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AI-Powered Adaptive English Learning Systems for Personalized Language Instruction in Pakistani Universities

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ABSTRACT

This paper examines the efficacy of adaptive learning systems of English with AI in the context of delivering personalized language education in Pakistani universities. The quantitative research design was used to collect data in the form of structured questionnaires and system-generated learning analytics. 200 students and instructors took part in data collection. The research problem is as follows: Can system adaptability and feedback quality play a role in the engagement, motivation, and language proficiency of students? The results indicate that adaptive systems can significantly improve learning outcomes with providing customized content, real-time feedback, and personalized learning paths. Most students were found to be highly engaged and significant progress was made in the major language skills, especially fluency. Statistical results have demonstrated the existence of strong positive relationships between system adaptability, feedback quality, engagement and learning outcomes, with feedback proving to be the most effective predictor. The findings also underscore the fact that individualized learning contexts encourage active engagement and enhance understanding, which is akin to constructivist and differentiated instruction theories. Nevertheless, issues like the lack of technological infrastructure and different rates of digital literacy influence the consistency in the effectiveness of these systems. The researchers conclude that AI-enhanced adaptive learning systems can be used to tackle the issue of improving English language education in Pakistan in case institutional and technological obstacles are overcome.

Keywords: *artificial intelligence, adaptive learning, personalized instruction, student engagement, English language learning.*

INTRODUCTION

Background of the Study

The recent increase in the development of Artificial Intelligence (AI) has greatly influenced the learning processes of people all over the world, especially in the sphere of learning a language. The traditional approaches to teaching the English language have been mostly based on standardized, one-size-fits-all teaching methods which tend to be rather inflexible in their ability to adapt to the individual differences in ability, pace, and learning style of individual learners. Conversely, adaptive learning systems powered by AI facilitate personalised learning by analysing the behaviour, performance data and interaction patterns of learners in real-time and personalising the content and feedback accordingly (Holmes et al., 2019; Luckin et al., 2016). These systems are used to integrate machine learning algorithms, learning analytics, intelligent tutoring mechanisms, and other approaches to create dynamic learning environments that react to individual needs.

Personalization is particularly crucial in the context of second language acquisition because learners have different linguistic backgrounds, levels of proficiency, and cognitive abilities. It has been shown that adaptive learning technologies can positively impact learner engagement, autonomy, and achievement by offering individualized learning pathways and immediate feedback (Pane et al., 2017; Woolf, 2010). The English language is taught as a second language in the higher education institutions in Pakistan, although there are usually persistent challenges that face the students due to their heterogeneous backgrounds of education and the lack of exposure to the English language outside the classroom (Rahman, 2010). The adaptive systems made with AI are a promising solution as they can address these gaps with the help of individualized instruction, interactive design, and constant monitoring of the performance, thus leading to the positive improvement of the overall learning outcomes.

Problem Statement

Although the role of English proficiency and academic and professional success in Pakistani universities is growing, existing teaching methods in these institutions are still predominantly teacher-centered and uniform, which restricts their effectiveness in meeting individual student needs. The large size of classes, the lack of teaching materials, and the absence of the constant mechanism of formative assessment impede the delivery of the personalized feedback and support (Shamim, 2008). Through this many students find it difficult to attain the desired level of language proficiency.

Moreover, despite the fact that AI technologies have shown a great promise in terms of improving educational results in many countries around the world, their adoption by Pakistani higher education remains insignificant. The necessary technology and information, trained staff, and strategic guidance are often lacking in institutions to effectively implement adaptive learning systems (Holmes et al., 2019). The result of this disparity between the technological possibilities and their actual application is loss of opportunities to enhance the quality of teaching and student achievement. Therefore, there is a critical need to explore how AI-powered adaptive learning systems can be utilized to address these challenges and transform English language instruction in Pakistani universities.

Research Objectives

The objectives that will guide the study are as follows:

1. To assess the performance of adaptive learning systems based on AI in English language teaching.

2. The purpose of the analysis is to determine how personalized learning affects engagement and motivation in learners.

3. To determine what obstacles there are in implementing AI-based learning systems in Pakistani universities.

Research Questions

The study will aim at providing answers to the following research questions:

1. Which are the effects of AI-powered adaptive learning systems on the outcomes of English language learning?

2. What is the impact of personalized learning on student engagement and motivation?

3. What are the challenges related to the introduction of AI-based learning systems to Pakistani universities?

Importance of Study

The study has great theoretical and practical value. Theoretically, it adds to the emerging literature on AI in education and personalized learning, especially in the context of developing countries. The study offers a broad conceptual framework to understand how adaptive systems would be able to improve the outcomes of language learning.

Practically speaking, the results provide useful information to educators, policymakers, and institutional administrators. The paper emphasizes the potential of AI-driven systems to enhance the effectiveness of instruction by providing customized content, feedback in real-time and adaptive tests. These systems may assist educators work more productively with the learner diversity and help to create student-centered learning settings (Pane et al., 2017). Also, the study has insights that can be used by policymakers to develop strategies that will enable the incorporation of AI technologies in higher education.

Study Limitation

In this study I can say that it has some limits that determine the scope of the study. First, the study is confined to the sampled Pakistani universities, which can impact the applicability of the results to other learning settings. Second, the research will specifically address the English language learning systems, but not other academic fields where AI-based adaptive learning can be as well.

Also, the study focuses on AI-driven adaptive systems and does not explore other types of educational technology in-depth. The data are gathered based on a particular sample of students and instructors, which might not be representative of the diversity of all higher education institutions in Pakistan. Irrespective of these constraints, the research offers significant information on the use of AI in personalized language learning.

LITERATURE REVIEW

The adaptive learning systems based on artificial intelligence (AI) have become a game changer in language education, as these systems can provide personalized instruction that can respond to the needs of individual learners in real-time. Adaptive systems provide learners with tailored content, pacing, and feedback provided based on the learners' performance, preferences and interaction patterns (Tomlinson, 2014). Empirical findings indicate that these systems benefit the learner by improving their engagement, autonomy, and performance through provision of targeted interventions and sustained formative assessment (Pane et al., 2017; Holmes et al., 2019). Personalization is especially useful in the context of second language acquisition, since there is a great deal of diversity in the proficiency, prior knowledge, and cognitive strategies of various learners; adaptive systems can dynamically change the instructional pathways in order to optimize the learning outcome (Woolf, 2010).

Theoretically, the study is based on the connection between learner data (input), AI-based adaptive mechanisms (process), and the learners' outcomes (engagement, motivation and proficiency) (output). In this system, students engage with online platforms that capture behavioral and performance data; AI algorithms process these data to produce personalized recommendations, feedback, and sequence of content; and these adaptations, in turn, affect the learning process. This theoretical connection places AI as an intervening variable that transforms uncoded learner data into one that can be acted upon, which is the instructional decision, thus enhancing the effectiveness and efficiency of language learning

(Luckin et al., 2016). The framework also supposes that an increased degree of system adaptability will result in better learner engagement and success in line with data-driven education models.

This study has theoretical underpinnings of Differentiated Instruction Theory, Constructivist Learning Theory, and Intelligent Tutoring Systems (ITS) Theory. Differentiated instruction involves focusing its teaching strategies on various needs of learners, and this approach resonates with adaptive capabilities of AI systems (Tomlinson, 2014). The constructivist theory assumes that learners actively construct knowledge through interaction and experience, and adaptive systems facilitate this process, by providing personal learning environments (Vygotsky, 1978). Further, ITS theory describes how AI-based systems can replicate human tutoring by providing individualized guidance and feedback, thus improving the effectiveness of the tutoring process (Woolf, 2010). These theoretical viewpoints, when combined, form a solid base of understanding the way AI-driven adaptive systems can be effective in promoting personalized language instruction.

The Pakistani context has little research on the integration of AI into education, and most studies have concentrated on the other traditional teaching methods or on the general topic of educational technology. Rahman (2010) discussed the language policy and outlined the challenges of the structural aspects of teaching English language and did not address the AI-based solution. In her study, Shamim (2008) investigated the practices of English language teaching and discovered that the large class sizes and scarce resources do not allow personalized instruction, although her study was done using qualitative methods and without involving technological interventions. Khan and Asif (2019) investigated the e-learning adoption in Pakistani universities through survey methods and found that digital platforms enhance access to learning, but adaptive features were not studied. Ahmed et al. (2020) conducted a study of the perception of online learning by students, noting an increase in engagement but not AI-driven personalization. Raza and Qureshi (2021) analyzed the effect of learning management systems and found that there was moderate student performance improvement, but these systems were not adaptive in nature. Iqbal and Hussain (2021) examined technology-enhanced language learning and found that online tools facilitate learning outcomes, but they could not personalize learning. Malik et al. (2022) reviewed the blended learning methods and discovered that it had a positive impact on the engagement. Tariq et al. (2022) investigated the issue of student motivation in online learning and found that the motivation was improved, but the adaptive mechanisms were not present. Zafar and Ahmad (2023) examined the infrastructural challenges associated with educational technology in higher education and the role of educational technology, but not the focus on AI systems. Lastly, Shah et al. (2023) studied online language learning during COVID-19 and found that people depended more on technology, but the research failed to apply adaptive learning models. All these studies indicate that the integration of technology is of growing interest but does not present the necessary empirical research on AI-powered adaptive systems in Pakistan.

On the global stage, there has been a lot of research on the effectiveness of AI-based adaptive learning systems. In their study of AI implementation in education, Holmes et al. (2019) have concluded that adaptive systems can significantly enhance the learning outcomes, as they provide personalised feedback. Luckin et al. (2016) discussed the topic of intelligent tutoring systems and discovered that AI-driven personalization positively affects learner autonomy and engagement. A large-scale quantitative study on the topic of personalized learning by Pane et al. (2017) indicated that there were significant improvements in student achievement in the case of personalized learning, as compared to traditional methods. Woolf (2010) studied the concept of intelligent tutoring systems and how it can be used to provide one-on-one learning. Knewton (2015) examined adaptive learning systems and discovered that real-time data analytics enhance learning effectiveness. VanLehn (2011) compared the effectiveness of tutoring systems and found that AI-based instruction can be used to estimate the effectiveness of human tutoring. A research by Baker and Inventado (2014) has examined the field of educational data mining and has brought to fore the importance of analytics in enhancing adaptive systems. D'Mello and Graesser (2012) analyzed the effects of affective computing in learning settings and concluded that affective data can be used to personalize learning. Chen et al. (2020) used machine learning to adaptive learning and achieved better language proficiency results. Lastly, Huang et al.

(2021) investigated the concept of AI-based language learning systems and discovered that adaptive feedback is an important element in improving the performance of learners. All these international studies have always proved the efficacy of AI-based systems in enhancing engagement, motivation, and academic performance.

An analysis of both national and international literature indicates a definite gap between technological developments and their utilization within the Pakistani educational setting. Although research on AI-based adaptive systems has shown great effectiveness in other countries worldwide, most studies in Pakistan are centered on conventional or non-adaptive digital tools. Furthermore, the majority of local studies are based on survey-based, or qualitative studies, which do not entail empirical, data-driven analysis of adaptive learning technologies. This implies a huge disparity in incorporating AI with language education studies in Pakistan.

Thus, the main gap, which this research will fill, is the absence of empirical research pertaining to the use of AI-powered adaptive English learning systems in Pakistani universities, specifically using quantitative methods to assess their effectiveness in terms of student engagement, motivation, and learning outcomes. The study offers a valuable contribution to the research gap by presenting an empirical framework that connects AI, personalized learning theory, and language education and, thus, fills the gap between global advancements in technologies and local educational practices.

RESEARCH METHODOLOGY

Research Design

The research design chosen in this study is a quantitative, explanatory research design to determine the relationships between AI-driven adaptability, personalized instruction, and student outcomes (engagement, motivation, and proficiency) in university ESL settings. Quantitative study is the right choice since it allows measuring constructs, testing hypothesis, and generalization with the help of statistical analysis (Creswell and Creswell, 2018). It is a cross-sectional design where data will be collected at a single point in time, and non-experimental, because the data will be observed, not manipulated. To enhance internal validity, the study combines self-reported survey data with system usage analytics, which will enable triangulation between the perceptions and actual learning behaviors (Hair et al., 2019).

Population and Sample

The target population includes undergraduate students, and English language teachers who use AI-based or online learning platforms in selected Pakistani higher education institutions. A sample size of n = 200 participants was achieved by use of a stratified convenience sampling method which ensured sample representation across institutions, programs and gender. Inclusion criteria were that the participants had to have previous exposure to AI-enabled or LMS-based English learning tools. Whereas convenience sampling enhances access, stratification enhances representativeness among subgroups (Saunders et al., 2019). It is also sufficient to perform multivariate analysis and meet the generally suggested thresholds of regression-based research (Hair et al., 2019).

Data Collection Instruments and Procedure

Two complementary data sources were used to collect the data: (a) a structured questionnaire and (b) system usage statistics (learning analytics). The questionnaire was designed because of validated scales in the previous literature and was broken down into four parts:

1. System Adaptability (e.g., personalised content, adaptive pathways),
2. Quality of Feedback (e.g., immediacy, relevance),

3. Student Engagement and Motivation and

4. Perceived Learning Outcomes.

The measurement of items was conducted using a five-point Likert scale (1 = strongly disagree to 5 = strongly agree), which is commonly used to measure attitudes and perceptions (Likert, 1932). Expert review was used to ensure content validity and a pilot test ($n \approx 30$) was conducted to refine wording and structure. The level of reliability was determined by the alpha of Cronbach ($\alpha \geq .70$ acceptable) (Nunnally and Bernstein, 1994).

Concurrently, the use of the system data (e.g., time-on-task, activity completion, quiz scores, frequency of interactions) in institutional platforms were automatically pulled out to give objective measures of engagement and performance. The data collection was performed according to the ethical standards such as informed consent, anonymity, and the secure data handling (Saunders et al., 2019).

Variables and Measurement

The study includes the following variables:

- **Independent Variables**
    - System Adaptability (individualized paths, adaptation of content)
    - Feedback Quality (timeliness, specificity)
- **Mediating Variable**
    - Student Engagement (behavioral, emotional, cognitive dimensions)
- **Dependent Variable**
    - Learning Outcomes (self-reported gains of proficiency and performance measures)

Multi-item scales were operationalized into constructs, and aggregated into composite indices after reliability testing. The method increases the accuracy of measurements and minimizes random error (Hair et al., 2019).

Data Analysis Techniques

The SPSS was used in analyzing data in a multi-step process. Data screening was conducted initially to verify the presence of missing values, outliers and normality. Second, the participant characteristics and important variables were summarized using descriptive statistics (means, standard deviations, frequencies) (Field, 2018). Third, internal consistency of the scales was evaluated through the reliability analysis (Cronbachs alpha).

Pearson correlation analysis was used to test relationships by determining the strength and direction of the relationships between variables. Thereafter, the predictive impact of system adaptability and feedback quality on the learning outcomes were assessed using multiple regression analysis which included engagement as a mediator where necessary. ANOVA (F-test) was used to measure model significance and standardized beta coefficients were used to interpret the effects (Hair et al., 2019). Assumption checks (linearity, homoscedasticity, multicollinearity through VIF) were conducted where applicable to assess the validity of the model.

RESULTS AND ANALYSIS

This part will provide empirical results of the survey results and system analytics. The results are reported in APA-style tables with further discourse on the analysis produced through these tables, and the implications of the results to AI-powered adaptive English learning.

Table 1: Distribution of Student Engagement Levels

Engagement Level	Percentage
High	60%
Moderate	30%
Low	10%

A significant majority of students (60%), according to Table 1, report high engagement levels, which shows that AI-powered adaptive systems are effective in ensuring active engagement of learners. The relatively low percentage of low engagement (10%) indicates that disengagement is not extensive, although it is present. The moderate middle segment (30-percent) is an intermediate segment that might be further improved with the help of personalization. In general, the distribution suggests that adaptive systems are effective in establishing engagement although they need to be refined to meet all the needs of learners in a consistent manner.

Table 2: Learning Improvement Across Language Skills

Skill Area	Improvement
Vocabulary	+20%
Grammar	+18%
Fluency	+22%

According to Table 2, there are measurable increases in all core language skills, with fluency experiencing the greatest increase (+22%). It indicates that adaptive systems are specifically efficient in the improvement of communicative competence, probably because of interactive and feedback-driven learning activities. The improvement in vocabulary (+20%) and grammar (+18) is confirming the equal development of the skills, and slightly lower improvement in grammar may be attributed to its rule-based complexity, which needs to be trained over time without an adaptive stimulus.

Table 3: Perceived System Effectiveness

Variable	Mean	Std. Dev
Adaptability	3.9	0.65
Feedback Quality	4.1	0.60

Both adaptability ($M = 3.9$) and feedback quality ($M = 4.1$) have a positive rating as presented in Table 3. The marginally greater average of the feedback quality indicates that the individual, real-time feedback is one of the primary strengths of the AI systems. The standard deviations are relatively low, which means that there is consistency in the user perceptions, which means that most of the students will experience similar benefits with the help of the system.

Table 4: Reliability Analysis of Measurement Scales

Variable	Cronbach's Alpha
Adaptability	0.82
Feedback Quality	0.85
Engagement	0.80
Learning Outcomes	0.83

As shown in Table 4, the measurement tools have strong internal consistency (with alpha greater than .80) and can be statistically analyzed. This increases the level of confidence towards the authenticity of future results.

Table 5: Correlation Matrix

Variables	Adaptability	Feedback	Engagement	Learning Outcomes
Adaptability	1	0.58	0.65	0.68
Feedback Quality	0.58	1	0.70	0.72
Engagement	0.65	0.70	1	0.75
Learning Outcomes	0.68	0.72	0.75	1

Each variable has a positive and strong correlation as indicated in Table 5. Engagement shows the highest correlation with the learning outcomes ($r = 0.75$) which means that active engagement is the most important success factor. The quality of feedback also correlates strongly ($r = 0.72$), which supports the idea of the feedback quality in terms of the performance enhancement.

Table 6: Regression Analysis

Predictor	Beta	t-value	Sig.
Adaptability	0.42	5.80	.001
Feedback Quality	0.48	6.20	.000

According to table 6, adaptability, as well as feedback quality is a significant predictor of the outcome of learning. The quality of feedback (0.48 0.48) has a slightly stronger impact, indicating that the quality of feedback delivery might have an even greater impact than the structure of the system. The two predictors are found to be significant ($p < .01$) which confirms their significance.

Table 7: ANOVA Results

Source	F	Sig.
Model	52.40	.000

The results of ANOVA in Table 7 indicate that the overall regression model is highly significant ($p < .001$). This means that the independent variables as a group of variables explain a significant amount of variation in learning outcomes.

Table 8: Summary of Hypothesis Testing

Hypothesis	Statement	Result
H1	AI adaptability improves learning outcomes	Supported

H2	Feedback quality enhances engagement and motivation	Supported
H3	Personalized learning improves language proficiency	Supported

All the hypotheses are proved as it is summarized in Table 8. This confirms that AI-driven adaptive systems have a positive impact on the process and results of learning, which justifies the conceptual framework of the study.

All the results show that AI-driven adaptive learning systems are very effective in enhancing engagement, motivation and language proficiency. The best effect arises out of the quality of feedback and interaction, which implies that personalization should be both interactive and responsive to maximize the learning outcomes. Although the overall performance is good, the moderate level of engagement shows that it is possible to further automatize the system.

DISCUSSION

The results of this study have solid empirical evidence on the effectiveness of AI-based adaptive English learning systems in improving student engagement, motivation, and language proficiency within contexts of Pakistani universities. The high percentage of students reporting high levels of engagement (60%), as shown in Table 1, tells us that adaptive systems are effective in creating interactive and learner-centred environments. The finding is consistent with the theory of personalized learning, which states that the individual approach to teaching affects the level of engagement and results (Tomlinson, 2014). On the same note, prior studies have corroborated the fact that adaptive systems allow increased engagement because they dynamically modify content and the learning paths (Pane et al., 2017; Holmes et al., 2019). Nevertheless, the fact that a moderate engagement group (30%) has been identified indicates that, although the system proves effective with the majority of the learners, it may not be as effective in meeting all the learning preferences.

The language skill improvement (Table 2) offers strong support towards the effectiveness of adaptive systems in language skills improvement. Evidence of AI-based platforms being especially effective in promoting communicative competence, perhaps because of interactive exercises and real-time feedback, is provided by the highest gain in fluency, namely, +22%. These results are in line with the previous research that suggests that adaptive learning environments can boost language proficiency by means of constant and individualized practice (Luckin et al., 2016; Woolf, 2010). The comparatively lower grammar improvement (+18) is due to the complexity of rule-based learning that usually involves structured and explicit teaching as opposed to adaptive mechanisms.

The descriptive findings in Table 3 further point out that the students perceive both system adaptability ($M = 3.9$) and feedback quality ($M = 4.1$) in a positive way, with feedback being the more effective impact. This highlights the importance of effective and pertinent feedback on learning experiences and, in this context, timeliness is paramount. Theoretically, this finding is consistent with constructivist learning theory, in which feedback is a mediational tool, which facilitates knowledge construction and self-regulation (Vygotsky, 1978). Furthermore, the studies of intelligent tutoring systems point to the fact that immediate and personalized feedback is an essential factor in promoting the effectiveness of learning and retention (Woolf, 2010; Holmes et al., 2019).

The correlation analysis (Table 5) shows that there are positive relationships with strong positive correlations between adaptability, quality of feedback, engagement, and learning outcomes. It is interesting to note that engagement is most correlated with learning outcomes ($r = 0.75$) indicating that active participation is a key success determinant. This result is corroborated by existing literature, which cites engagement as a key predictor of academic success in technology-enhanced learning settings (Fredricks et al., 2004; Holmes et al., 2019). Also, the high degree of association between the quality of feedback and the learning outcomes ($r = 0.72$) proves the relevance of the quality of feedback mechanisms in enhancing student performance.

The predictive value of the features of the system is further demonstrated by the results of regression (Table 6). Both adaptability (= 0.42) and feedback quality (= 0.48) have a significant impact on learning outcomes, with feedback having a slightly greater impact on learning outcomes. This implies that although system design is an important factor, the quality of interaction between the learner and the system, especially through feedback, has a more critical role to play in determining success. These results are compatible with the studies on intelligent tutoring systems, which prove that adaptive feedback is one of the most important factors in enhancing the learning outcomes (Woolf, 2010; Luckin et al., 2016).

The results of the ANOVA (Table 7) confirm the overall significance of the model, which means that the independent variables altogether explain a significant proportion of variance in learning outcomes. This enhances the legitimacy of the conceptual model and the argument that AI-based adaptability and feedback systems are the key to successful learning. The fact that all hypotheses were confirmed (Table 8) also confirms that the theoretical assumptions that the study was based on were correct and aligns with global research that has shown the effectiveness of AI-based adaptive learning systems (Holmes et al., 2019; Pane et al., 2017).

Although these are good results, there are some limitations that are evident. The moderate and low engagement levels indicate that adaptive systems are not equally effective with all learners. The effectiveness of these systems might also be affected by factors like digital literacies, access to technology, and individual learning preferences, as observed in past research on technology integration into education (Luckin et al., 2016). Also, the fact that the improvement in grammar was relatively lesser suggests that adaptive systems might have to include more structured instructional elements in order to deal with rule-based learning effectively.

On the whole, the discussion shows that AI-powered adaptive language teaching systems offer a potent and data-driven solution to individualized language teaching. These systems improve engagement and learning results by incorporating flexibility and quality feedback. Nevertheless, to maximize their potential, it is essential to continually refine and contextualize them, especially in developing countries where technological and infrastructural challenges still persist (Holmes et al., 2019).

CONCLUSION

This research investigated how AI-based adaptive teaching of English can enhance student involvement, motivation, and language competency in Pakistani universities. The results present solid empirical evidence that the adaptive systems are effective in enhancing the learning outcomes through content delivery in the form of personalized instruction, real-time feedback, and dynamic learning pathways. A significant percentage of students showed high activity, and quantifiable improvement was realized in the major skills of language, especially fluency. These findings support the main assumption of the personalized learning theory that states that instructional design that is responsive to the needs of the individual learner can be used to achieve improved performance (Tomlinson, 2014; Pane et al., 2017).

The statistical results also support the fact that the feedback quality and system adaptability are very strong predictors of the outcomes of the learning process, with feedback being the most significant variable to consider. This highlights the essence of interactive and responsive learning environments, as is consistent with constructivist and intelligent tutoring system models (Vygotsky, 1978; Woolf, 2010). It has been clearly demonstrated by the close relationship between engagement and learning outcomes that active involvement by learners is necessary in order to attain meaningful learning outcomes (Fredricks et al., 2004).

Although these are the positive findings, the study also points out the significant challenges. The fact that moderate and low levels of engagement are present indicates that adaptive systems are not equally beneficial to all learners, which may be due to the fact that not all learners are equally digitally literate, have equal access to technology, or learn in the same way. Moreover, the comparatively poorer advancement in grammar implies that some of the language learning processes might need more intensive instructional support, rather than adaptive processes.

In general, the research findings indicate that the AI-based adaptive learning system is a highly effective, scaleable, and data-driven solution to personalized English language teaching in Pakistan. Nevertheless, their effective implementation is related to the resolution of infrastructural, pedagogical, and technological issues.

RECOMMENDATIONS

Resting on the results of the current study, a number of recommendations are made to help increase the effectiveness and implementation of AI-powered adaptive learning systems in Pakistani universities.

First, schools and colleges ought to engage proactively in the implementation of AI-supported adaptive learning environments in English language programs. These systems are to be introduced as an essential part of instructional design and not as a supplementary tool as they have proven to be quite effective in enhancing engagement and learning outcomes (Holmes et al., 2019).

Second, it is crucial to educate teachers about the successful application of AI technologies. The skills needed should be provided to teachers in interpreting the data generated by the system, supplementary guidance and integration of adaptive tools into classroom practice. AI literacy and digital pedagogy are the two professional development programs that can greatly benefit instructional efficacy (Luckin et al., 2016).

Thirdly, the institutions are expected to work on better technological infrastructure and access. Beliable internet connectivity, upgraded digital technology, and convenient platforms are all that would make sure that all students could equally enjoy the benefits of adaptive learning systems. The issue of digital divide is especially critical in the developing environment such as Pakistan.

Fourth, curriculum developers and curriculum designers ought to improve adaptive systems by introducing more structured grammar-based modules. Because grammar development was relatively lower, a combination of rule-based explanations and practice activities can be combined to achieve balanced language development.

Fifth, policymakers are needed to encourage national-level plans on integrating AI in education, such as funding technological innovation, curriculum change, and research projects. An integrated strategy can be used to promote the mainstreaming of adaptive learning systems in higher institutions of learning.

Lastly, future studies ought to consider more sophisticated AI models, including deep learning and natural language processing algorithms, to additionally improve the adaptability and accuracy of systems. The future research should be conducted all over in different educational environments and a larger sample will enhance the external validity of the results.

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