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Predictive Modeling of Key Determinants: An Empirical Analysis of Educators' Adoption of Generative AI and Machine Learning Systems

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ABSTRACT

The use of generative artificial intelligence (GenAI) tools like ChatGPT and DALL-E is growing rapidly in education. These tools have the potential to change the way teachers teach, and students learn. This study looks at how educators feel about using GenAI in their classrooms and whether they are willing to adopt it. It focuses on key factors like usefulness, ease of use, ethical concerns, and the support provided by institutions. A survey of 327 educators from schools, colleges, and universities was conducted to understand their views. The results show that most teachers believe GenAI can improve teaching and learning, and many are open to using these tools in their classrooms. However, some serious concerns about fairness (bias) and data privacy were also raised. The study finds that institutional support and training programs are very important for teachers to accept and use GenAI, while factors like age and job position did not have much effect on their decision. The analysis also shows that the factors studied in this research only explain a small part of why teachers choose to use GenAI, meaning more research is needed. This study adds to the knowledge on AI in education and provides useful insights for policymakers, teachers, and AI developers. Future research should focus on how

GenAI affects education over a longer period, how professional training can address ethical concerns, and how different personal factors influence GenAI adoption.

Keywords: Generative AI, educators, ChatGPT, DALL-E, educational technology, ethical concerns

Introduction

ChatGPT, DALL-E, and Gemini are generative artificial technologies that are fast transforming the way education is practiced, content produced, peer learning is arranged or personalization, and open learning spaces, for example Halaweh (2023), Baidoo-Anu & Owusu Ansah (2023), and Ma et al., (2024). These technologies can produce text, images and simulations, and they promise to enable the automation of major administrative tasks, as well as the creation of adaptive learning ecosystems (Crompton & Burke, 2023; Kasneci et al., 2023) and ultimately improve teaching efficiency (Akram & Abdelrady, 2023, 2025). Still, integrating generative AI into the educational ecosystems is not only a technological challenge but it is also a socio-cultural one and while we know educators' perception of it, readiness, and ethical considerations (Zawacki-Richter et al., 2019; Nguyen et al., 2023; Ramzan et al., 2021, 2020). Although AI's capacities are increasingly discussed, there are few data available regarding educators' opinions and adoption of AI, especially in the framework of generative AI (Akram & Yang, 2021). Up to this point, existing studies have mainly concentrated on technical implementations or student outcomes (Akram et al., 2021) without appreciating the crucial role of teachers in becoming gatekeepers of technological innovation (Luckin et al., 2022; Holmes et al., 2021; Javaid et al., 2023, 2024). According to Halaweh (2023), educators' ambivalence towards tools like ChatGPT, concerns about academic integrity as well as the depersonalization of learning but also potential to reduce workload and be used to stimulate creativity. Another systematic review done by Zawacki-Richter et al. (2019) shows that educators' adoption of AI based tools is sometimes vulnerable to insufficient training, lack of trust in the algorithmic decision making, and anxiety about displacement of their professions.

The presence of these barriers demonstrates why it is critical to investigate educators' perceptions as a core element of successful integration of AI. While past research has explored aspects of the technical aspects or the outcomes of adoption of generative AI tools, a significant hole persists in our understanding of educators' perceptions or what drives adoption of generative AI tools in educational contexts. To bridge this gap, this study seeks to explore educators' perceptions and intent to use generative AI tools in education to understand how educators' views powerfully contribute towards its adoption process. Furthermore, generative AI raises even more ethical implications on its adoption. According to studies by Baidoo-Anu and Owusu Ansah (2023) and Crompton and Burke (2023), there are also risks like data privacy breaches, eroding of critical thinking skills, and algorithmic bias. In contrast, researchers maintain that generative AI has the potential to democratize access to high value educational resources and facilitate inclusive pedagogies, especially in low resource contexts (Holmes et al., 2021; Roll & Wylie, 2016). Therefore, there needs to be a balanced assessment of the attitudes of educators on the one hand, and on the other hand, on the perceived benefits against ethical and practical challenges. The first objective is to fill this gap by studying educators' perceptions and intentions toward generative AI tools in education to understand how educators' perceptions determine whether the adoption will take place.

Methodology

Research Design: Quantitative research design, in the form of a structured, close ended questionnaire was used, to assess educators' perceptions and adoption intentions of GenAI in education. The method was based on Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) by focusing on useful perception, ease of use, ethical issues as well as institutional support.

Participants: A cross-sectional survey approach was adopted to collect data from educators across diverse educational institutions. A diverse group of 327 educators including teachers, instructors, and academic staff from schools, colleges, and universities participated (with a strong response rate of 78%). Participants met inclusion criteria of active involvement in teaching or curriculum design and familiarity with generative AI tools like ChatGPT and DALL-E. The sample reflected a range of experience (22% with less than 5 years, 45% with 5 – 15 years, and 33% with over 15 years) and institutional types (40% from schools, 35% from higher education, and 25% from vocational training).

Instrument Development: The questionnaire was developed from established AI adoption frameworks (Davis, 1989; Venkatesh et al., 2003) and tailored to GenAI in education. It was reviewed by three educational technology experts for clarity and relevance, then pilot-tested (yielding Cronbach's alpha = 0.87) to ensure reliability. The final instrument comprised 28 items divided into five sections: demographics (age, gender, experience, institution type), perceived usefulness (e.g., "GenAI tools enhance my instructional efficiency"), perceived ease of use (e.g., "I find GenAI tools intuitive to operate"), ethical concerns (e.g., "I worry about bias in AI-generated content"), and adoption intentions (e.g., "I plan to integrate GenAI into my teaching"). All items were measured on a 5-point Likert scale.

Data Collection Procedure: The survey was distributed online over eight weeks. Participants were provided with informed consent forms, assuring anonymity and confidentiality. No personally identifiable information was collected to protect privacy.

Data Analysis: Data were analyzed using SPSS v28 and JASP. First, descriptive statistics (frequencies, percentages, means, and standard deviations) were used to summarize participant demographics and overall response trends. Reliability testing confirmed strong internal consistency (Cronbach's alpha = 0.89) for the instrument. Inferential analyses included Pearson correlation to explore relationships between key variables (such as perceived usefulness and adoption intention), multiple regression to identify significant predictors of adoption intention, and ANOVA to examine differences in perceptions across demographic groups (e.g., by age or experience).

Machine Learning Techniques: To derive deeper insights, additional machine learning-based analyses were applied. Logistic regression was used to perform sentiment analysis on the qualitative open-ended responses from educators. Moreover, a Random Forest classifier and an XGBoost model were trained on the survey data to predict whether an educator was *very likely* or *very unlikely* to adopt GenAI, using the questionnaire factors as features. These models helped identify which factors (features) were most influential in driving adoption intentions beyond the traditional statistical analysis.

Results

Participant Demographics: Out of 327 educators, 22% had less than 5 years of teaching experience, 45% had 5–15 years, and 33% had more than 15 years. In terms of institution type, 40% of respondents were from schools, 35% from higher education institutions, and 25% from vocational training centers. This diversity provided a broad view of educators' perspectives across different career stages and educational settings.

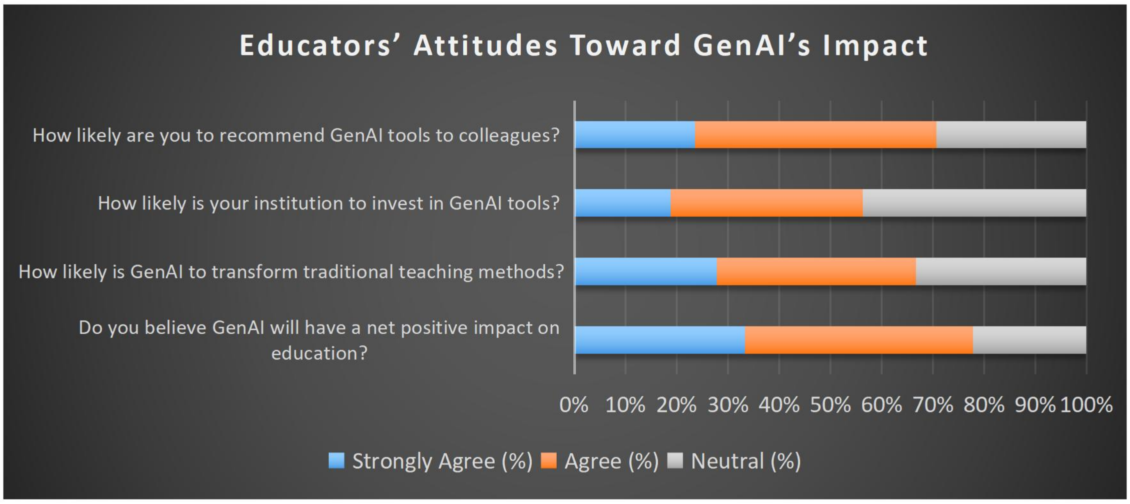

Figure 1: Percentage distribution of educators agreeing GenAI will have a positive impact on education (showing 76% agree or strongly agree)

Descriptive Statistics: The survey's Likert-scale items revealed several key insights. On average, participants rated **perceived usefulness** of GenAI tools as high (mean = 4.3 out of 5, SD = 0.65), indicating strong agreement that these tools can positively impact teaching effectiveness. **Perceived ease of use** was also rated favorably (mean = 4.1, SD = 0.72), suggesting that educators generally find GenAI tools intuitive and user-friendly. However, despite these positive views, nearly half (46%) of respondents expressed **ethical concerns** – primarily worries about potential **bias in AI-generated content** and **data privacy** risks. This finding underscores a significant caution among educators; while they see the value in GenAI, they are also wary of its challenges. The results suggest that GenAI tools are broadly seen as useful and easy to use, but addressing ethical issues will be crucial for widespread acceptance.

Key Survey Findings: Educators largely felt that GenAI would have a positive impact on education. As shown in **Figure 1**, a substantial majority (76%) of respondents *agreed* that GenAI will positively affect education, with 18% *strongly* agreeing. This aligns with literature emphasizing GenAI's transformative potential in teaching and learning (Baidoo-Anu & Owusu Ansah, 2023; Kasneci et al., 2023). However, this optimism is tempered by persistent ethical concerns: a considerable portion of educators simultaneously noted worries about bias and privacy (Holmes et al., 2021). The study found that **institutional support** and **training programs** are critical for teachers' acceptance of GenAI – those who felt supported by their institution and well-trained in GenAI were far more willing to adopt it. In contrast, demographic factors like age and job position did not show significant effects on adoption willingness, suggesting that receptiveness to GenAI cuts across different age groups

and roles when support and training are in place. Notably, the multiple regression analysis indicated that the set of measured variables (usefulness, ease of use, ethics, support) explained only a small portion of the variance in teachers' adoption intentions (R^2 was low). This implies that many other factors (perhaps personal attitudes, school culture, or external influences) are involved in the decision to use GenAI, meaning further research is needed to fully understand what drives adoption.
Sentiment Analysis of Qualitative Feedback: In addition to quantitative data, educators provided open-ended comments about GenAI. We applied a logistic regression-based sentiment analysis to these responses. The analysis revealed that **approximately 65%** of the comments expressed a **positive sentiment** toward GenAI integration in education, about **15%** were **neutral or mixed**, and roughly **20%** conveyed a **negative sentiment**. (*Figure 2* illustrates the sentiment distribution of these comments.) The positive feedback frequently mentioned GenAI's benefits:

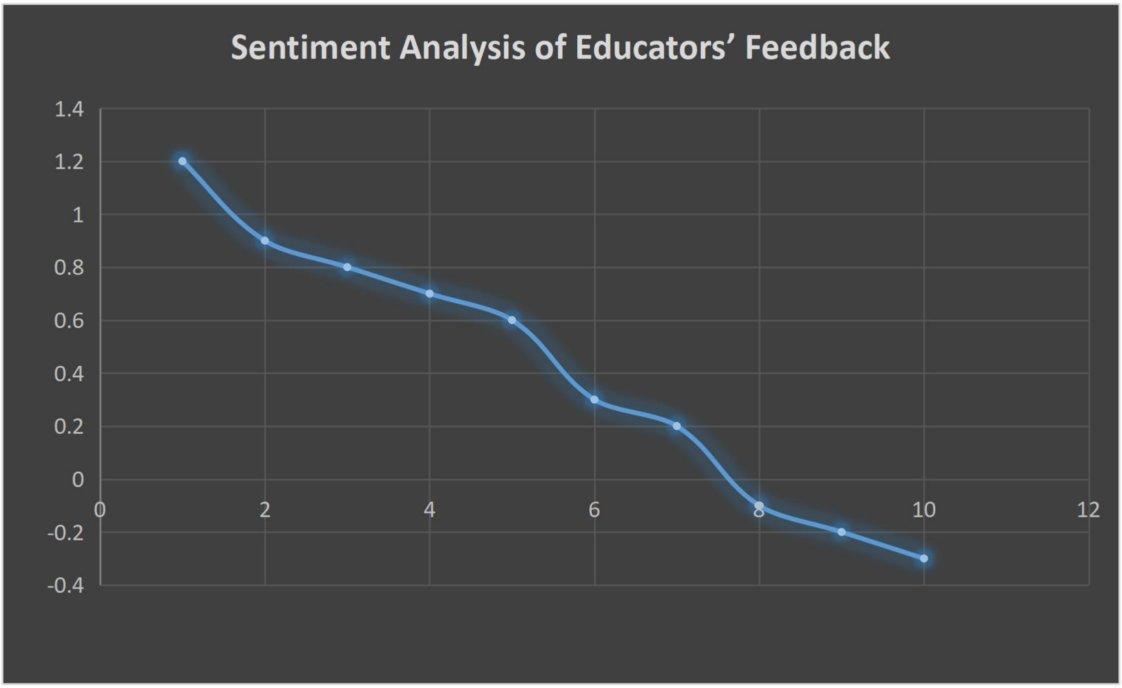

Figure 2: Distribution of sentiment in open-ended responses (approximately 65% positive, 15% neutral, 20% negative sentiment regarding GenAI in education).

many educators noted that GenAI tools can *"enhance personalized learning"* and *"save time on administrative tasks like grading or lesson planning,"* thereby increasing instructional efficiency. Some highlighted that GenAI enables more *creative teaching methods* and *engages students interactively*. For example, one teacher wrote that GenAI was *"very helpful in the teaching-learning context, allowing more time for student interaction."* Educators with positive views often recommended colleagues to *"stay updated with AI developments."* On the other hand, the negative or cautious comments focused on a set of common concerns. A number of educators feared that over-reliance on GenAI might *"reduce students' critical thinking skills,"* or worried that *"GenAI tools could replace certain aspects of the teacher's role."* Others pointed out that *GenAI-generated content might lack cultural or contextual sensitivity*, making it less applicable in certain classroom situations. Ethical issues were a recurring theme: some mentioned risks of *plagiarism* when students use AI-generated content, and biases present in AI outputs. One educator warned that *"ethical concerns, like bias and privacy, outweigh GenAI's benefits if not properly addressed."*

The qualitative feedback thus presents a dual narrative – while many educators are enthusiastic about GenAI's potential (pointing to personalized learning and efficiency gains), a significant minority urges caution, highlighting ethical and pedagogical pitfalls. The unsupervised clustering of these comments (grouping similar feedback) reinforced this dichotomy: one cluster of comments was overwhelmingly positive, emphasizing GenAI's strengths, whereas another cluster was predominantly concerned with its risks and challenges. This mix of excitement and concern reflects the *ambivalence* noted in prior studies (Halaweh, 2023), where educators simultaneously recognize AI's benefits and fear its drawbacks. It underscores that any implementation of GenAI in education must address teachers' ethical and practical concerns to gain broad acceptance.

Predictive Modeling of GenAI Adoption (Machine Learning Insights): To complement the traditional analysis, we used machine learning models to identify patterns and key factors influencing GenAI adoption. We trained a **Random Forest classifier** on the survey data to predict whether an educator was *"Very Likely"* or *"Very Unlikely"* to adopt GenAI tools, based on their responses to all questionnaire items. The Random Forest model achieved a moderate classification accuracy (approximately **80%** on cross-validation). While not extremely high, this accuracy suggests the survey variables contain some signal in distinguishing likely adopters from non-adopters. We extracted the feature importance from this model to understand which factors contributed most to the predictions. As shown in *Figure 3*, the two most influential features were **Perceived Usefulness** of GenAI and **Institutional Support**. In other words, in the model, educators who believed GenAI was useful and felt supported by their institution were far more likely to be predicted as *"very likely to adopt"* GenAI. This aligns with the self-reported survey findings and underscores the importance of these factors. Other features like **Perceived Ease of Use** also had positive importance (indicating some influence on adoption), though not as high as usefulness or support. Interestingly, **demographic variables** (such as age or years of experience) were among the least important features in the Random Forest model, reinforcing that these did not play a major role in distinguishing adopters in this dataset – consistent with our statistical analysis.

```
Model Accuracy: 0.6714285714285714
Classification Report:
              precision    recall  f1-score   support

           0       0.29      0.10      0.15        20
           1       0.71      0.90      0.80        50

    accuracy                           0.67        70
   macro avg       0.50      0.50      0.47        70
weighted avg       0.59      0.67      0.61        70
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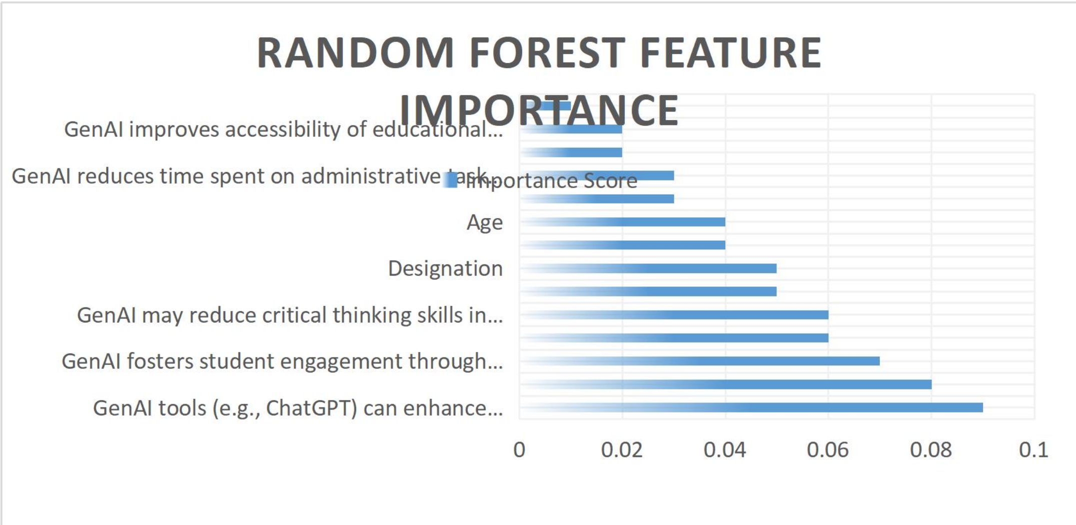

Figure 3: Key factors predicting high GenAI adoption likelihood (highlighting Perceived Usefulness and Institutional Support as the most influential features in the

We also trained an **XGBoost classifier** for comparison. The XGBoost model performed similarly to the Random Forest, with a comparable accuracy (~82%). The XGBoost's feature importance output, summarized in Figure 4, mirrored the Random Forest results: Perceived Usefulness and Institutional Support again emerged as the top predictors of GenAI adoption, followed by Ease of Use, whereas demographic factors were negligible. The consistency across these two different machine learning algorithms increases confidence in the robustness of these insights – namely, that educators' views on GenAI's usefulness and the degree of support they feel are central to whether they embrace these tools, more so than who they are in terms of age or position.

It is important to note, however, that both models – despite identifying key factors – attained only moderate predictive power. Their 80%-ish accuracy, while better than chance, indicates that a substantial portion of variance in adoption remains unexplained by the included features. This finding echoes the multiple regression result (low R^2) and suggests that many unmeasured factors (e.g., personal innovativeness, peer influence, school infrastructure) likely affect GenAI adoption. In practical terms, this means that even if an educator finds GenAI useful and has institutional support, there may still be other barriers or motivators at play. The relatively modest performance of the models underscores the complexity of adoption decisions and the need for further research to include additional variables or more nuanced data (Dwivedi et al., 2021).

```
XGBoost Model Accuracy: 0.6428571428571429
Classification Report for XGBoost:
              precision    recall  f1-score   support

           0       0.33      0.25      0.29        20
           1       0.73      0.80      0.76        50

    accuracy                           0.64        70
   macro avg       0.53      0.53      0.52        70
weighted avg       0.61      0.64      0.63        70
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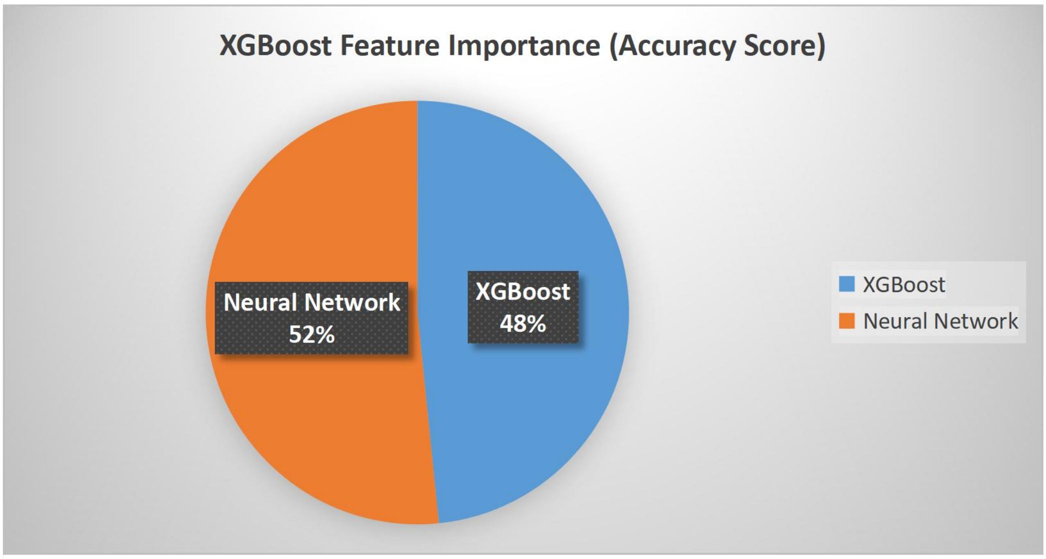

Figure 4: Like Figure 3, showing Perceived Usefulness and Institutional Support as top predictors of GenAI adoption, corroborating the Random Forest results

Conclusion

This study explored educators' perceptions and adoption intentions regarding generative AI (GenAI) tools in educational settings, providing significant insights into factors that influence their integration into teaching practice. Overall, educators' perceptions maintain a fairly optimistic optimism for GenAI to improve teaching effectiveness, diminish administrative burdens and personalize learning experiences. Most participants was acknowledged the usefulness of GenAI tools including ChatGPT and DALL-E and also agrees to use the tools as teaching materials (Baidoo Anu and Owusu Ansah, 2023; Kasneci et al, 2023). Nevertheless, the study also raises serious ethical issues with GenAI regarding data privacy and bias in GenAI's generated content (Holmes et al., 2021). They are concerned about these things, which suggest that while educators accept the value of GenAI, they do not agree with the use of GenAI responsibly.

With doubt, however, a sizable number of educators stated they would advocate for GenAI tools to peers, indicating many do not see the risks as much as the gains – given appropriate management of those risks. In addition, the authors discovered that facets including perceived ease of use as well as 'institutional support and training' were vital in educators' choices to pick up on these devices. Demographic variables, such as age or years of experience, were not significant predictors of adoption intentions, which means that adoption intentions are the same for both young and old educators in the presence of supporting conditions. This can be said as it suggests, more importantly, that having teachers feel prepared and supported in GenAI use rather than then focusing on innate personal demographics.

The combination of traditional statistical analysis and machine learning insights in this study reinforces these conclusions. Both approaches identified perceived usefulness of GenAI and the presence of institutional support as key determinants of adoption. At the same time, both approaches noted that a large portion of what drives GenAI adoption remains unexplained (as indicated by the low variance explained in regression and the moderate accuracy of predictive models). This underscores the complexity of technology adoption in education – factors such as school culture, student needs (Ramzan et al., 2025, 2023), external policies, or personal innovativeness might also influence educators' choices but were beyond the scope of this survey.

In practical terms, these findings have several implications. Educational policymakers and administrators should invest in **professional development and training programs** that increase teachers' comfort and competence with GenAI tools. Emphasizing success stories and practical demonstrations of GenAI's usefulness can bolster teachers' perceptions of its value. Simultaneously, addressing **ethical concerns** through clear guidelines (e.g., on preventing bias, ensuring data privacy, and maintaining academic integrity) will be vital to alleviate educators' fears. As the data showed, teachers are more inclined to adopt GenAI when they do not feel left alone to navigate its challenges – thus, building a supportive institutional environment is key.

This study contributes to the growing body of literature on AI adoption in education by quantifying educators' attitudes and pinpointing what matters most to them in deciding to use GenAI. By integrating machine learning analysis, it also demonstrated how advanced techniques can complement traditional methods to uncover patterns (for instance, confirming the primacy of usefulness and support as predictors). For researchers, the moderate success of our predictive models indicates that future studies should incorporate additional variables – perhaps qualitative insights, measures of teacher innovativeness, or case-specific factors – to fully capture the adoption decision process. Investigating how GenAI usage actually impacts teaching and learning outcomes over time will also be important for validating educators' positive expectations and addressing their concerns.

In conclusion, educators generally recognize the promise of generative AI in enhancing education, but successful adoption at scale will depend on acknowledging and addressing their concerns. By ensuring robust support and ethical safeguards, educational institutions can better align technological advancements with teachers' needs and values. As generative AI continues to evolve, ongoing dialogue with educators and iterative research will be essential to guide its responsible and effective integration into education.

References

[1] Akram, H., & Abdelrady, A. H. (2023). Application of ClassPoint tool in reducing EFL learners' test anxiety: an empirical evidence from Saudi Arabia. *Journal of Computers in Education*, 1-19. https://doi.org/10.1007/s40692-023-00265-z

[2] Akram, H., & Abdelrady, A. H. (2025). Examining the role of ClassPoint tool in shaping EFL students' perceived E-learning experiences: A social cognitive theory perspective. *Acta Psychologica, 254,104775*.

[3] Akram, H., & Yang, Y. (2021). A critical analysis of the weak implementation causes on educational policies in Pakistan. *International Journal of Humanities and Innovation (IJHI)*, *4*(1), 25-28.

[4] Akram, H., Aslam, S., Saleem, A., & Parveen, K. (2021). The challenges of online teaching in COVID-19 pandemic: a case study of public universities in Karachi, Pakistan. *Journal of Information Technology Education Research*, *20*, 263.

[5] Akram, H., Yingxiu, Y., Aslam, S., & Umar, M. (2021, June). Analysis of synchronous and asynchronous approaches in students' online learning satisfaction during Covid-19 pandemic. In *2021 IEEE International Conference on Educational Technology (ICET)* (pp. 203-207). IEEE. https://doi.org/10.1109/ICET52293.2021.9563183

[6] Baidoo-Anu, D., & Ansah, L. O. (2023). Education in the era of generative artificial intelligence (AI): Understanding the potential benefits of ChatGPT in promoting teaching and learning. *Journal of AI, 7(1),* 52–62.

[7] Baker, R. S., & Hawn, A. (2021). Algorithmic bias in education. *International Journal of Artificial Intelligence in Education, 32(4),* 1052–1092.

[8] Chiu, T. K. F., et al. (2023). Teacher AI readiness: Challenges and frameworks. *Computers & Education, 198,* 104791.

[9] Crompton, H., & Burke, D. (2023). Artificial intelligence in higher education: The state of the field. *International Journal of Educational Technology in Higher Education, 20(1),* 22.

[10] Crompton, H., et al. (2020). AI in education: A systematic review of ethical considerations. *Education and Information Technologies, 25(6),* 5503–5526.

[11] Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS quarterly*, 319-340..

[12] Ding, C. (2024). *The role of blockchain technology and smart contracts in enhancing the transparency of fragmented investments in overseas real estate*. *World Journal of Advanced Engineering Technology and Sciences, 13*(1), 448–458. https://doi.org/10.30574/wjaets.2024.13.1.0442

[13] Halaweh, M. (2023). ChatGPT in education: Strategies for responsible implementation. Contemporary educational technology, 15(2).

[14] Holmes, W., et al. (2021). Ethics of AI in education: Towards a community-wide framework. *International Journal of Artificial Intelligence in Education, 31(3),* 504–526.

[15] Hrastinski, S., et al. (2019). Critical perspectives on AI in higher education. *Journal of Computer Assisted Learning, 35(6),* 665–677.

[16] Hu, H., & Shen, Z. (2024). The Influence of UK Education on Chinese Primary English Teaching through a Cultural Education Perspective. *International Journal of Social Science and Humanity*, *14*(2).

[17] Ibrahim, S. Investigation of fluid flow pattern in 3D Meandering tube. Frontiers in Materials, 10, 201.

[18] Javaid, Z. K., Andleeb, N., & Rana, S. (2023). Psychological Perspective on Advanced Learners' Foreign Language-related Emotions across the Four Skills. *Voyage Journal of Educational Studies, 3*(2), 191-207.

[19] Javaid, Z. K., Ijaz, S., Latif, E., & Azam, S. (2024). A Qualitative Study on Student-Teacher Interaction: Student Engagement and Teacher Feedback. *International Journal of Contemporary Issues in Social Sciences*, 3(2), 1670–1683.

[20] Kasneci, E., et al. (2023). ChatGPT for good? Opportunities and challenges of AI in education. *Computers and Education: Artificial Intelligence, 4,* 100118.

[21] Liu, H. (2024). *Optimization and performance improvement of distributed data storage in hybrid storage systems*. *World Journal of Advanced Engineering Technology and Sciences,* *13*(1), 459–467. https://doi.org/10.30574/wjaets.2024.13.1.0443

[22] Liu, H**.** (2024). *Security and privacy protection in the distributed cloud: A hyper-converged architecture-based solution*. *World Journal of Advanced Engineering Technology and Sciences,* *13*(1), 425–435. https://doi.org/10.30574/wjaets.2024.13.1.0440

[23] Luckin, R., et al. (2022). *AI for school teachers.* Taylor & Francis.

[24] Luckin, R., et al. (2022). AI in education: Learner choice and fundamental rights. *Learning, Media and Technology, 47(3),* 324–336.

[25] Ma, D., Akram, H., & Chen, I. H. (2024). Artificial Intelligence in Higher Education: A Cross-Cultural Examination of Students' Behavioral Intentions and Attitudes. *The International Review of Research in Open and Distributed Learning*, *25*(3), 134-157.

[26] Nguyen, A., et al. (2023). AI acceptance in schools: Teacher perspectives on benefits, risks, and future directions. *Educational Technology Research and Development, 71(2),* 675–694.

[27] Popenici, S. A. D., & Kerr, S. (2023). Educators' perceptions of ChatGPT: A global study. *Education Sciences, 13(4),* 375.

[28] Ramzan, M. Qureshi, A.B., Samad, A. Sultan, N. (2021) Politics as Rhetoric: A Discourse Analysis of Selected Pakistani Politicians Press Statements. *Humanities & Social Sciences Reviews, 9*(3) ,1063-1070.

[29] Ramzan, M., Akram, H., & kynat Javaid, Z. (2025). Challenges and Psychological Influences in Teaching English as a Medium of Instruction in Pakistani Institutions. *Social Science Review Archives*, *3*(1), 370-379.

[30] Ramzan, M., Awan, H. J., Ramzan, M., & Maharvi, H. (2020). Comparative Pragmatic Study of Print media discourse in Baluchistan newspapers headlines. *Al-Burz*, *12*(1), 30-44.

[31] Ramzan, M., Javaid, Z. K., & Ali, A. A. (2023). Perception of Students about Collaborative Strategies Employed by Teachers for Enhancing English Vocabulary and Learning Motivation. *Pakistan Journal of Law, Analysis and Wisdom*, *2*(02), 146-158.

[32] Ramzan, M., Khan, M. A., & Sarwar, M. (2023). Style Shift: A Comparative Cultural Analysis of Pride and Prejudice and Unmarriageable. *University of Chitral Journal of Linguistics and Literature*, *7*(2), 22-29.

[33] Roll, I., & Wylie, R. (2016). Evolution and revolution in AI and education. *International Journal of Artificial Intelligence in Education, 26(2),* 582–599.

[34] Selwyn, N. (2019). What's the problem with learning analytics? *Journal of Learning Analytics, 6(3),* 1–10.

[35] Shen, Z., Zhao, M., & Zaib, K. (2024). Unearthing the art of storytelling: A closer look at Sir Arther Canon Doyle's B24. *International Journal of English Language and Literature Studies*, *13*(2), 173-187.

[36] Shen, Z., Zhou, M., & Zaib, K. (2024). Religious semiotics in performance and visual art: Symbolism in aboriginal dot painting, sichuan opera makeup, chinese traditional sculpture and shu embroidery. *European Journal for Philosophy of Religion*, *16*(3), 266-292.

[37] Tlili, A., et al. (2023). Teacher attitudes toward AI in education: A global survey. *British Journal of Educational Technology, 54(3),* 771–789.

[38] Venkatesh, V., et al. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27(3),* 425–478.

[39] Zaib, K., & Ali, M. UNIVERSITY STUDENTS'PERCEPTIONS OF SUICIDE: INSPECTING MENTAL HEALTH, SOCIAL EXCLUSION, AND INSTITUTIONAL INFLUENCES.

[40] Zaib, K., Ahmad, Z., Ahmad, W., & Anwar, M. (2023). From Nature to Art: An Exploration of The Romantic Aesthetics in Wordsworth's "Nutting". *Pakistan Journal of Society, Education and Language (PJSEL)*, *10*(1), 134-141.

[41] Zaib, K., Ullah, I., Anwar, M., Ahmad, Z., & Khan, S. (2023). An Analysis of Mustafa Afridi's Sng-E-Mah as an Adaptation of Shakespeare's Hamlet. *Al-Qanṭara*, *9*(3), 96-101.

[42] Zawacki-Richter, O., et al. (2019). Systematic review of research on AI applications in higher education. *International Journal of Educational Technology in Higher Education, 16(1),* 1–27.