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The Impact of Machine Learning on Student Progress in Higher Education: A Case Study of Smaller City in Developing Countries

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Abstract: - Using machine learning (ML) in customised learning systems has shown significant potential for improving student engagement and academic achievement in higher education. However, successfully scaling these individualised techniques remains a considerable issue, especially among huge student populations in underdeveloped countries. This study investigates the influence of (ML) on student advancement in a smaller city in a developing nation like Peshawar, Pakistan. We conducted a cross-sectional study at the University of Engineering and Technology Peshawar and surveyed 550 students enrolled in BS, MS, and PhD programs using a stratified random sampling technique. The data was collected using a standardised questionnaire, and the results were using correlation matrices, composite reliability, and regression models. The findings revealed substantial connections between ML applications and better educational outcomes, with the regression model accounting for 67% of the variation in enhanced tailored learning experiences. The remarkable representativeness of the model (R2=0.656) indicates that (ML) has a significant ability to improve institutional effectiveness and student learning. In addition, younger learners expressed tremendous enthusiasm for using ML in their teaching methods. The findings demonstrate machine learning's revolutionary potential in higher education, particularly in developing countries, by promoting cooperation, customised learning, and increased institutional efficiency.

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1. Introduction

Personalised learning raises motivation, engagement, and academic accomplishment since it is designed to meet each student's individual needs, strengths, and weaknesses. Personalised education strategies may reduce achievement gaps, promote a deeper understanding of subjects, and ultimately result in better educational results by providing information corresponding to students' interests and learning styles [1]. Recent advancements in artificial intelligence (AI) and machine learning (ML) have significantly transformed several sectors, including higher education, by offering fresh prospects for improving student achievement.[2].Despite these advances, the efficient scalability of personalised learning continues to be a tremendous issue. Conventional approaches for customisation are frequently excessively time-consuming and unfeasible for extensive student populations. Nevertheless, AI and ML technologies provide very encouraging answers. Novel advancements in artificial intelligence algorithms, like Gram-CF(Gram Matrix – Collaborative Filtering), FCNN-CF(Fully Connected Neural Network - Collaborative Filtering), and User-CF (User-Based Collaborative Filtering)recommendation models, have become increasingly popular in higher education because they can improve learning experiences and offer useful suggestions to students[3]. Furthermore, implementing bidirectional Long Short-Term Memory Recurrent Neural Networks (BiLSTM-RNN) has significantly enhanced the comprehension of word associations in educational data, outperforming conventional LSTM models [4]. The incorporation of Recurrent Neural Networks (RNN) and Convolutional Neural Networks (CNN) into educational systems has greatly enhanced the processing of language and analysis of data, catalysing the advancement of deep learning methods such as Deep Cooperative Neural Networks (DeepCoNN) and Neural Attentional Rating Regression (NARRE) [5], [6]. These technologies are crucial in developing algorithms that maximise student learning and involvement. Nevertheless, the implementation of AI in higher education presents inherent difficulties. Algorithmic accuracy, fairness, privacy, and ethical concerns must be resolved to guarantee the responsible use of AI technologies [7]. Empirical evidence suggests that artificial intelligence (AI) has the potential to significantly influence student learning results, cognitive capacities, and the general standard of education. The result underscores the need for meticulous integration of AI in educational settings [8]. Using artificial intelligence algorithms and deep learning approaches, educational institutions can convert conventional educational processes into more flexible and efficient systems, enhancing student success rates [9]. The dynamic progress in artificial intelligence (AI) technologies and the increasing focus on ethical AI development highlight the necessity for ongoing research to address the changing requirements of higher education[10], [11]. [12]Integrating artificial intelligence (AI)

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algorithms, deep learning models, and neural networks presents institutions with novel prospects to augment instructional methodologies, heighten student involvement and enhance educational results, facilitating a more individualized and effective learning environment [13], [14], [12], [15]. Further expanding upon this basis, we surveyed the University of Engineering and Technology Peshawar in Pakistan, which included a sample of 550 students. Utilizing correlation matrices, composite reliability, and regression models, we analyzed student feedback to evaluate the influence of machine learning (ML) at higher education institutions (HEIs). The results demonstrate that machine learning not only advances institutional safety and efficiency but also greatly improves teaching and learning results, emphasizing the importance of our study.

2. Literature Review

Recent advancements in machine learning (ML) have revolutionized personalized learning in higher education, with models such as Gram-CF (Gram Matrix - Collaborative Filtering), FCNN-CF (Fully Connected Neural Network - Collaborative Filtering), and User-CF (User-Based Collaborative Filtering) improving student engagement and academic performance [3], [5]. However, significant gaps remain in how these technologies integrate with traditional teaching methods, which continue to be essential in educational settings. Studies like those by Zhang and Rangwala (2018) have demonstrated that advanced ML models, including Decision Trees, K-nearest neighbors, Random Forests, and Support Vector Machines (SVMs), show promise in predicting student performance [16]. Nonetheless, these models often rely on limited data for training, affecting their predictive accuracy, and educators may lack the training required to effectively interpret and integrate these advanced ML outputs into daily classroom instruction [16].

Furthermore, new AI algorithms have evolved to improve cognitive capacities in higher education students by prioritizing quality learning experiences and self-esteem, outperforming previous models such as Gram-CF, User-CF, and FCNN-CF. These systems use the ReLu (Rectified Linear Unit) activation function to generate text feature vectors, with the goal of increasing cognitive capacities through real-time text comprehension. However, these improvements are not without difficulties. Validating the precision of AI algorithms, addressing potential biases, protecting student data privacy, and ensuring that AI tools are aligned with higher education goals, particularly in terms of fostering critical thinking and creativity rather than simply automating tasks remain major concerns [5].

ML applications frequently ignore student populations' different backgrounds, such as cultural, linguistic, and socioeconomic differences which influence learning preferences and results. Current models do not adequately account for these variations [17]. Bote-Lorenzo et al. (2020) found that the characteristics of input data may influence the performance of models like Support Vector Machines. This highlights the need for future research on addressing diversity

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in ML-based educational tools [16]. These difficulties demonstrate that while machine learning and artificial intelligence have significant potential in education. The research focusses exclusively on ML applications without thoroughly investigating their integration with current pedagogical teaching techniques and the different needs of student populations.

3. Methods

A comprehensive methodology encompassed document analysis, case study modelling, observations, and participant observation. We also conducted survey research with current and prospective students to evaluate their level of knowledge about machine learning and their understanding of the benefits and drawbacks that ML presents in higher education institutions. The study was conducted using a cross-sectional design at the Peshawar campus of the University of Engineering and Technology (UET). The inclusion criteria encompassed students of both genders, aged between 20 and 45 years, who were presently registered in Bachelor of Science, Master of Science, and Doctor of Philosophy programs in diverse fields of study. Data on the overall student enrollment for the 2023-24 session was acquired from the Human Resources department of UET Peshawar. Out of the total student population of 6,500, 3,000 were registered in the Bachelor of Science program, 2,780 in the Master of Science program, and 720 in the Doctor of Philosophy program. An online sample size calculator (Open Epi) determined a sample size 550 based on the entire student population. The calculations were made with a 95% confidence interval and a 4% margin of error. The sample was selected from the target population using a stratified random sampling technique. The population was divided into three homogeneous strata according to students' education level: stratum I for BS students, stratum II for MS students, and stratum III for PhD students. The sample size for each stratum was calculated using the proportional allocation method (stratum size/population size) sample size. Using this formula, the sample sizes for each stratum were 254, 235, and 61, respectively. Participants were randomly selected from each stratum to participate in our study using the attendance register as a reference. The data collection process employed a structured questionnaire, including close-ended questions. The questionnaire included questions regarding participants' demographics, familiarity with machine learning, and comprehension of the advantages and disadvantages of ML in higher education institutions. Ethical approval for this study was obtained from the university's IRB committee, and formal permission for data collection on the premises of UET Peshawar was obtained from the university dean. Informed consent was obtained from each participant before being included in the study. After completing the data collection process, the gathered data was entered and analysed using SPSS version 25. Inferential statistical tools, including correlation matrix and regression analysis, were employed.

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3.1.Data Collections and Variables

The analysis is considered exploratory research because it was done using data from 550 UET Peshawar students. Consequently, the findings are preliminary and foundational research for the next stage, which will be a complete, fresh study on a representative sample rather than being generalisable to the whole statistical population. This study considered ten factors, which are listed in Table II. These variables were chosen to ensure the best possible model fit, allowing for precise prediction-making. Furthermore, the study that provided our foundation used these factors [18].

Table I: Variables and its definitions

Variable	Definition
ML1	It has the potential to improve customised learning experiences.
ML2	It can develop skills among students.
ML3	It can create a collaborative learning environment within HEI.
ML4	It can facilitate maintaining lifelong connectivity with alums.
ML5	It holds significant potential for enhancing institutional security.
ML6	It has a great deal of ability to improve institutional effectiveness.
ML7	It enables the sharing and storage of large volumes of data.
ML8	It provides researchers with a quiet, adaptable, and easily accessible operating environment so they may concentrate on their work without interruptions.
ML9	It provides a reachable research environment for researchers.
ATYPE	Which type of activity?
Age	What is the Age of the student?
MLUSE	Use ML in your daily lives.
MLDEF	Computer systems are designed to learn and adapt autonomously, utilising algorithms and statistical models to analyse data patterns and make inferences without explicit instructions.
MLOC	Is ML an Opportunity?

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3.2.Data Analysis

The analysis of the body of research highlights the advantages and disadvantages of using ML at HEIs. Motivated by this, we initiated an exploratory study in Pakistan to examine the impact of ML adoption in HEIs. Since young people are our future and are interested in technology, we created a poll to help Pakistani HEI management and authorities adopt and incorporate ML into the higher education system. The survey was conducted among students at UET Peshawar, KPK, and Pakistan, to gather data to assess the level of ML knowledge among the student population in HEIs. The results of the ML study described in [6] were followed when conducting this academic research survey.

In our research work, we tackle the following key concerns:

- Being aware of the current knowledge and viewpoints held by research based on machine learning at HEIs.
- Determining optimal methods for ML use in Higher Education Institutions.
- Measuring how much ML is known by the students.
- Determining how students view the potential and difficulties that machine learning poses for HEIs.

3.3.Hypothesis 1 (HP1)

ML is a fundamental technology that enriches the learning experience by improving students' capabilities, promoting collaborative learning within HEIs, and offering researchers a convenient research field. We programmed and carefully chose variables during the study procedure to solve HP1. The data was coded, and insights were extracted using various analytical methods and applications (Tables II and III, Figure 1) such as regression modelling, correlation matrix analysis, and composite reliability evaluation. Initially, the variables were identified using Smart-PLS3. [11] After that, we verified the model's dependability, correlated the data, coded the variables, and built a regression model based on HP1.

Table II: Variables Correlation

	Age	**ATYPE**	**ML1**	**ML2**	**ML3**
Age	1.00				
ATYPE	0.55	1.00			
ML1	-0.07	-0.10	1.00		
ML2	0.03	-0.04	0.96	1.00	
ML3	-0.04	-0.04	0.96	0.91	1.00

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Table III: Variables Correlation

	ML4	ML5	ML6	ML7	ML8	ML9
ML4	1.00					
ML5	-0.01	1.00				
ML6	-0.02	0.96	1.00			
ML7	-0.03	0.01	0.07	1.00		
ML8	-0.04	-0.03	-0.05	0.04	1.00	
ML9	0.01	-0.02	0.01	-0.10	0.96	1.00

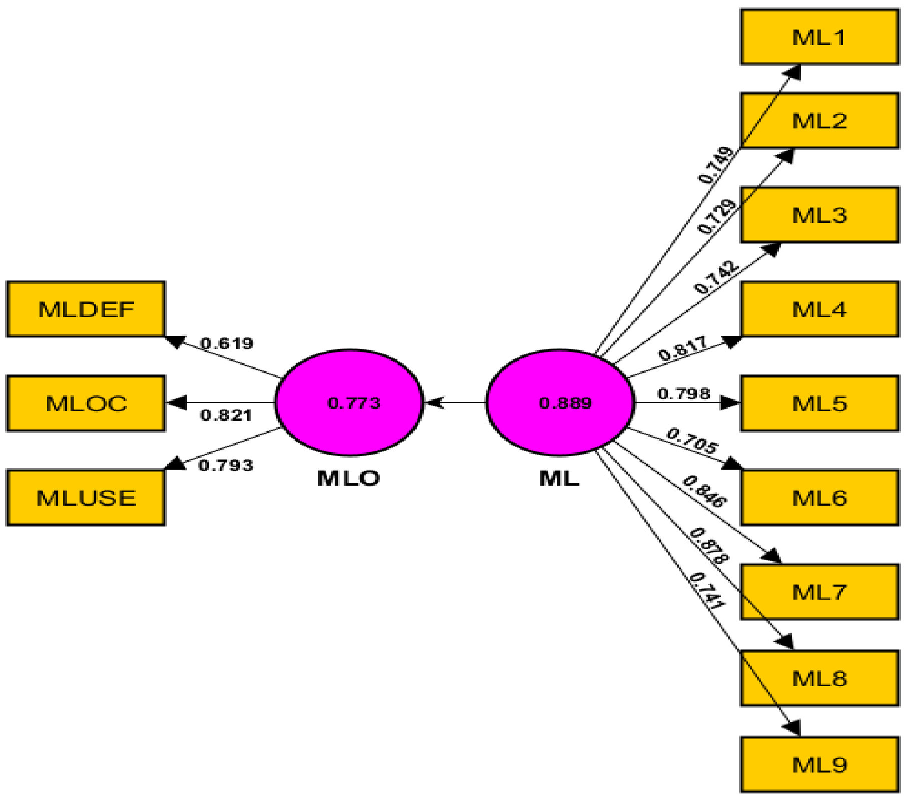

Figure 1: Composite Reliability Model

4. Results and Discussion

In statistical analysis, we aimed to assess whether the indicators were reflexive and, consequently, belonged to the same theoretical dimension. To accomplish this, we utilised the

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Correlation Matrix and Composite Reliability. Subsequently, the results were evaluated through regression analysis.

4.1.Stage 1. Correlation Matrix

Our analysis reveals robust correlations between ML1 and ML2, ML3 and ML5, ML6 and ML8, and ML9. These correlations suggest that ML holds the potential to enhance customized learning in many ways, including skill development among students, fostering a collaborative learning environment in higher education, improving institutional security and efficiency, offering researchers a peaceful and flexible computing environment, enabling them to focus on research without constraints, and providing an accessible research environment. A clear positive link between activity and age is given in Tables IIIa and IIIb, suggesting that younger students are overly excited about using ML in their lessons.

4.2.Stage 2. Composite Reliability

To confirm if there is an overall element among the indices and, as a result, a theoretical dimension to the construct, composite reliability is used as a precautionary measure [19]. It may be assessed using reliability alpha, which should be greater than 0.80, and internal consistency beta coefficient. [20] Which should be greater than 0.70. A valid reflective measurement is already indicated by values greater than 0.7 [21]. If additional indications are available for comparison, loadings of 0.5 or 0.6 would be considered acceptable[22]. Reflective indications with loadings less than 0.4, however, are to be disregarded [23]. The reflecting measurements of the constructs may also be evaluated by looking at the correlation between the indicators. Internal consistency, reliability, factor average variance extracted (AVE), and factor loadings are among the empirical tests advised in reference [24] as given in the Table 4.

Table IV: Validation Process

Reflexive Construct	**Composite Reliability (>0.7)**	**Alpha Cronbach (>0.7)**	**AVE (>0.5)**	**$\sqrt{AVE}$ (>0.5)**	**Factor Loading (>0.5)**
ML	0.889	0.72	0.53	0.66	0.68

With a reliability rating of 0.889, the composite reliability for the ML variable shows that the model is robust and meets the requirements to be considered in the regression model. However, markers ML4, ML5, ML7, and ML8 failed to satisfy AIDEF, AIOC, and the first discriminant validity criteria. As suggested in [25] a bootstrapping process was carried out with SPSS software to evaluate the model further. This process aimed to determine the Variance Inflation Factor (VIF) for every construct with a 95% reliability level and 5000 samples. Tables V (a) and (b) give the summarised results.

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Table V (a): Samples Bootstrapping

ML1	ML2	ML3	ML4	ML5	ML6
18.13	15.24	13.09	8.37	9.23	21.12

Table V (b): Sample Bootstrapping

ML7	ML8	ML9	MLUSE	MLDEF	MLOC
8.44	8.71	23.11	8.17	3.06	2.52

4.3.Stage 3. Output of Regression Model

The regression model that is shown below validates the results that were previously reported. It is clear from the regression model that ML is a crucial technology that improves learning, especially by helping students develop their skills, creating collaborative learning environments in HEIs, and enhancing institutional security and efficiency, all of which contribute to a favorable research environment. With a R^2 with a value of 0.656, the model demonstrates representativeness overall, showing that ML has several advantages for HEIs. More specifically, 67% of the variance in the dependent variable (ML1) is explained by the change in the independent variables (ML2, ML3, and ML9). Other variables like ML4, ML5, ML6, ML7, and ML8, as well as external factors like instructional approaches and socioeconomic changes within the socio-economic setting, are likely to impact the remaining percentage.

Given that the estimated F value is more than the critical F value ($F > F\_crit$) and the significance level ($Sig\ F$) If it is less than 0.01, the ANOVA test supports the previously indicated conclusions. Furthermore, the ANOVA test's presumptions are met:

- A continuous scale is used to assess the dependent variable.
- Four separate categories and independent groupings make up the independent variables.
- Since there is no correlation between the observations inside each group or between the groups themselves, the observations are independent.
- Extreme values are not present.
- In general, the variable is distributed throughout the independent variable's groups.
- Table VI shows that the variance is homogeneous.

Table VI: Assessment of Regression Model

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Parameters1						
Multiple R	0.80917					
R^2	0.65643					
Tuned R^2	0.65981					
the standard deviation of the mean	0.64001					
Observation	550					
Parameters2						
ANOVA	**df**	**SS**	**MS**	**F**	**Sig F**	
Regression	3	82.0145	28.165	69.5	$X\ 10^{-19}$	
Residual	99	44.56	0.4234			
Total	102	130.081				
Parameters3						
	Coefficients	**Standard error**	**t state**	***p*-Data**	**Lower 95%**	**Upper 95%**
Intercept	0.15021	0.3055	0.4794	0.6405	−0.513	0.65
ML2	0.38435	0.09663	4.0386	0.0002	0.1784	0.58
ML3	0.351	0.99784	3.2944	0.0009	0.1427	0.58
ML9	0.30653	0.07938	3.4022	0.0012	0.1266	0.47

There is a significant correlation between the independent and dependent variables, as indicated by the Multiple R-value of 0.809. When it is less than the significance level, the alternative hypothesis (H1) is accepted, as shown by the p-value, which represents the marginal

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significance level of the F-test and is lower than 0.05. The p-values for ML2, ML3, and ML9 in Table 6, which displays the modified model findings, are all less than 0.01 and indicate a high likelihood of receiving accurate results and well-estimated coefficients for these variables. The vehicle is regarded as dependable overall. With a $R^2$with a value of 0.80917, changes in the causative factors can explain 82% of the variance in the ML1 variable, with the model unable to account for the remaining 18%.

The following outcomes were obtained using statistical t-tests performed for each variable:

- The coefficient for the ML2 variable is 0.38, and the standard error is a little 0.09663. It is most likely to be detected in the range of 0.18 to 0.6 with a 95% confidence level.
- The coefficient for the ML3 variable is 0.351, and its low standard error is 0.997. It is most likely to be discovered in the range of 0.14 to 0.6 with a 95% confidence level.
- The coefficient for the ML9 variable is 0.306, and its low standard error is 0.079. It is most likely to be discovered in the range of 0.12 to 0.5 with a 95% confidence level.
- The value of the intercept coefficient is 0.15, and its p-value is more significant than 0.05 at 0.064. A 95% confidence level indicates that the coefficient is not accurately assessed and is most likely in the interval (-0.45, 0.7).

Given the circumstances, the t-tests support the model's validity and increase the regression's predictive ability. Ideally, the variables' significance level should be less than or around 0.05 (Table 6). Considering these findings, we may state that the regression analyses support our hypothesis.

The regression formula gets to:

$$ML1 = 0.15 + 0.38 \times ML2 + 0.35 \times ML3 + 0.30 \times ML9 \qquad (1)$$

In this study, the variables ML2, ML3, and ML9 were deliberately selected to comprehensively represent essential aspects of machine learning (ML) and their influence on improving learning environments. The selection of ML2 as a fundamental element of ML is based on its pertinence to customised learning experiences and how it fits with our research inquiry on enhancing institutional performance. The inclusion of ML3 was based on its importance in promoting skills development and establishing collaborative learning environments in higher education institutions (HEIs). This corroborates our premise of improving educational results using adaptive learning technology. The ML9 study examines the security component of machine learning (ML), specifically highlighting its capacity to improve institutional safety and sustain long-term connections with alums. This underscores the many advantages of ML in higher education institutions (HEIs). These variables were selected based on their thorough depiction of machine learning capabilities, therefore assuring a rigorous investigation of their impact on educational environments.

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Analysis and Further Recommendation

Given the validated hypothesis and the checked reliability of the model, it is apparent that ML technology plays a pivotal role in enhancing the safety and efficiency of institutions while contributing to the learning process. This assumption suggests a strong correlation between ML and ML1 and its potential to improve customized learning. For instance, research has shown that digital algorithms can significantly improve medical care. Furthermore, it has been demonstrated that tactics utilizing secure computing technologies and machine learning-based digital techniques work [26]. Our study also revealed strong relationships between ML1 and ML2, ML3, ML5, ML6, ML8, and ML9, suggesting that ML can improve customized learning in several ways. These associations imply that ML can enhance students' abilities, offer HEIs a collaborative learning environment, increase institutional efficiency and security, and give researchers a comfortable atmosphere to conduct research. Furthermore, younger students are incredibly excited about incorporating ML into their learning activities based on the substantial association between age and activity [27]. The regression model emphasises that ML is important to improving learning, especially regarding skill development, collaborative learning in HEIs, increased institutional security and efficiency, and a favourable research environment. The representativeness of the model (R^2 = 0.656) indicates that machine learning offers several advantages to HEIs in developing nations. The independent variables (ML2, ML3, and ML9) can explain 67 per cent of the variance in the dependent variable (ML1), contextual factors and other variables, such as instructional methods and macroeconomic shifts explain the remaining percentages. The importance of ML in boosting tailored learning is highlighted by improving institutional security and efficiency, offering a favourable research environment, and helping students build their abilities and a collaborative learning environment in HEIs [28]. Studies reveal that students favour using recent technologies in the classroom because of their prominent levels of engagement, motivating demands, and possibilities for experimentation and simulation. Colleges must adopt these technologies and create innovative teaching and training strategies to satisfy millennial expectations and keep up with the technological transformation [29].

5. Conclusion

This study underlines the potential of machine learning (ML) to enhance interactive learning environments in higher education by exploiting vast data sets to adapt educational experiences for various learners. Despite this potential, ML implementation in educational institutions has been sluggish, especially in middle-income nations. This delayed acceptance has been made worse by issues like enrolment and financial limitations. There are still large gaps, particularly in low- and middle-income countries where generalizability and social acceptability are still problems. We understand the value of longitudinal research in addressing these issues by determining the long-term effects of ML technology on student learning results. Using the cross-sectional methodology of our current study, we intend to highlight its shortcomings and

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provide directions for future research that focus on long-term effects. Furthermore, we recognize the need for expanding our findings beyond a single location or university. Our updated manuscript will address this geographical barrier and provide solutions for conducting investigations in varied settings. By widening the breadth of our research, we hope to validate and generalize our findings, ultimately contributing to best practices in ML applications across a variety of educational settings.

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