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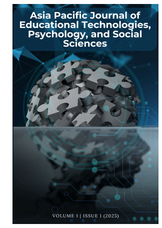

Research Article

Teachers' Attitudes Toward Generative AI In Assessment Planning: A UTAUT-Based Structural Equation Model

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Abstract

The quick rise of generative AI, particularly in educational settings, brings challenges to instructional practices; however, its impact on teachers' attitudes, especially in assessment planning, is still largely unexamined. This study uses the Unified Theory of Acceptance and Use of Technology (UTAUT) framework to explore teachers' attitudes towards generative AI in assessment planning with a focus on key constructs such as performance expectancy (PE), effort expectancy (EE), and social influence (SI), aimed at supporting more effective integration of these technologies in assessment planning. The study collected data from 419 educators and used the Partial Least Squares-Structural Equation Modeling (PLS-SEM). The findings show that performance expectancy significantly affects opinions ($\beta = 0.392$, $t = 7.122$, $p < 0.001$), indicating that teachers who believe AI will be helpful are likelier to use it. Similarly, effort expectancy (EE) strongly influences attitudes ($\beta = 0.319$, $t = 5.528$, $p < 0.001$), indicating the significance of ease-of-use beliefs in order for teachers to use generative AI in their assessment planning. Although social influence had a lesser impact ($\beta = 0.133$, $t = 2.589$, $p = 0.01$), it is still considered significant. These insights stress the importance of providing targeted professional development among teachers to improve their acceptance and implementation of generative AI in assessment planning.

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1. Introduction

The field of education is changing quickly, and generative artificial intelligence (AI) technologies are becoming robust instruments (Obenza, 2024) that have the potential to transform the way assessments are planned thoroughly. These developments offer previously unheard-of chances to improve teaching methods (Adiguzel et al., 2023). Generative AI technologies have the potential to revolutionize educational methods by improving feedback systems, creating individualized learning experiences, and simplifying procedures (Owan et al., 2023). For example, using AI in formative assessments has shown increased accuracy and efficiency in assessing student performance (Obenza et al., 2024). However, according to Nazaretsky et al. (2022), knowing how instructors feel about generative AI in assessment planning is essential since their opinions can significantly impact how well these technologies are adopted and used. Despite encouraging advantages, Hopfenbeck et al. (2023) claimed that many teachers want assistance integrating AI into their evaluation procedures, such as trouble facilitating peer assessments and giving insightful feedback.

Research indicates that significant barriers hinder the integration of generative AI in education, including misconceptions, lack of training, and insufficient support for curriculum planning (González-Calatayud et al., 2021). Moreover, Nazaretsky et al. (2022) and Obenza et al. (2024) found that the swift pace of technological improvements is overwhelming many teachers, indicating the necessity for professional development to effectively manage these advancements. Obenza (2024) stressed that to properly utilize generative AI's potential in assessment planning, it is becoming increasingly crucial to comprehend how educators view and feel about it. This means that teachers can be assisted better in using AI tools to improve their instruction by highlighting the incorporation of generative AI in their assessment planning.

Existing research often overlooks the nuanced attitudes of teachers, leading to a limited understanding of technology acceptance. The specific relevance of the UTAUT model to teachers' views on generative AI in assessment planning has yet to be investigated, even though it has been applied to various educational contexts as claimed by Dwivedi et al. (2017). According to Garone et al. (2019), Obenza et al. (2023) and Wu et al. (2022), several factors, such as performance expectations, effort expectancy, and social influence, significantly impact teachers' adoption of technology. Understanding therefore the interactions between these components is necessary to encourage the usage of generative AI in assessment planning.

This study fills these gaps using the UTAUT framework to examine teachers' opinions regarding incorporating generative AI into assessment design. This study specifically looks at how teachers' adoption and use of AI technology are impacted by performance expectancy, effort expectancy, and social influence. By emphasizing these elements, educational stakeholders can create focused interventions and professional development programs that support teachers' ability to use AI in assessment planning. The findings of this study will contribute to a deeper understanding of how generative AI can enhance educational assessment and identify the factors that promote or hinder its adoption in classrooms. By focusing on integrating AI into assessment practices, we can better understand the potential implications of teachers' attitudes toward AI on learning outcomes and the overall effectiveness of educational assessment strategies.

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2. Materials and Methods

This study employed a quantitative research design utilizing Partial Least Squares Structural Equation Modeling (PLS-SEM) to investigate teachers' attitudes toward generative AI in assessment planning, framed by the Unified Theory of Acceptance and Use of Technology (UTAUT). PLS-SEM was chosen for its ability to combine exploratory and confirmatory factor analyses, providing robust goodness-of-fit indices and precise correlations, which are essential for enhancing measurement accuracy in educational research (Hair et al., 2017; Alamer & Marsh, 2022; Marsh et al., 2014). The method is particularly effective for complex models with multiple constructs, making it suitable for studies involving non-normal data distributions and smaller sample sizes (Sarstedt et al., 2017; Hair et al., 2022).

Respondents were selected using a stratified random sampling technique, enhancing reliability and accuracy in understanding teachers' acceptance of technology (Parsons, 2017). This method optimized sample testing and improved the generalizability of results from the 419 teachers surveyed across Regions XI and XII, all of whom had integrated generative AI into their assessment planning. A sample size of at least 400 respondents was deemed sufficient for PLS-SEM analysis, as evidenced by Sánchez-Prieto et al. (2017) and Fadda and Morin (2017). The survey instrument was designed based on established technology acceptance models, focusing on performance expectancy, effort expectancy, and social influence.

The sample size was calculated using G*Power. An a priori power analysis for multiple regression showed that at least 146 respondents were needed to achieve adequate statistical power, assuming a medium effect size (f^2 = 0.15), an alpha level of 0.05, a desired power of 0.95, and six predictors (Faul et al., 2009). A total of 419 participants were included, exceeding the minimum requirement, which improved statistical power and reduced the risk of Type II errors (Obenza et al., 2024).

Data were collected through a structured questionnaire administered via Google Forms, which included items measuring constructs such as Attitude toward AI, Effort Expectancy, Performance Expectancy, and Social Influence using a Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). The questionnaire was adapted from prior studies (Malazzab, 2024; Yılmaz & Karaoğlan, 2023) to ensure alignment with the study's objectives.

The questionnaire was administered through Google Forms, selected for its user-friendly interface, accessibility, and efficiency in collecting data (Mondal et al., 2019; Fu'adin et al., 2023). This platform facilitated remote access and allowed for effective management of responses, making it well-suited for the educational research context (Kovalchuk, 2013).

To evaluate internal consistency and ensure the reliability of the measurement model, Cronbach's alpha and Composite Reliability were utilized (Jöreskog, 1971; Taber, 2018). Convergent validity was assessed using Average Variance Extracted (AVE), confirming that the constructs adequately captured variance from their indicators (Hair et al., 2017). Discriminant validity was established through the Heterotrait-Monotrait Ratio (HTMT), which demonstrated that the constructs were distinct and did not excessively overlap with other variables (Henseler et al., 2015).

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3. Results

3.1. Construct Reliability, Construct Validity, and Discriminant Validity

Table 1 shows that factor loadings for constructs related to teachers' attitudes toward AI exhibit strong alignment between items and their respective constructs, with values ranging from 0.787 to 0.916. According to Petras et al. (2023), Hayes & Coutts (2020), and Raykov et al. (2022), consistently high factor loadings, particularly those exceeding 0.85, indicate strong measurement reliability and are highly representative of their constructs. The Attitude toward AI construct has consistently high loadings (0.801–0.848), indicating strong item consistency, particularly for AC2 and AC4. Effort Expectancy also demonstrates high alignment across items (0.787–0.906), with EE4 standing out as the strongest measure. Performance Expectancy shows consistently high alignment (0.857–0.900), with PE2 and PE4 being especially representative. Social Influence exhibits two identical, exceptionally high loadings (0.916), highlighting equal and robust contributions.

On the other hand, Cronbach's alpha and composite reliability are widely utilized measures for evaluating internal consistency, derived from the relationships among observed variables (Hamid et al., 2017). Cronbach's alpha values for the questionnaires are as follows: 0.981 for Attitude towards AI, 0.824 for Effort Expectancy (EE), 0.903 for Performance Expectancy (PE), and 0.809 for Social Influence (SI). These values indicate that the questionnaires have a high degree of internal consistency. Composite reliability and Cronbach alpha values that fall within the range of 0.60 to 0.70 are considered acceptable; however, in the more advanced stage, the value absolutely must be greater than 0.70 (Hair et al., 2014).

The evaluation of the instruments' convergent validity was conducted by calculating the average variance extracted (AVE) as noted by Cheung et al. (2024). Convergent validity is the degree of agreement regarding the correlation between multiple indicators of the same construct (Hamid et al., 2017). AVE values for the constructs are as follows: Attitude toward AI (0.690), EE (0.740), PE (0.775), and SI (0.839). All these values surpassed the 0.50 threshold, which is deemed acceptable because an acceptable minimum AVE is 0.50. An AVE value of 0.50 or greater signifies that the construct accounts for a minimum of 50 per cent of the variance exhibited by the items comprising the construct (Bagozzi & Yi, 1988; Fornell & Larcker, 1981; Hair et al., 2014; Henseler et al., 2015).

Table 1. Construct Reliability and Validity.

Construct	Item	Loading	Alpha	rho-A	CR	AVE
Attitude toward AI	AC1	0.837	0.981	0.982	0.982	0.690
	AC10	0.801				
	AC2	0.848				
	AC3	0.813				
	AC4	0.848				
	AC5	0.827				
	AC6	0.840				
	AC7	0.831				
	AC8	0.823				
	AC9	0.823				
Effort Expectancy	EE2	0.787	0.824	0.841	0.895	0.740
	EE3	0.883				
	EE4	0.906				
Performance Expectancy	PE1	0.873	0.903	0.904	0.932	0.775

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	PE2	0.900				
	PE3	0.857				
	PE4	0.891				
Social Influence	SI2	0.916	0.809	0.809	0.913	0.839
	SI3	0.916				

The subsequent test conducted was the HTMT values as shown in Table 2. This assessment examined the discriminant validity of the scales, which refers to the degree to which the items differentiate from one another in an empirical context (Henseler et al., 2015). To enhance discriminant validity, items EE1, SI1, and SI4 were removed due to cross-loading, following the recommendations of Farrell (2021). Additionally, constructs related to Attitude toward AI were merged, improving discriminant validity, following still the recommendations of Farrell (2021).

The HTMT ratios of the constructs span in the following construct pairs: Attitude toward AI and Effort Expectancy (0.788), Attitude toward AI and Performance Expectancy (0.776), Attitude toward AI and Social Influence (0.726). The analysis shows strong discriminant validity between the constructs, as all ratios and HTMT values are below the critical threshold of 0.85 (Kline, 2016; Henseler et al., 2015)

Table 2. Heterotrait-Monotrait Ratio (HTMT)

Construct	Attitude toward AI	Effort Expectancy	Performance Expectancy	Social Influence
Attitude toward AI				
Effort Expectancy	0.788			
Performance Expectancy	0.776	0.883		
Social Influence	0.726	0.877	0.848	

Before assessing the structural relationships, it is essential to examine collinearity to ensure it does not introduce bias into the regression outcomes (Becker et al., 2015). Table 3 presents the examined relationships' Variance Inflation Factor (VIF) values. The VIF is a diagnostic tool to identify multicollinearity among predictor variables in regression analysis. According to Kim (2019), VIF is an effective diagnostic tool for identifying multicollinearity among predictor variables in regression analysis and helps ensure that the statistical results are reliable and accurate.

Hair et al. (2019) noted that variance inflation factor (VIF) values exceeding five may indicate potential collinearity problems among predictor constructs, while values between three and five can also suggest collinearity (Mason & Perreault, 1991; Becker et al., 2015).

In this study, all reported VIF values fall below the threshold, suggesting that there is no notable collinearity among all constructs. Specifically, the VIF values for Effort Expectancy (2.821), Performance Expectancy (2.843), and Social Influence (2.459) reinforce the finding that there is no substantial collinearity among these constructs.

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Table 3. Variance Inflation Factor (VIF)

	VIF
Effort Expectancy → Attitude toward AI	2.821
Performance Expectancy → Attitude toward AI	2.843
Social Influence → Attitude toward AI	2.459

3.2. Assessment of the Structural Model

Hair et al. (2021) emphasize that structural model assessment in PLS-SEM involves analyzing path coefficients. Everitt and Skrondal (2010) add that the t-statistic tests whether sample means significantly differ from a population mean, an essential step in hypothesis testing for structural models. Typically, a p-value threshold of 0.05 is used; values ≤ 0.05 suggest statistically significant results, implying the results are unlikely due to chance (Bevans, 2020).

Examining the path from Effort Expectancy (EE) to Attitude toward AI the path coefficient (β=0.319) indicates a positive correlation. This suggests that as teachers perceive AI as easier to use, their attitude toward AI becomes more favorable. Moreover, the t-statistic (t=5.528) and a p-value of (p=0.000) further confirm this relationship as highly significant, reinforcing the notion that ease of use plays a crucial role in shaping positive attitudes toward AI. This aligns with findings from Chen and Chang (2013), which indicate that when teachers perceive generative AI as easy to use, they are more likely to view it positively and integrate it into their practices. Moreover, Buabeng-Andoh and Baah (2020) found that higher effort expectancy significantly enhances teachers' intention to adopt educational technologies, such as learning management systems, underscoring the role of ease of use in fostering positive attitudes.

Additionally, Berg and Plessis (2023) demonstrate that generative AI tools, such as ChatGPT, simplify lesson planning by providing ready-to-use resources, which can reduce teachers' workload and strengthen their openness to adopting these tools. Similarly, Jauhiainen and Guerra (2023) show that generative AI's ability to tailor educational materials for diverse learners helps lower the effort required for content customization, further boosting teachers' receptiveness. Consequently, positive perceptions of effort expectancy enhance teachers' attitudes toward generative AI by making the technology seem more accessible and valuable in supporting educational practices.

On the other hand, Performance Expectancy (PE) has the highest path coefficient (β=0.392), highlighting an even stronger positive relationship with Attitude toward AI. This finding suggests that when people believe AI will enhance their performance or productivity, they are more likely to have favorable attitudes toward it. Additionally, the high t-statistic (t=7.122) and p-value (p=0.000) underscore the statistical significance, making it clear that Performance Expectancy is a major factor in influencing attitudes toward AI. This aligns with prior research, which highlights a positive link between performance expectancy and favorable attitudes toward generative AI among educators, influencing their openness to use AI in assessments (Davis et al., 1989). Studies reveal that when educators see generative AI as advantageous and effective, they are more likely to adopt these tools, emphasizing the importance of performance benefits (Alzahrani, 2023; Bervell et al., 2020). This association, observed across educational contexts, suggests that cultivating positive expectations about AI's potential can boost acceptance and increase teacher engagement with AI technologies in education (Arning & Ziefle, 2007).

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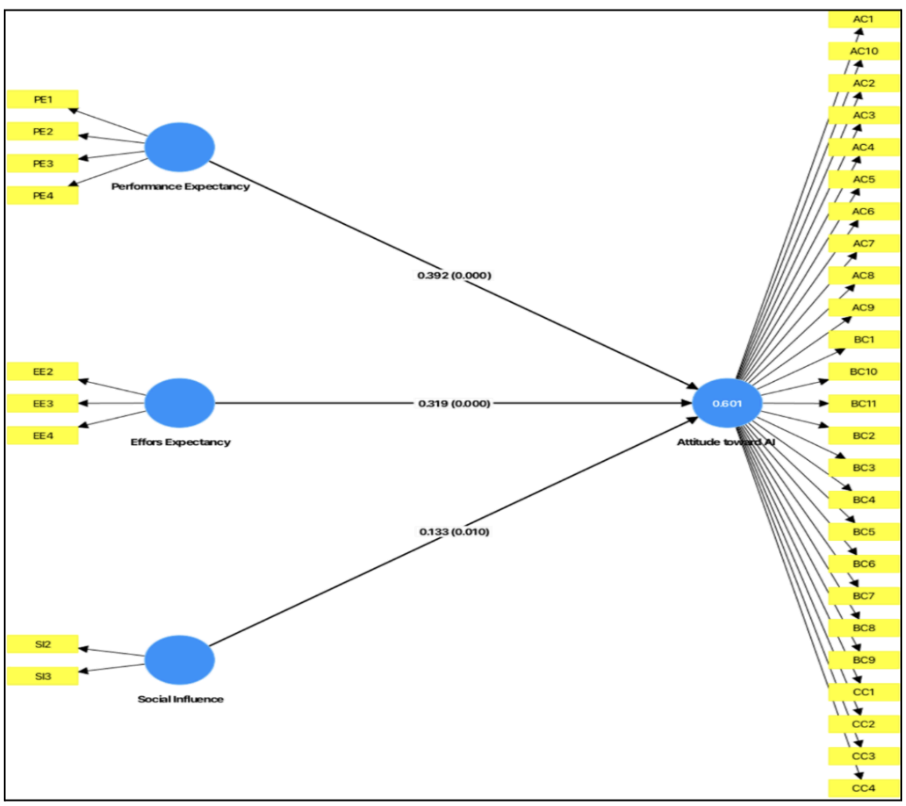
Lastly, the path coefficient for Social Influence (β=0.133), indicates a positive yet weaker relationship with Attitude toward AI. This suggests that while social factors, such as peer and cultural influences, do affect attitudes toward AI, they do so to a lesser extent compared to perceptions of ease of use and productivity enhancement. The t-statistic (t=2.589) and p-value (p=0.01) indicate that while it is not as robust as the other two predictors, the relationship is still statistically significant. This finding aligns with Cialdini and Goldstein's (2004) research, which emphasizes the role of social elements, such as peer opinions and societal trends, in shaping teachers' attitudes toward generative AI in assessment planning. Additionally, the result supports claims that while some educators view AI as potentially threatening to academic integrity and creativity (Smolansky et al., 2023), others recognize its value in lesson planning and personalized learning (Berg & Plessis, 2023). This study further reinforces that as teachers engage with AI, their professional communities play a role in building confidence and adaptability in its use (Sharples, 2023). Thus, social influence provides a positive but limited framework for teachers contemplating generative AI adoption, balancing peer support, professional norms, and ethical considerations (Qiang et al., 2017).

Figure 1: Partial Least Squares Structural Equation Modeling (PLS-SEM) Results Using Smart PLS 4.0



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3.3. Model Fit Assessment

Assessing model fit is essential for determining the effectiveness and predictive accuracy of a structural equation model (Gegenfurtner, 2022). The R^2 value of 0.601 indicates that 60.1% of the variance in attitudes toward AI can be explained by the model's independent variables. This finding suggests a good fit, where R^2 values are generally lower than 0.5 (Cheung et al., 2024). Furthermore, the adjusted R^2 of 0.598 offers a more nuanced measure by accounting for the number of predictors. This adjustment ensures that the model remains adequately simple while effectively explaining the variance (Nakagawa & Schielzeth, 2013).

In addition to R^2 values, the Q^2 predict value of 0.592 implies moderate predictive relevance, indicating that the model can reasonably predict the dependent variable (Tóth et al., 2013). Moreover, the lower values of RMSE (0.643) and MAE (0.459) suggest that the model's predictions are close to the actual values. However, it is important to note that the acceptability of these metrics can vary depending on the scale of the dependent variable (Dai et al., 2023).

Regarding the comparison between the saturated model and the estimated model, metrics such as d_ULS (0.883) and d_G (0.808) highlight the discrepancy between the observed and estimated covariance matrices (Xia & Yang, 2018). Finally, the Normed Fit Index (NFI) of 0.867, while below the typical threshold of 0.9, still indicates an acceptable fit, as values above 0.8 are generally considered satisfactory (Lombardi & Pastore, 2012).

Table 4. Model Fit

Endogenous Variables	R^2	Adjusted R^2	Q^2 predict	RMSE	MAE
Attitude toward AI	0.601	0.598	0.592	0.643	0.459
Saturated model	**Estimated model**				
SUMMER	0.039				
d_ULS	0.883				
d_G	0.808				
Chi-square	1932.154				
NFI	0.867				

4. Implications

The findings of this study emphasize the significant relationships between the constructs of the UTAUT model and teachers' attitudes toward generative AI in assessment planning, particularly focusing on effort expectancy, performance expectancy, and social influence. The strong positive correlation of effort expectancy with teachers' attitudes suggests that those who perceive AI as easy to use are more likely to have favorable attitudes toward it. This aligns with the UTAUT framework, which emphasizes that the perceived ease of using technology significantly impacts behavioral intention (Venkatesh et al., 2003). Moreover, performance expectancy showed an even stronger relationship, reinforcing the idea that when teachers believe AI can enhance their performance, their willingness to integrate such technologies increases. These findings stress the importance of designing user-friendly AI tools and demonstrating their practical benefits to foster a positive attitude among educators (Chen

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& Chang, 2013; Buabeng-Andoh & Baah, 2020).

Moreover, social influence, while showing a weaker correlation, still plays a noteworthy role in shaping teachers' attitudes toward AI in assessment planning. This construct suggests that teachers are somewhat influenced by the opinions of their peers and the broader educational community. However, the findings indicate that personal perceptions of ease of use and performance outweigh social factors in influencing attitudes (Cialdini & Goldstein, 2004). This aspect reflects the complexity of technology acceptance, as individual beliefs about AI often take precedence over external social pressures. Thus, while professional communities can provide support and encouragement for AI adoption, the emphasis should be on enhancing teachers' confidence in their perceptions of the technology's utility and usability (Sharples, 2023; Smolansky et al., 2023).

Furthermore, the findings have significant implications for assessment planning. Educators' positive attitudes toward AI can lead to more innovative approaches to assessments, fostering the development of personalized and adaptive learning experiences for students (Alzahrani, 2023; Berg & Plessis, 2023). The study suggests that effective assessment planning should consider not only the technical features of AI tools but also how they align with teachers' expectations of ease of use and potential performance benefits (Jauhiainen & Guerra, 2023). By actively involving teachers in the design and implementation phases of AI integration, educational institutions can ensure that these tools are not only user-friendly but also directly aligned with pedagogical goals. Additionally, creating professional development programs that address both the practical application of AI and the surrounding social contexts can enhance teachers' readiness to adopt these technologies, ultimately leading to more effective and engaging educational practices (Obenza, 2023).

5. Conclusion

This study investigates teachers' attitudes toward the integration of generative AI in assessment planning through the framework of the Unified Theory of Acceptance and Use of Technology (UTAUT). By emphasizing how attitudes influence behavioral intentions and technology adoption, it identifies key factors driving AI acceptance in educational settings, including performance expectancy, effort expectancy, and social influences. The findings underscore the importance of fostering supportive professional environments to enhance the effective integration of AI in education.

Employing a quantitative research design, the study utilized Partial Least Squares Structural Equation Modeling (PLS-SEM) to analyze the attitudes of 419 teachers, selected via stratified random sampling, using a structured questionnaire. The research ensured reliability and validity through methods like Cronbach's alpha and Average Variance Extracted (AVE). The results demonstrated robust reliability, with factor loadings between 0.787 and 0.916, indicating strong alignment in the measurement of constructs related to teachers' attitudes toward AI. Furthermore, the evaluation of convergent validity showed AVE values surpassing the acceptable threshold of 0.50, confirming the instruments' effectiveness in capturing the intended constructs.

Discriminant validity was assessed using Heterotrait-Monotrait (HTMT) ratios, revealing distinct differentiation among constructs, with values below the critical threshold of 0.85. The removal of items with cross-loading and the merging of constructs related to Attitude toward AI resulted in HTMT ratios of 0.788 for Effort Expectancy, 0.776 for Performance Expectancy,

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and 0.726 for Social Influence. Prior to evaluating structural relationships, the study addressed collinearity through Variance Inflation Factor (VIF) values, all of which fell below the critical threshold, ensuring reliability in regression outcomes.

The structural model assessment indicated significant positive relationships between teachers' attitudes toward generative AI and both Effort Expectancy (β=0.319, t=5.528, p=0.000) and Performance Expectancy (β=0.392, t=7.122, p=0.000). This suggests that perceptions of ease of use and performance enhancement are crucial for fostering favorable attitudes toward AI integration. While Social Influence also played a role (β=0.133, t=2.589, p=0.01), its impact was comparatively weaker. Overall, the results highlight that perceptions of usability and productivity are more influential in shaping teacher acceptance of AI in educational contexts.

The model fit assessment revealed that the structural equation model explains 60.1% of the variance in attitudes toward AI, with an R^2 value of 0.601, indicating a good fit. Additionally, the model demonstrated moderate predictive relevance, as indicated by a Q^2 predict value of 0.592, with acceptable RMSE (0.643) and MAE (0.459) metrics, despite a slightly below-ideal Normed Fit Index (NFI) of 0.867. This comprehensive analysis contributes valuable insights into the factors that influence teachers' acceptance of generative AI, providing a foundation for fostering a culture of innovation in educational assessment practices.

6. Recommendations

The findings of this study emphasize the importance of enhancing teachers' acceptance of generative AI in assessment planning. To achieve this, it is recommended that educational programs emphasize the demonstrable benefits and ease of use of generative AI technologies. Tailored professional development initiatives are essential to showcase the practical applications of AI tools, equipping teachers with the necessary skills and confidence to integrate these innovations into their assessment practices. Additionally, creating a collaborative environment for educators to share experiences and best practices can enhance social influence, ultimately increasing the overall acceptance of AI technologies. Future research should also investigate specific social factors that may enhance teachers' willingness to adopt generative AI. While this study identifies Social Influence as significant, its relatively minor effect suggests a need for initiatives that address misconceptions and resistance among educators. Promoting peer support and institutional backing can be pivotal in bridging this gap. Furthermore, exploring the varying impact of demographic factors on AI acceptance can provide insights into personalized training and support systems, leading to more effective integration of generative AI in educational assessment planning.

7. Limitations and Future Research Directions

While this study provides valuable insights into teachers' attitudes toward generative AI in assessment planning, several limitations must be acknowledged. The specific focus of the study may restrict the applicability of findings to other educational contexts. Therefore, future research should explore additional factors influencing AI acceptance, such as teachers' confidence in technology, prior experiences, and ethical considerations. Ongoing studies are essential to understand the evolving impact of AI on teaching practices, and longitudinal research is recommended to track changes in teachers' attitudes over time as they become more familiar with AI tools. Expanding the participant pool and examining diverse educational settings will also enhance understanding of technology acceptance, as the current study's homogeneous

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sample limits generalizability and highlights the need to include diverse educators in future research.

Moreover, while Social Influence (SI) had a weaker impact, investigating the role of leadership support and peer collaboration is crucial for facilitating AI adoption, as Venkatesh et al. (2003) noted. Qualitative methods like focus groups or interviews could provide deeper insights into this area. Additionally, evaluating Facilitating Conditions (FC), including access to training and technical support, will offer a more comprehensive view of AI adoption, as Hwang et al. (2015) suggested. It is also essential to address cross-loading issues in research instruments to ensure clarity and precision in findings, as Hair et al. (2010) highlighted. Ethical considerations, such as bias and data privacy, should be prioritized (O'Neil, 2016), and incorporating qualitative methods alongside quantitative findings can enrich the understanding of teachers' experiences, as Creswell and Poth (2018) suggested. Lastly, continued refinement of the research model is necessary to ensure robust construct validity (Kline, 2016), and tailored professional development along with ongoing technical support can significantly aid in the successful adoption of AI technologies, as indicated by Kohnke et al. (2023).

8. Disclosure Statement

This is to declare that artificial intelligence (AI) tools were used in a limited, ethical, and supportive manner during the completion of the study titled: "Investigating The Attitude Of Teachers Towards Generative Ai In Assessment Planning Using The Unified Theory Of Acceptance And Use Of Technology". The following AI tools were used: ChatGPT (OpenAI) and Grammarly. These tools were utilized solely for enhancing grammar, clarity, and academic tone; and assisting in organizing and refining survey questions and literature content. No AI tool was used to generate the conceptual framework, original analysis, or conclusions. All scholarly content and findings represent the independent work of the author. The authors assume full responsibility for the originality, accuracy, and academic integrity of this research.

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