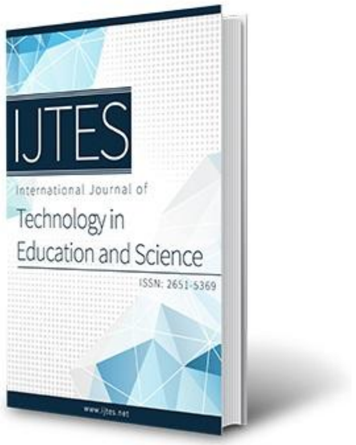

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AI and Academia: Navigating the Adoption of Artificial Intelligence in Universities

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To cite this article:

Mijan, A., Hasan, M.R., & Hasan, M. (2025). AI and academia: Navigating the adoption of artificial intelligence in universities. *International Journal of Technology in Education and Science (IJTES), 9*(1), 54- 65. https://doi.org/10.46328/ijtes.602

International Journal of Technology in Education and Science
2025, Vol. 9, No. 1, 54-65 https://doi.org/10.46328/ijtes.602

AI and Academia: Navigating the Adoption of Artificial Intelligence in Universities

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Article Info

Article History

Received:
11 September 2024
Accepted:
17 December 2024

Keywords

Artificial intelligence
Higher education
AI adaptations
Logistic regression

Abstract

This study investigated the utilization of artificial intelligence (AI) platforms in Bangladeshi higher education institutions, with an emphasis on determining which AI platforms are most widely used and assessing the variables that affect AI adoption. The particular criteria influencing platform preferences and the comparative analysis of various types of institutions remain unclear despite the abundance of research on AI adoption. The study employed logistic regression analysis to test two primary hypotheses: (1) private universities had a higher level of AI adoption compared to public universities, and (2) better technological infrastructure was positively associated with higher AI adoption levels. Data was collected through a structured survey administered to a representative sample of 100 participants from various higher education institutions, capturing information on AI adoption levels, institutional type, technological infrastructure, technical expertise, and financial constraints. The analysis revealed that the most widely adopted AI platforms were ChatGPT, followed by AWS, Google Cloud Platform, and Google Gemini. The logistic regression results supported the hypotheses, indicating that private universities were more likely to adopt AI at higher levels compared to public institutions. Additionally, better technological infrastructure was associated with higher AI adoption levels. The confusion matrix demonstrated that while the model performed well in predicting AI adoption levels, there were some misclassifications, particularly between high and medium adoption categories.

Introduction

Artificial intelligence (AI) has quickly developed from a specialized science to a force that is transforming a wide range of businesses, improving productivity, and changing how people interact with technology (Farahani et al., 2024). In the educational domain, AI has emerged as a powerful tool with the potential to revolutionize how institutions operate, how educators teach, and how students learn (Farahani et al., 2024; Zhang & Lu, 2021). The adoption of AI in education is not just about incorporating new tools; it's about fundamentally rethinking the processes of teaching, learning, and administration to create more personalized, efficient, and effective educational experiences (Almufarreh & Arshad, 2023).

The use of AI in education spans a broad range of applications, including administrative AI tools that optimize resource allocation and expedite institutional operations, as well as adaptive learning systems that customize instructional content to meet the requirements of specific students. AI's potential to enhance educational outcomes is significant, particularly in higher education, where it can support more personalized learning experiences, improve student engagement, and provide educators with deeper insights into student performance (Ahmad et al., 2024; Mittal et al., 2020). But there are a number of obstacles to overcome before AI can be widely used in higher education. These include worries about data privacy, the need for significant infrastructure and technology investments, and the possibility that AI would worsen already-existing educational disparities (Onesi-Ozigagun et al., 2024; Young, 2024).

Globally, higher education institutions are increasingly recognizing the potential of AI to address these challenges and are exploring ways to integrate AI into their educational practices (Katsamakas et al., 2024). In developed countries, AI adoption in higher education is more advanced, driven by significant investments in technology and research. Universities in the United States, Europe, and Asia have been at the forefront of this transformation, leveraging AI to enhance both academic and administrative functions (Felten et al., 2023; Fütterer et al., 2023). However, in developing countries like Bangladesh, the adoption of AI in higher education is still in its nascent stages. The challenges faced by Bangladeshi higher education institutions, such as limited access to technology, insufficient funding, and a lack of expertise in AI, make the adoption of AI a complex and multifaceted issue that warrants in-depth investigation (Sultana & Faruk, 2024).

An area of growing interest in Bangladeshi higher education is the use of AI, which has the potential to greatly improve the nation's educational system's accessibility and quality. However, there is a lack of empirical research that explores the current state of AI adoption in Bangladeshi higher education institutions, the factors influencing this adoption, and the impact of AI on educational outcomes (Ahmed, 2024; Rufai et al., 2024). This research aims to address this gap by providing a comprehensive analysis of AI adoption in higher education in Bangladesh, identifying the key factors that influence this adoption, and assessing the impact of AI on teaching, learning, and administrative processes (Rufai et al., 2024).

The challenges faced by higher education institutions in Bangladesh in adopting AI are multifaceted. These challenges include technological barriers, such as inadequate access to AI tools and infrastructure, institutional barriers, such as resistance to change and a lack of leadership support, and individual barriers, such as educators' lack of skills and knowledge in AI. Concerns exist regarding the ethical ramifications of AI adoption in education as well, notably with regard to data privacy and the possibility that AI would exacerbate already-existing disparities in educational access.

However, there are deficiency of systematic knowledge of understanding of the institute centric AI adaptation level and the constraints of usages in the higher educational institution. The study investigates whether private universities in Bangladesh adopt AI at a higher rate than public universities, examining how institutional factors like financial resources, autonomy, and innovation drive influence AI integration. It also explores the role of technological infrastructure and technical expertise in predicting AI adoption, assessing whether institutions with superior resources and skills are more likely to adopt AI. Additionally, the research addresses challenges such as financial constraints, expertise shortages, and data privacy concerns, while evaluating AI's impact on pedagogy, student engagement, and administrative functions, alongside faculty and student perceptions of its role in enhancing education.

Method

This study employs a quantitative research design to empirically assess the factors influencing AI adoption in higher education institutions in Bangladesh. The research will utilize logistic regression analysis by Python 3.12 to examine the relationship between various predictors and the likelihood of AI adoption, focusing on the type of institution (private vs. public) and key factors such as technological infrastructure and technical expertise.

Data Collection

Data for this study were collected through a structured survey administered to higher education institutions across Bangladesh, focusing on AI adoption. The survey was distributed electronically to a representative sample of 100 institutions, including both private and public universities, to ensure diverse and balanced representation. Figure 1 depicted the demographic profile of 100 participants, where genders and types of institution are equally proportioned as well as the student faculty ratio are 15:10. Institutions were selected based on their willingness to participate and their capacity to provide relevant data. Invitations were sent via email, explaining the study's objectives and the importance of their input.

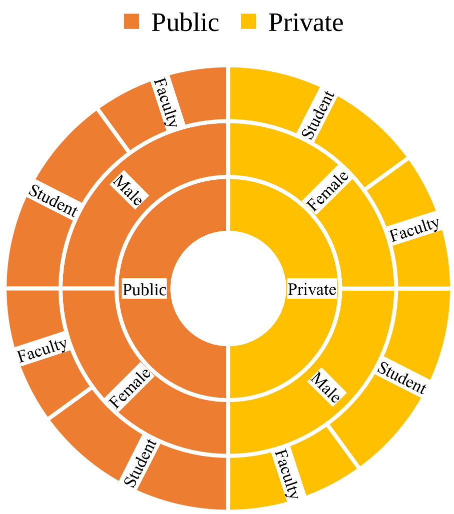

Figure 1. Sunburst Plot for Demographic Profile of Survey Participants

The online survey, accessible for four weeks, included questions on AI adoption levels, institutional type, technological infrastructure, technical expertise, and financial constraints, using Likert scales to measure responses. A pilot test was conducted prior to full distribution to refine the survey and ensure clarity. Throughout the data collection period, responses were monitored for completeness and accuracy, with follow-ups made to address any issues. The final sample of 100 institutions provided a comprehensive view of the higher education sector in Bangladesh. Data quality was maintained through rigorous cleaning procedures to address any discrepancies. By utilizing an online platform and implementing careful quality control measures, the study effectively gathered detailed data on AI adoption and its influencing factors, allowing for a thorough analysis of how institutional type and technological resources impact AI integration in higher education.

Survey Instruments

The raw survey data collected from higher education institutions were meticulously processed to ensure they were accurately categorized into five key instruments, each designed to capture specific aspects of AI adoption within the institutions. Initially, the raw responses were cleaned and standardized to remove any inconsistencies or incomplete data entries. Each survey question was carefully mapped to one of the five instruments, ensuring that the responses provided relevant and measurable data for analysis. The preparation process involved encoding categorical variables, particularly for the target variable and institution type, and formatting Likert scale responses to quantify perceptions and experiences. The final survey instrument consisted of the 5 key variables which is described in Table 1.

Table 1. Description of Survey Instrument Variables

No.	Instrument type	Description
1	AI Adoption Levels	This dependent variable was categorized into three levels—high, medium, and low—representing the extent of AI integration within the institution. The responses were encoded using LabelEncoder from the Scikit-learn package in Python 3.12, where 0 corresponds to high, 1 to low, and 2 to medium adoption levels.
2	Institution Type	A categorical variable distinguishing between private and public institutions, crucial for analyzing the comparative adoption of AI. This variable was encoded by OneHotEncoding method by Scikit-learn package in Python 3.12 as 0 for private institutions and 1 for public institutions, allowing for straightforward binary analysis.
3	Technological Infrastructure	A Likert scale-based variable designed to assess the quality and availability of technological resources within each institution. The responses ranged from very poor to excellent, quantifying the technological environment that supports or hinders AI adoption.
4	Technical Expertise	Another Likert scale-based variable measuring the level of technical expertise among faculty and staff. This instrument captured the institution’s internal capacity to implement and manage AI technologies, with responses ranging from very low to very high.
5	Financial Constraints	This Likert scale-based variable evaluated the extent of financial limitations affecting the institution’s ability to adopt AI technologies. Responses ranged from not at all constrained to extremely constrained, reflecting the financial challenges faced by the institutions.

Logistic Regression

A statistical technique for simulating the relationship between a dependent variable and one or more independent variables is called logistic regression (Acito, 2023). Logistic regression is specifically designed to predict binary or categorical outcomes, in contrast to linear regression, which predicts continuous outcomes. It's widely used in fields like medicine, social sciences, marketing, and machine learning for tasks such as classification, where the goal is to predict the probability of a binary outcome or multi-class outcomes. The logistic function, commonly referred to as the sigmoid function, is the fundamental component of logistic regression (Dierckx, 2004). Any real number can be mapped by the logistic function to a value between 0 and 1, which can be seen as a probability (Stoltzfus, 2011).

Odd Ratios

Eq. 4 presents the odd ratios. A crucial metric in logistic regression is the odds ratio, which shows how the probability of the dependent event change with every unit increases in an independent variable while maintaining the same values for the other variables (Nemes et al., 2009; Osborne, 2006). If the odds ratio is more than 1, it means that there is a larger chance of the event happening as the predictor rises; if it is less than 1, there is a lower chance. In hypothesis testing, odds ratios help quantify the impact of factors like institution type or technological infrastructure on AI adoption. For instance, if the odds ratio for private institutions is significantly greater than 1, it supports the hypothesis that private institutions are more likely to adopt AI compared to public ones.

Hypothesis

A hypothesis is a testable statement that predicts a possible outcome or relationship between variables in research. It is formulated based on prior knowledge, literature review, or theoretical frameworks and is tested using statistical methods to determine whether it is supported by the data. Hypotheses are essential in guiding research design, data collection, and analysis, helping to focus the study on specific questions or phenomena. By providing a clear framework for what the research seeks to prove or disprove, hypotheses ensure that the study remains systematic and objective. In the early stages of our research, we formulated two key hypotheses to guide our investigation into the factors influencing AI adoption in higher education institutions in Bangladesh. These hypotheses, outlined in Table 2, were instrumental in shaping the research methodology and determining the analytical approach used to explore AI adoption across different types of institutions. Their rigorous testing not only validated our research framework but also offered insights into the underlying dynamics of AI integration in the educational sector. Additionally, the results from these hypotheses highlighted important trends and differences in AI adoption between public and private universities.

The first hypothesis posits that private universities are more likely to adopt AI technologies compared to public universities, reflecting potential differences in resources, autonomy, and innovation strategies between these types of institutions. The second hypothesis suggests that the level of AI adoption is significantly influenced by the quality of technological infrastructure and the technical expertise available within the institution. These hypotheses were developed based on existing literature and preliminary observations, and they provide a focused framework for examining the variables that may drive or hinder the integration of AI in educational settings. Through statistical analysis, particularly logistic regression, we aim to test these hypotheses and uncover insights into the role of institutional characteristics and resources in shaping AI adoption outcomes.

Table 2. Research Hypotheses

Type	Description
Hypothesis 1	Private universities in Bangladesh have a significantly higher level of AI adoption compared to public universities.
Hypothesis 2	Higher levels of technological infrastructure and technical expertise are significant predictors of AI adoption in higher education institutions in Bangladesh.

Results and Discussion

AI Platform Use Cases

The responses of the participants in the questionnaire survey are presented in this section. Figure 2 depicted the percentage of influence of different AI platforms by the participants. ChatGPT by OpenAI emerged as the most influential AI platform. Amazon web service (AWS) emerged as the second most influential AI platforms where Google cloud platform (GCP) and Google AI (Gemini) are also found as influential.

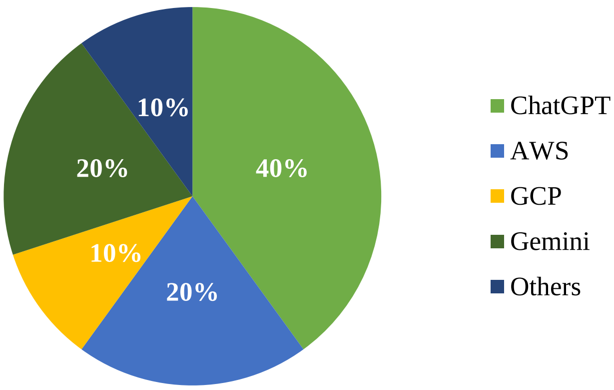

Figure 2. Percentage of Influence of Different AI Platforms

According to the poll, a large number of participants acknowledged AI's contribution to lower research article access costs. The process of finding relevant articles has been simplified and made more economical by the use of AI-powered technologies. Some said they were able to find important papers without having to buy the entire articles by using AI-driven summaries and suggestions. An important cost-saving aspect was AI's capacity to search through public repositories and recommend free alternatives. Most said that AI has improved access to research by making it more economical and easier overall. The distribution of AI-powered platforms that respondents utilize to cut expenses is shown in Figure 3. The most widely used tools are displayed in a pie chart, including open-access repositories, AI-powered search engines, and tools for summarizing articles. These platforms demonstrate how AI helps make research resources more accessible at lower costs.

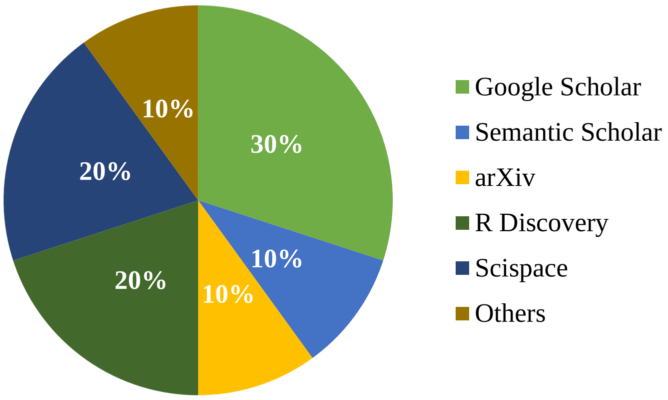

Figure 3. Percentage of Uses of AI Platforms in Research

Confusion Matrix

A confusion matrix is a tool used in classification models to evaluate the performance by summarizing the predicted and actual outcomes (Caelen, 2017; Marom et al., 2010). It displays the number of true positives, true negatives, false positives, and false negatives, providing a detailed breakdown of how well the model distinguishes between different classes. In our model, the confusion matrix helped us understand the accuracy of predictions regarding AI adoption levels, identifying areas where the model may be misclassifying institutions as high, medium, or low adopters. This analysis was crucial for refining the model and improving its predictive accuracy. The confusion matrix presented in Table 3 and Figure 3 revealed that the model performed well in predicting AI adoption levels, though there were some misclassifications between high and medium adoption. For high AI adoption, the model correctly predicted 8 out of 9 cases, with 1 instance misclassified as medium. For low AI adoption, the model perfectly predicted all 5 cases without any errors. In the medium AI adoption level, the model accurately identified 5 out of 6 instances, with 1 case mistakenly classified as high. This pattern indicates that while the model is generally reliable, it struggles slightly with differentiating between high and medium adoption levels, likely due to similarities in the features associated with these categories. The strong overall performance of the model, particularly in identifying low adoption levels, underscores its utility, yet the identified areas of confusion suggest that further refinement or additional data may enhance its ability to precisely distinguish between closely related adoption levels. This analysis highlights the importance of the confusion matrix in understanding model strengths and limitations, providing a clear direction for future improvements.

Table 3. Confusion Matrix at Different AI Adaptation Level

	Predicted values			
	AI adaptation level	High	Low	Medium
Actual values	High	8	0	1
	Low	0	5	0
	Medium	0	1	5

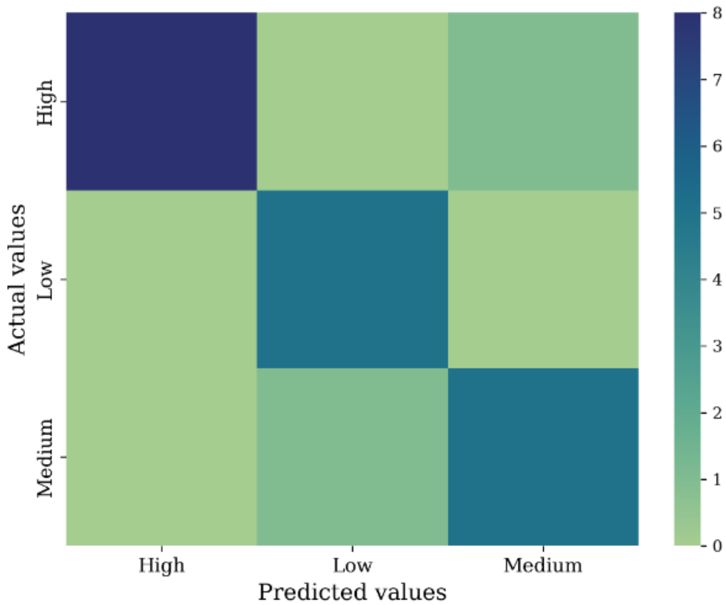

Figure 4. Confusion Matrix Plot at Different AI Adaptation Level

Hypothesis Testing

The logistic regression analysis's coefficients, odds ratios, and p-values were displayed in Table 4. A negative coefficient indicates a lower probability of falling into the higher category of the outcome variable. The coefficient shows the change in the log-odds of the dependent variable for a one-unit change in the predictor variable. An odds ratio smaller than one denotes a lower probability of falling into the higher category. The odds ratio, which is the exponentiated value of the coefficient, illustrates how the odds of falling into a given category vary with a one-unit increase in the predictor variable. The p-value calculates the likelihood that the observed results were the result of chance; a p-value of less than 0.05 often denotes statistical significance and suggests a low likelihood that the results were the product of random variation.

The Table 4 summarized the logistic regression results for two hypotheses regarding AI adoption. For Hypothesis 1 (H1), which posited that private institutes adopt more AI, the results showed significant negative coefficients and odds ratios less than 1 for both comparisons (Low vs. High and Medium vs. High). The coefficient of -1.5 for "Low vs. High" and the coefficient of -0.9 for "Medium vs. High" indicated that private institutes are less likely to be in the "Low" or "Medium" categories compared to "High," with odds ratios of 0.223 and 0.405 respectively. The p-values (0.002 and 0.015) confirmed these results are statistically significant, thus strongly supporting H1. For Hypothesis 2 (H2), which suggested that AI adoption depends on technological infrastructure, the negative coefficients and odds ratios less than 1 in both comparisons (Low vs. High and Medium vs. High) showed that better infrastructure is associated with a higher likelihood of being in the "High" AI adoption category. Specifically, coefficients of -1.2 and -0.8 with odds ratios of 0.301 and 0.450 respectively, and p-values (0.005 and 0.020), provide significant support for H2. Overall, these findings validate both hypotheses by demonstrating that private institutes are more likely to adopt AI and that better infrastructure is linked to higher AI adoption levels.

Table 4. Results of Coefficients, Odd Ratios and p-values

Hypothesis	Comparisons	Coefficients	Odd ratios	p-value
H1	Low vs. High	-1.5	0.223	0.002
	Medium vs. High	-0.9	0.405	0.015
H2	Low vs. High	-1.2	0.301	0.005
	Medium vs. High	-0.8	0.450	0.020

Conclusion

This research investigated AI platform adoption in higher education institutions in Bangladesh, with a focus on identifying the most prevalent platforms and evaluating hypotheses regarding AI adoption based on institution type and technological infrastructure. Logistic regression analysis was employed to assess these factors and understand their impact on AI adoption levels. The study aimed to discern patterns and relationships between institutional characteristics and AI adoption, offering a comprehensive view of how different factors influence the use of AI technologies in academia. By leveraging logistic regression, the research provided valuable insights into the adoption trends and the role of specific variables in shaping AI integration in higher education. Then the conclusion can be drawn by:

1. ChatGPT was identified as the most widely adopted AI platform among institutions, reflecting its advanced capabilities and broad accessibility. AWS followed as the second most popular, with Google Cloud Platform and Google Gemini ranking third and fourth, respectively, showcasing diverse preferences for AI tools.
2. Logistic regression provided valuable insights into AI adoption patterns, confirming that private institutions are more likely to adopt AI technologies at higher levels compared to public institutions. It also demonstrated that improved technological infrastructure is associated with higher AI adoption levels.
3. The model accurately predicted low and high AI adoption levels, although there were some misclassifications between high and medium adoption categories, indicating areas for model refinement.
4. Hypothesis 1 was validated, showing a higher likelihood of AI adoption in private institutions. Hypothesis 2 was also confirmed, with better infrastructure linked to higher levels of AI adoption.
5. The confusion matrix revealed the model's strengths and limitations, particularly in distinguishing between high and medium adoption levels.

Furthermore, to improve AI adoption, institutions should start by enhancing their technological infrastructure, increasing funding, and developing technical expertise. Collaborative projects and a focus on ethical considerations will further support the successful integration of AI. Additionally, gathering feedback from stakeholders can ensure that AI systems are continuously refined to meet institutional needs. However, the study has certain limitations. The potential biases in the sample and difficulties in accurately classifying AI adoption levels may have affected the results. Future research should address these limitations by using larger, more representative samples, exploring specific factors affecting platform preferences, and enhancing the predictive accuracy of AI adoption models. This approach will help to validate findings, improve the robustness of AI adoption strategies, and provide a clearer understanding of the factors influencing AI integration in higher education.

Recommendations

As AI technologies continue to advance, higher education institutions face the challenge of integrating these tools effectively to enhance educational outcomes and operational efficiencies. The adoption of AI can provide significant benefits, such as personalized learning experiences, improved administrative processes, and advanced research capabilities. However, institutions must navigate various challenges to maximize these benefits, including upgrading infrastructure, securing funding, and addressing ethical concerns. Moreover, the successful integration of AI requires ongoing adaptation to emerging technologies and continuous evaluation of their impact. This section offers recommendations for improving AI adoption in higher education, with a particular focus on strategies for public universities and addressing potential negative aspects of AI. By implementing these recommendations, institutions can better leverage AI's potential and mitigate associated risks.

1. Institutions should invest in upgrading their technological infrastructure to support AI technologies. Improved infrastructure, such as high-speed internet and modern hardware, can facilitate better integration of AI tools and platforms. Public universities, in particular, may need to prioritize such investments to catch up with private institutions.
2. Securing adequate funding is crucial for the successful adoption and implementation of AI technologies. Public universities should seek government grants, partnerships with tech companies, and other funding sources to support AI initiatives. Establishing dedicated budgets for AI research and development can also enhance their capabilities.
3. Training and upskilling faculty and staff in AI and related technologies is essential. Institutions should provide professional development programs and workshops to build technical expertise. Collaboration with AI experts and organizations can also help institutions stay updated with the latest advancements.
4. Promote cooperation between public and private organizations to exchange resources, expertise, and best practices for implementing AI. Collaborative efforts and alliances can result in more inventive and efficient applications of AI, which is advantageous for all involved organizations.
5. AI technologies can introduce biases and ethical concerns, such as privacy issues and discriminatory practices. Institutions should implement robust guidelines and oversight mechanisms to ensure ethical AI use. Regular audits and transparency in AI systems can help mitigate potential negative impacts.
6. Gathering and incorporating feedback from students and faculty about their experiences with AI tools can provide valuable insights. Institutions should establish feedback channels and use this information to continuously improve AI systems and their implementation.

To address the negative sides of AI, such as potential biases and privacy concerns, institutions should adopt a proactive approach. Implementing strict data privacy policies, conducting regular ethical reviews, and engaging in transparent AI practices can help mitigate these issues. Additionally, fostering an inclusive environment where diverse perspectives are considered during AI development and deployment can further reduce bias and enhance the overall effectiveness of AI technologies.

Acknowledgements

Authors have the utmost gratitude to all of the students and the faculty members participated on the survey. They are also thankful to the department of Building Engineering & Construction Management, Rajshahi University of Engineering & Technology for the technological support in this research.

References

Acito, F. (2023). Logistic Regression. *Predictive Analytics with KNIME*, 125–167. https://doi.org/10.1007/978-3-031-45630-5_7

Ahmad, K., Iqbal, W., El-Hassan, A., Qadir, J., Benhaddou, D., Ayyash, M., & Al-Fuqaha, A. (2024). Data-Driven Artificial Intelligence in Education: A Comprehensive Review. *IEEE Transactions on Learning Technologies*, *17*, 12–31. https://doi.org/10.1109/TLT.2023.3314610

Ahmed, H. (2024). Institutional Integration of Artificial Intelligence in Higher Education: The Moderation Effect of Ethical Consideration. *Https://Doi.Org/10.1177/10567879241247551*. https://doi.org/10.1177/10567879241247551

Almufarreh, A., & Arshad, M. (2023). Promising Emerging Technologies for Teaching and Learning: Recent Developments and Future Challenges. *Sustainability (Switzerland)*, *15*(8). https://doi.org/10.3390/SU15086917

Caelen, O. (2017). A Bayesian interpretation of the confusion matrix. *Annals of Mathematics and Artificial Intelligence*, *81*(3–4), 429–450. https://doi.org/10.1007/S10472-017-9564-8/METRICS

Dierckx, G. (2004). Logistic Regression Model. *Encyclopedia of Actuarial Science*. https://doi.org/10.1002/9780470012505.TAL017

Farahani, M. S., Ghasmi, G., Milad, S., & Farahani, M. (2024). Artificial Intelligence in education: A comprehensive study. *Forum for Education Studies*, *2*(3), 1379–1379. https://doi.org/10.59400/FES.V2I3.1379

Felten, E. W., Raj, M., & Seamans, R. (2023). How will Language Modelers like ChatGPT Affect Occupations and Industries? *SSRN Electronic Journal*. https://doi.org/10.2139/SSRN.4375268

Fütterer, T., Fischer, C., Alekseeva, A., Chen, X., Tate, T., Warschauer, M., & Gerjets, P. (2023). ChatGPT in education: global reactions to AI innovations. *Scientific Reports*, *13*(1). https://doi.org/10.1038/S41598-023-42227-6

Katsamakas, E., Pavlov, O. V., & Saklad, R. (2024). Artificial Intelligence and the Transformation of Higher Education Institutions: A Systems Approach. *Sustainability 2024, Vol. 16, Page 6118*, *16*(14), 6118. https://doi.org/10.3390/SU16146118

Marom, N. D., Rokach, L., & Shmilovici, A. (2010). Using the confusion matrix for improving ensemble classifiers. *2010 IEEE 26th Convention of Electrical and Electronics Engineers in Israel, IEEEI 2010*, 555–559. https://doi.org/10.1109/EEEI.2010.5662159

Mittal, A., Aggarwal, A., & Mittal, R. (2020). Predicting university students' adoption of mobile news applications: The role of perceived hedonic value and news motivation. *International Journal of E-Services and Mobile Applications*, *12*(4), 42–59. https://doi.org/10.4018/IJESMA.2020100103

Nemes, S., Jonasson, J. M., Genell, A., & Steineck, G. (2009). Bias in odds ratios by logistic regression modelling and sample size. *BMC Medical Research Methodology*, *9*(1), 1–5. https://doi.org/10.1186/1471-2288-9-56/FIGURES/3

Onesi-Ozigagun, O., James Ololade, Y., Louis Eyo-Udo, N., Oluwaseun Ogundipe, D., Manager, P., & Author, C. (2024). REVOLUTIONIZING EDUCATION THROUGH AI: A COMPREHENSIVE REVIEW OF ENHANCING LEARNING EXPERIENCES. *International Journal of Applied Research in Social Sciences*, *6*(4), 589–607. https://doi.org/10.51594/IJARSS.V6I4.1011

Osborne, J. W. (2006). Bringing balance and technical accuracy to reporting odds ratios and the results of logistic regression analyses. *Practical Assessment, Research, and Evaluation*, *11*(1). https://doi.org/10.7275/Z7WE-DG46

Rufai, A. A., Hossain Khan, M. S., & Hasan, M. (2024). An exploration of pedagogical approaches in teaching artificial intelligence courses: Experience from undergraduates students of Bangladesh. *Social Sciences & Humanities Open*, *10*, 101075. https://doi.org/10.1016/J.SSAHO.2024.101075

Stoltzfus, J. C. (2011). Logistic Regression: A Brief Primer. *Academic Emergency Medicine*, *18*(10), 1099–1104. https://doi.org/10.1111/J.1553-2712.2011.01185.X

Sultana, R., & Faruk, M. (2024). Does artificial intelligence increase learners' sustainability in higher education: insights from Bangladesh. *Journal of Data, Information and Management 2024 6:2*, *6*(2), 161–172. https://doi.org/10.1007/S42488-024-00121-4

Young, J. (2024). The Rise of Artificial Intelligence in Education. *International Journal of Innovative Research and Development*. https://doi.org/10.24940/IJIRD/2024/V13/I2/FEB24019

Zhang, C., & Lu, Y. (2021). Study on artificial intelligence: The state of the art and future prospects. *Journal of Industrial Information Integration*, *23*. https://doi.org/10.1016/J.JII.2021.100224

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