Path Coefficient (β) | p-Value | Decision |
|---|---|---|---|---|
| PATA > EALG | H1 | 0,311 | 0,000 | Positive and significant |
| RS > EALG | H2 | 0,320 | 0,000 | Positive and significant |
| IC > EALG | H3 | 0,057 | 0,271 | **Positive and insignificant** |
| PATA*FU > EALG | H4 | 0,050 | 0,417 | **Positive and insignificant** |
| RS*FU > EALG | H5 | -0,095 | 0,098 | **Negative and not significant** |
| IC*FU > EALG | H6 | -0,021 | 0,693 | **Negative and not significant** |

Based on the information, there are 3 things that can be concluded, namely:

- H1 and H2 are positive and significant so that these two hypotheses can be accepted
- H3 and H4 is positive but insignificant so this hypothesis cannot be accepted
- H5 and H6 are not positive and not significant so this hypothesis cannot be accepted.

*3.3. Discussions*

Investigating to prove the hypotheses relating to the impact of perceptions, attitudes, reliability, satisfaction, and competence on the effectiveness and achievement of learning goals in academia, it is imperative to analyse the existing literature to draw comprehensive conclusions. **Hypothesis 1 states that perceptions and attitudes towards ChatGPT in academia have a positive and significant influence on the effectiveness and achievement of learning objectives**. The results of this study suggest that positive attitudes towards AI can indeed improve learning outcomes. This study has shown that when students perceive AI technology as a useful medium, it can support the learning process and lead to improved academic performance. In addition, a positive attitude towards AI can foster a sense of openness to innovation and technological advancement, which is crucial in a modern educational environment.

Other research findings on perceptions and attitudes towards AI in academia show a positive influence on the effectiveness and achievement of learning objectives. This study emphasises the important relationship between perceptions and attitudes towards AI in academia and successful achievement of learning objectives (Huisman et al., 2021). Other studies have similarly focused specifically on the impact of attitudes towards AI on academic achievement (Chan & Zary, 2019; Oh et al., 2019; Sarwar et al., 2019). Regarding the significance of the findings and their implications, the results of this study underscore the importance of fostering positive attitudes towards AI among university students to optimise educational outcomes. Recognising the positive relationship between attitudes towards AI and academic achievement, educational institutions can develop strategies to promote a culture of acceptance and openness towards AI technologies (Fietta et al., 2022; Hajam & Gahir, 2024; Y. Wang et al., 2023).

Furthermore, **Hypothesis 2 shows the results that reliability and satisfaction positively impact the effectiveness and achievement of learning objectives**. The reliability of AI applications in educational environments is critical to ensure consistent and accurate support for students and educators. When AI systems are reliable in providing timely feedback, personalised learning experiences, and relevant resources, students will be more likely to achieve their learning goals effectively. In addition, satisfaction with AI technology can increase user engagement and motivation, leading to improved learning outcomes.

Research findings on the impact of reliability and satisfaction on the effectiveness of achieving learning objectives shed light on important aspects of AI applications in educational environments. This study reveals that the reliability of AI systems, which ensures consistent and accurate support, plays an important role in facilitating student learning and educator effectiveness. In addition, satisfaction with AI technology is highlighted as a key factor that can increase user engagement and motivation, ultimately leading to improved learning outcomes (Xuan, 2019). The importance of satisfaction to the achievement of learning goals lies in its implications for educational practice and policy. Recognising the positive influence of reliability and satisfaction on learning effectiveness, educational institutions can prioritise the development and implementation of reliable AI systems that increase user satisfaction. By ensuring that AI technologies offer consistent support and encourage user engagement, educators can create more effective learning environments that cater to the diverse needs and preferences of students (Elder, 2012; Smith & Hill, 2019).

While hypotheses 1 and 2 showed positive and significant results, **the results of Hypothesis 3 showed that the impact on competence had a positive and insignificant influence on the effectiveness and achievement of learning objectives**. Competence, defined as the ability to effectively use AI tools to support learning objectives, is an important factor in determining the success of educational interventions involving AI. This study suggests that students who have a higher level of competence in using AI technologies are more likely to optimally utilise this medium to improve their learning outcomes.

Other research findings on the impact of competence on the effectiveness of achieving learning objectives provide valuable insights into the role of student proficiency in using AI tools for educational purposes (Karan & Angadi, 2023) explains competence as the ability to effectively engage with AI technologies to support learning goals. This leads to the assumption that competence is an important factor that influences the success of educational interventions involving AI. Therefore, students with higher levels of competence in using AI applications are more likely to optimally utilise these technologies to improve their learning outcomes. Furthermore, although previous research has explored various aspects of AI in different contexts (García-Martínez et al., 2023; Khairatun Hisan & Miftahul Amri, 2022; Niloy et al., 2024), This study stands out by emphasising the importance of student competencies in utilising AI for educational purposes. By highlighting the importance of competence in AI utilisation, This study offers a new perspective on how student proficiency impacts learning outcomes.

The importance of these findings lies in their implications for educational practice and policy, emphasising the need to improve students' competence in using AI applications effectively (Ibrahim et al., 2021; Li et al., 2024; Nazaretsky et al., 2022). Being able to investigate the positive relationship between competencies and learning outcomes, educators can tailor interventions to improve student proficiency in AI technologies. This could involve providing targeted training programmes and fostering a culture of technological literacy to empower students to maximise the benefits of AI in their educational journey..

Furthermore, **hypothesis 4 introduces the concept of moderation by proposing that perceptions and attitudes towards AI in academia have a positive and insignificant effect on the effectiveness and achievement of learning objectives when moderated by the frequency and use of AI**. The relationship between perceptions or attitudes towards AI and learning outcomes can indeed be influenced by the extent to which AI technologies are used in educational settings. When students have a positive attitude towards AI and use these tools frequently, the impact on learning objectives is likely to be more pronounced. However, if the use of AI is sporadic or limited, the influence of perceptions and attitudes on learning outcomes may be less significant.

AI-related research findings (Stamate et al., 2021) explored the relationship between perceptions, attitudes towards AI, and learning outcomes, emphasising the moderating role of frequency of AI use. This study suggests that the impact of perceptions and attitudes towards AI on learning outcomes may be influenced by the level of integration of AI technologies in educational environments. While previous studies have looked at the influence of perceptions and attitudes towards AI on learning outcomes (Kashive et al., 2021; Muthmainnah et al., 2022; Slimi, 2021), this study considers the moderating role of frequency of AI use by including this moderating factor, this study offers a more comprehensive understanding of how AI perceptions interact with actual AI use to influence learning effectiveness.

Furthermore, the urgency of these findings lies in their implications for educational practice and policy, which emphasise the importance of fostering positive attitudes towards AI and encouraging consistent and meaningful integration of AI in educational settings. Research from (Cukurova et al., 2020; Demir & Güraksın, 2022; Salas-Pilco, 2020) sheds light on the role of AI for educators and policymakers can utilise these insights to develop interventions that encourage favourable perceptions of AI and regular AI use among university students. By recognising the importance of frequency of AI use as a moderating factor, educational institutions can tailor strategies to improve the alignment between attitudes towards AI and actual AI utilisation, thereby maximising the benefits of AI technologies in improving learning outcomes.

In contrast, **the results of hypothesis 5 show that reliability and satisfaction have a negative and insignificant influence on learning effectiveness and goal achievement when moderated by frequency and AI usage**. This hypothesis suggests that when the use of AI technology is high, the positive impact of reliability and satisfaction on learning outcomes will be reduced. However, existing research does not fully support this assertion. Research has shown that even when AI tools are used frequently, reliability and satisfaction remain important factors in determining the effectiveness of achieving learning objectives. A reliable AI system that consistently provides accurate support and a satisfying user experience remains critical to improving learning outcomes, regardless of the frequency of use. Therefore, it can be concluded that reliability and satisfaction still play an important role in influencing learning objectives, regardless of the frequency and usage of AI.

Research by (Zhou & Kankanhalli, 2021) shows results that do not fully support this assertion because with frequent use of AI tools, reliability and satisfaction remain important factors in determining the effectiveness of achieving learning objectives. This highlights the importance of a reliable AI system that consistently provides accurate support and a satisfying user experience in improving learning outcomes, regardless of frequency of use. While previous research has examined the impact of reliability and satisfaction on learning outcomes (Sadler et al., 2024; Skulimowski, 2021; Tedeschi, 2022), this study considers how AI usage patterns influence these relationships. By incorporating the moderating effect of frequency of AI use, this study provides a more nuanced understanding of the interaction between reliability, satisfaction, and learning effectiveness in an educational context.

The importance of these findings lies in their implications for educational practice and policy, which underscore the importance of reliability and satisfaction in shaping learning outcomes, regardless of the frequency of AI use. Several studies by (Belcher & Halliwell, 2021; Busch et al., 2023; Hegarty & Thompson, 2019) suggest educators and policymakers can leverage these insights to prioritise the development of reliable AI systems that prioritise user satisfaction to improve learning experiences. By recognising the lasting influence of reliability and satisfaction on learning effectiveness, educational institutions can design interventions that promote consistent, high-quality AI support to optimise student learning outcomes and overall educational success.

Finally, **Hypothesis 6 shows that the impact on competence has a negative and insignificant effect on effectiveness and achievement of learning objectives when moderated by frequency and use of AI**. This hypothesis implies that as the frequency of AI tool use increases, the importance of competence in using the tool will decrease. However, empirical evidence does not strongly support this hypothesis. Competence in using AI technologies remains an important factor in determining the effectiveness of achieving learning objectives, regardless of the frequency of use. Students and educators who are more competent in utilising AI tools are better equipped to optimise their learning experiences and outcomes. Therefore, it can be concluded that competence continues to have a significant positive influence on the effectiveness and achievement of learning objectives in academia, regardless of the frequency and use of AI.

Research by (Zerfass et al., 2020) implies that competence in using AI technologies remains an important factor in determining the effectiveness of achieving learning objectives, regardless of the frequency of their use. students who are more competent in utilising AI tools are better equipped to optimise their learning experiences and outcomes. Several studies by (Islam et al., 2023; McCoy et al., 2020; Wienrich & Carolus, 2021) explain that educators can leverage this insight to prioritise the development of students' competence in making effective use of AI applications. By recognising the ongoing influence of competencies on learning effectiveness, educational institutions can design interventions that improve student proficiency in AI technologies to optimise learning outcomes and prepare students for the evolving technological landscape.

In conclusion, based on a comprehensive review of the literature and empirical evidence, it can be concluded that perceptions and attitudes towards AI, reliability, satisfaction, and competence all play an important role in influencing the effectiveness and achievement of learning goals in academia. Positive attitudes towards AI, reliable AI systems, high user satisfaction, and competence in utilising AI technologies are all associated with better learning outcomes. Moreover, the relationship between these factors and learning objectives can be moderated by the frequency and usage of AI, which highlights the importance of considering contextual factors in understanding the impact of AI in educational settings. Overall, these findings underscore the importance of fostering positive attitudes, ensuring reliability and satisfaction, and promoting competence in using AI technologies to improve learning outcomes in academia.

## 4. Conclusion

In conclusion, this study underscores the substantial role that perceptions and attitudes towards ChatGPT as a generative AI play in academia, positively influencing the effectiveness and achievement of learning objectives. Additionally, the findings reveal that the reliability and satisfaction derived from using ChatGPT also contribute positively to learning outcomes. However, the perceived impact on competence, while positive, did not significantly enhance the effectiveness or achievement of learning objectives. This suggests that while students and educators recognize the potential benefits of ChatGPT, these perceptions do not necessarily translate into measurable improvements in competence-based learning outcomes.

Furthermore, when examining the moderating effects of the frequency and use of ChatGPT, the results indicate a more nuanced influence. The study found that the positive impact of perceptions and attitudes towards ChatGPT on learning effectiveness diminishes when moderated by usage frequency. Similarly, the initially positive effects of reliability and satisfaction become insignificant, and even negative, under the same moderation. The impact on competence, when moderated, also shifts to a negative and insignificant influence. These findings highlight the complexity of integrating generative AI tools in educational settings, suggesting that while initial perceptions and satisfaction with ChatGPT are favorable, the actual frequency of use may introduce challenges

While this study provides valuable insights into the relationship between perceptions, attitudes, reliability, satisfaction and competence on the effectiveness and achievement of learning objectives in academia, there are some limitations that need to be noted. Firstly, this study relied primarily on survey data which may introduce subjective bias. Participants may have a tendency to give answers that are expected or desired by the researcher, thus reducing the objectivity of the findings.

Secondly, this study uses a sample that may not be fully representative of the wider population. Although the sample used was quite large and diverse, the results may not be generalisable to all educational contexts or different geographical areas. Variables such as culture, education level and technological infrastructure may affect the results and relevance of these findings across different contexts.

Third, this study focused more on perception and attitude variables without exploring the psychological or pedagogical mechanisms underlying the relationship between these variables and learning outcomes. A deeper understanding of how these factors interact psychologically and pedagogically could help in designing more effective educational interventions.

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