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The role of AI-powered learning analytics in enhancing EFL curriculum design and learning outcomes in higher education

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Abstract

This study explores the role of AI-powered learning analytics in improving EFL curriculum design and student learning outcomes in higher education. Adopting a quasi-experimental mixed-methods design, the research engaged 120 undergraduate EFL students and 10 faculty members over a 16-week semester, integrating quantitative data—such as AI-generated engagement metrics and pre/post-test scores—with qualitative insights from student focus groups and faculty interviews. Results revealed a significant increase in academic performance, with post-test scores rising substantially. Engagement indicators, including time-on-task and online participation, were strong predictors of success, allowing for the early identification of at-risk learners. EFL students reported that personalized, real-time feedback enhanced motivation, accountability, and self-regulated learning, while faculty used analytics to adjust teaching strategies and revise curriculum elements, such as embedding targeted workshops. Despite these benefits, challenges emerged in the form of privacy concerns, the psychological burden of continuous monitoring, and faculty difficulties in interpreting complex data due to limited data literacy. The study concludes that AI-powered analytics has transformative potential, provided institutions invest in professional development, ethical data frameworks, and balanced integration with human judgment.

Keywords: AI in education, EFL curriculum design, EFL, Higher education, Learning analytics, Student outcomes.

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1. Introduction

The digital transformation of higher education has increasingly positioned artificial intelligence (AI) as a key driver of innovation in teaching, learning, and curriculum development. Among its most impactful applications, AI-powered learning analytics (LA) enables institutions to systematically collect, interpret, and apply large volumes of learner data to improve educational practices. By transforming raw data into actionable insights, learning analytics has become a cornerstone of adaptive pedagogy and evidence-based curriculum design [1].

Traditional approaches to curriculum design often follow static, one-size-fits-all models that fail to account for the diversity of learners' needs, preferences, and learning trajectories. Such rigidity limits the capacity of curricula to adapt to emerging challenges and learner variability. By contrast, AI-powered learning analytics introduces a dynamic, data-informed framework for continuous curriculum improvement, enabling faculty to align course content and assessments with real-time evidence of student performance [2].

AI-driven learning analytics supports higher education in two significant ways. First, at the institutional level, it empowers educators and administrators to refine curricula, monitor learner engagement, and identify at-risk EFL students through predictive modeling [3]. Second, at the individual level, it fosters personalized learning pathways by offering learners customized content recommendations, adaptive feedback, and early interventions that enhance motivation and achievement [4, 5].

The growing importance of AI in higher education is reflected in global investment and adoption trends. The learning analytics market is projected to grow substantially between 2024 and 2025, underscoring institutions' increasing reliance on AI to improve both efficiency and educational quality. However, this rapid integration also raises challenges related to ethics, transparency, and governance [6]. Concerns about student privacy, algorithmic bias, and the accountability of AI-driven systems highlight the need for robust frameworks to ensure equitable and responsible use of AI in higher education [7, 8].

This study examines the role of AI-powered learning analytics in higher education, focusing on its dual impact: (1) enabling institutions to refine curricula based on real-time data and (2) supporting EFL students through personalized learning experiences. By doing so, it contributes to the ongoing discussion on how AI can shape the future of higher education in both innovative and ethical ways.

2. Literature Review

2.1. AI in Higher Education

Artificial intelligence (AI) has become a transformative force in higher education, reshaping the traditional ways of teaching, learning, and assessment. Far from being a futuristic concept, AI is already an integral part of much of the practice of academics, from automated tutoring systems to predictive analytics services that institutions use to keep track of learner success. According to Heffernan and Heffernan [9] AI is no longer limited to experimental or niche applications; on the contrary, it has become a central element of digital transformation of education systems globally.

One of the most notable applications of AI in higher education is intelligent tutoring systems (ITS), which replicate one-to-one human tutoring for learners by offering adaptive, context-sensitive feedback [10]. Unlike traditional static courseware, ITS employs natural language processing and machine learning algorithms to dynamically adapt content delivery, thereby customizing the speed and intensity of instruction. Empirical research demonstrates that ITS enhances student engagement and student achievement, especially in STEM disciplines [11, 12]. AI has also been extensively used in the area of automated testing, from grading essays to automatically creating multiple-choice tests. Not only are such systems associated with a reduced faculty workload, but they also offer EFL students immediate feedback, an environmental factor that has been linked to higher levels of student learning [9].

Chatbots are another increasing network of AI application in which students can find 24/7 academic assistance. Studies show that chatbots are used to increase accessibility, to minimize administrative bottlenecks, and to encourage learner autonomy [13]. More recently, AI has been used to increase retention and success rates by using predictive models to identify at-risk learners early on. For example, Zawacki-Richter, et al. [3] showed that early-warning systems based on AI can greatly decrease dropout rates by warning instructors of patterns of disengagement or falling performance. These predictive capabilities are particularly useful in larger higher education institutions where faculty members might not have the ability to keep a close eye on an individual student. In addition, AI has been used successfully to increase learner motivation and autonomy. Students tend to be more engaged, persistent, and self-directed learners with adaptive platforms that adjust instructional content to the strengths and weaknesses of learners [4, 14].

In other words, AI makes it possible to deliver at scale what we have long sought in the classroom as a pedagogical ideal, but has thus far been too challenging to accomplish in traditional classrooms: personalised learning. However, the incorporation of AI in the higher education sector does not come without challenges. Specifically, the ethical issues related to the algorithms, such as privacy, algorithmic bias, and transparency have been reported extensively [15, 16]. Students can feel nervous about data collection at all times, and educators can be suspicious of black box algorithms influencing crucial decisions about learners' futures. Furthermore, there are concerns of digital inequalities due to the differences in institutional resources with richer universities able to adopt more advanced AI systems than others [17]. These challenges underscore the importance of seeing AI not as a purely technical tool but as part of a broader socio-educational ecosystem that must be carefully regulated and governed. In conclusion, the literature suggests that AI holds great potential to positively impact higher education through personalization, efficiency, and student outcomes, but this potential must be balanced by considerations of ethics, pedagogy, and equity.

2.2. Learning Analytics

Learning analytics (LA), defined by Siemens as "the systematic use of data, collected about learners and their activities, to improve learning outcomes and the learning environment" [18] has moved forward in higher education, especially when combined with AI technologies. Together, AI and LA form a critical feedback loop that not only documents student behaviors but also makes sense of them in ways that are beneficial for teaching and learning. That LA's power for prediction is one of its basic strengths. By examining patterns in learner data, AI-enabled LA can predict future performance, identify students likely to fail, and recommend timely interventions [19]. For example, dashboards showing the progress of pupils against benchmarks give up-to-the-minute insight to both learners and teachers about what needs to be done to improve. Research shows that such predictive systems enhance retention rates and academic success, particularly when institutions use the data to implement targeted support services [20].

Learning analytics also shifts pedagogy from being primarily retrospective—evaluating outcomes after instruction—to proactive and adaptive, where instruction is adjusted dynamically based on emerging data [21]. This is part of a wider move throughout higher education, towards models of formative assessment from models of summative assessment, and away from end-of-cycle judgment and towards continuous improvement. For instance, Sajja, et al. [1] note that AI-powered LA can crunch large amounts of data, identify hidden relationships in student behavior, and suggest individualized learning resources, opening up possibilities for more student-centered learning spaces [1]. From a faculty perspective, LA provides diagnostic tools that help to improve instructional planning. Visual dashboards enable educators to see which topics are mapped to most students' weak points, and to change lesson plans accordingly [22].

However, researchers warn against an over-dependence on quantitative measures. While LA offers insight, Gašević, et al. [23] argue that LA alone is unable to capture the affective dimensions of student learning such as student motivation, resilience, or socio-economic factors external to the learning environment and affecting learning outcomes. Ethics is also a big part of LA research. The acquisition of fine-grained data on learners has been associated with issues of surveillance, consent, and data protection Slade and Prinsloo [24]. Macfadyen, et al. [25] emphasize that LA should be underpinned by ethical frameworks to ensure that the practice does not become skewed towards misuse and that learners retain trust in institutions of education [25]. Also, the interpretability of algorithms is a growing concern: without transparency, neither students nor faculty may be able to see how predictions are made, which can undermine confidence in the system [26]. Despite these challenges, LA remains a growing force as one of the pillars of higher education's digital ecosystem. When used appropriately, it is a pathway out of a one-size-fits-all approach to instruction toward adaptive and evidence-based pedagogy.

2.3. Curriculum Design and Learning Outcomes

Curriculum design is a fundamental aspect of higher education, as it dictates how instructional goals, pedagogical approaches, and assessment practices are intertwined to facilitate desired learning outcomes. Traditional curricula have often been static, and have emphasized standardization rather than personalization that do not take into consideration the diverse needs of learners in dynamic academic and professional environments [27]. Learning outcomes (i.e., measurable knowledge, skills, and attitudes that students are expected to learn) are increasingly seen as needing to be continually assessed and redefined. AI-driven learning analytics has opened new windows for data-driven curriculum development. By continuously tracking patterns of engagement and performance, institutions can fine-tune curricular elements to ensure alignment between intended learning outcomes and achieved student success [7]. For instance, in Tirado, et al. [8] the data from real-time analytics are shown to guide curriculum redesign in areas where students tend to score below expectations.

This way, educators including EFL practitioners can adapt their instructional content, create targeted tests, and include scaffolding mechanisms to fill in learning gaps. Such an evidence-informed feedback loop increases both the relevance and effectiveness of curricula. AI analytics also helps to create adaptive curricula that adapt content delivery to learner profiles. These curricula go beyond strict structures and establish tailored pathways which account for differences in prior knowledge, speed, and mode of students' engagement [28]. This flexibility is especially important in diverse classrooms where students are coming to the table with different levels of preparedness and expectations. Furthermore, AI and LA can offer insights into higher-order learning outcomes, such as critical thinking, collaboration, and problem-solving. While these outcomes are more difficult to measure, researchers have argued that carefully devised analytics frameworks can capture proxies for such skills based on patterns of discourse, peer interaction, and problem-solving strategy [21]. However, there are still problems. One of the most commonly reported findings was that faculty members have low levels of data literacy and cannot interpret analytics reports or translate those reports into curriculum changes [29].

Second, institutional infrastructure may also constrain the extent to which analytics can be integrated into curriculum design, particularly in resource-constrained contexts. In addition, critics caution that the overuse of data could potentially limit curricula to only that which is measurable, thereby ignoring educational goals that are wider in scope, such as civic engagement and ethical reasoning [30]. Despite such concerns, there is strong evidence for the positive impact of data-informed curriculum design on student learning outcomes, survival, and student engagement [22]. When used responsibly, AI-powered analytics offers a toolkit for keeping curricula dynamic, responsive, and student-centered to meet the higher education imperative of preparing learners for rapidly changing academic and professional landscapes.

2.4. Synthesis

A reoccurring theme throughout the reviewed literature is that AI-powered learning analytics is changing the game for higher education. While LA helps to generate actionable insights for students and faculty, AI applications help to increase personalization, automate routine tasks, and make proactive interventions possible. Together they facilitate ongoing curriculum development, alignment of intended outcomes with student achievement, and more adaptive and inclusive learning environments. At the same time, issues such as ethical considerations, faculty preparedness, infrastructure gaps, and the risk of excessive dependence on quantitative measures serve as reminders of the importance of implementation being both careful and contextual. Future research should therefore shift from celebratory narratives about AI and LA to investigations of the conditions under which they can be included into diverse higher education contexts in a sustainable and ethical manner.

3. Methodology

3.1. Research Design

This study used a quasi-experimental mixed-methods design that integrated both quantitative and qualitative methods in order to holistically assess the potential of AI-powered learning analytics to improve EFL curriculum design and learning outcomes in higher education. Mixed-method research is especially well-suited to educational contexts because of its ability to enable both statistical generalization (quantitative) and in-depth exploration (qualitative) of learner and faculty experiences [31]. The design had two primary phases: (1) data collection of quantitative information via AI-generated analytics and student performance measures, and (2) data collection of qualitative information via focus group discussions and semi-structured interviews with EFL students and instructors.

3.2. Research Site and Participants

The study was carried out at the National University of Modern Languages (NUML), Islamabad, Pakistan, a premier public sector university that is dedicated to language and communication studies, but also has a broad curriculum of social sciences and applied subjects. The study population consisted of first-year undergraduate EFL students from programs in English and related social science subjects, because these were linguistically and academically diverse. A total of 120 undergraduate EFL students were recruited through a stratified random sampling approach in order to ensure representation from various semesters and departments. In addition, 10 EFL faculty members involved in curriculum delivery and assessment were interviewed. Inclusion criteria were based on student experience of using a Learning Management System (LMS) integrated with AI-powered analytics tools used at the university.

3.3. Data Collection Instruments

1. AI-Powered Learning Analytics Dashboard
   The main source of quantitative data was the analytics produced by the university's LMS (integrated with AI analysis tools to monitor EFL student engagement, assignment submission, and performance patterns). Measures included time spent on learning materials, participation in online activities, quiz scores, and progression rates.
2. Pre- and Post-Intervention Tests
   Standardized academic assessments were developed to evaluate pupil learning outcomes before and after the intervention. The tests focused on critical thinking and problem-solving as well as on subject-specific knowledge corresponding to the program's learning goals.
3. Questionnaire
   A structured questionnaire was administered to EFL students to collect perceptions about the effectiveness of AI-powered analytics in supporting personalized learning. The instrument was adapted from validated scales on technology acceptance and educational analytics [32].
4. Focus Groups and Semi-Structured Interviews

To capture in-depth perspectives, three focus groups (8–10 EFL students each) were conducted, along with semi-structured interviews with EFL faculty members. These explored participants' experiences with AI-based analytics, challenges faced, and perceived impact on curriculum design.

3.4. Procedure

The study was conducted over one academic semester (16 weeks). In the first two weeks, EFL students completed the pre-test and initial questionnaires. During weeks 3–12, AI-powered learning analytics were applied to monitor EFL student engagement and performance, with EFL faculty members receiving periodic data-driven insights to adjust their teaching strategies. In weeks 13–14, focus groups and interviews were conducted, while in weeks 15–16 EFL students completed the post-test and final survey.

3.5. Data Analysis

Quantitative data were analyzed using SPSS. Descriptive statistics (means, frequencies, standard deviations) were used to summarize learner engagement, while paired-sample t-tests compared pre- and post-test scores to assess the impact on learning outcomes. Regression analysis was performed to determine whether specific analytics indicators (e.g., time on task, online participation) predicted academic improvement.

Qualitative data from interviews and focus groups were transcribed verbatim and analyzed using thematic analysis [33]. Coding was conducted in NVivo, with themes emerging around curriculum alignment, personalization, student motivation, and challenges in AI adoption. Integration of quantitative and qualitative findings provided a holistic understanding of AI-powered analytics in shaping curriculum design and learning outcomes.

The figures presented in the findings were generated directly from the results of the data analyses. Figure 1, a combined bar and line chart, was produced from descriptive statistics of LMS dashboard data to compare weekly averages of time-on-task and participation rates. Figure 2 was created by plotting mean pre- and post-test scores obtained through the paired-sample t-test. Figure 3, a scatterplot, visualized the regression analysis by showing the relationship between time-on-task and score improvement. Finally, Figure 4, a categorical chart, was developed from predictive thresholds identified in the quantitative analysis to classify EFL students into "at-risk" and "successful" groups.

3.6. Ethical Considerations

This study involved human participants (EFL students and faculty members) and was conducted in accordance with established ethical research guidelines. Prior to data collection, ethical clearance was obtained from the Institutional Review Board (IRB) of the National University of Modern Languages (NUML), Islamabad, Pakistan (Approval No: NUML/IRB/2025/07). Participation was voluntary, and all participants provided informed consent before taking part in the study. Confidentiality and anonymity of respondents were strictly maintained, and all data were used solely for academic purposes.

4. Findings

4.1. Quantitative Results

4.1.1. Student Engagement through AI-Powered Analytics

The findings of learning analytics dashboard activity showed that student engagement improved significantly during the semester through the use of the AI-powered learning analytics tool. The most obvious trend was the steady rise in the average time-on-task per week. At the start of the semester (Week 1), the average number of hours per week that EFL students spent on online learning materials was 4.2 hours. By Week 16, this figure increased to 7.5 hours, nearly doubling the value that they started with. This growth indicates that students not only became more familiar with the system, but also came to depend more heavily on it as an integral part of their learning experience. Also, the number of online academic activities followed a positive trend. Discussion board posts, online quizzes and collaboration assignments increased by 28% throughout the semester. This suggests that, in addition to learning, the platform served to support active participation in the wider learning community, in line with earlier research that digital platforms support collaboration and increase participation by learners [32].

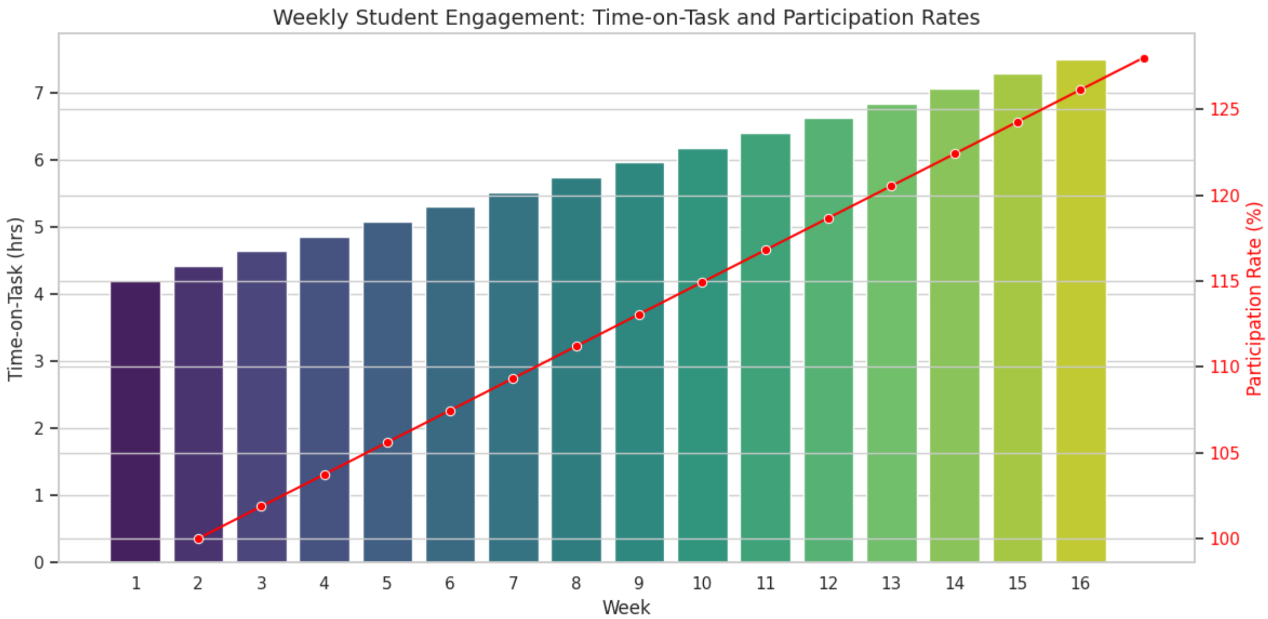

Figure 1.
Comparison of average time-on-task and participation rates across weeks 1–16.

Figure 1 indicates that EFL students' engagement was increasing over the 16-week semester, as captured by the AI-powered learning analytics dashboard. The bar graph shows weekly average time-on-task, which was rising from 4.2 hours in Week 1 to 7.5 hours in week 16, showing increasing confidence in using the platform for academic purposes. In addition, the chart shows a 28% increase in participation rates including discussion board participation, online quiz completion, and participation in collaborative activities. This ongoing growth underscores the platform's success in promoting deeper engagement and active learning.

4.1.2. Learning Outcomes: Pre- and Post-Test Performance

To evaluate the impact of AI-powered analytics on academic achievement, EFL students completed pre- and post-intervention assessments. The mean pre-test score was 61.4 (SD = 8.2)**,** while the mean post-test score improved to 74.9 (SD = 7.6)**.** A paired-sample t-test confirmed this improvement was statistically significant, $t(119) = 12.37$, $p < .001$**,** suggesting that AI-supported learning environments can lead to measurable gains in student performance.

Further regression analysis provided deeper insights. Both *time-on-task* ($\beta = .41$, $p < .01$) and *online participation* ($\beta = .35$, $p < .05$) emerged as strong predictors of performance improvement. This finding indicates that EFL students who spent more time engaging with digital resources and participated actively in online activities demonstrated greater academic gains.

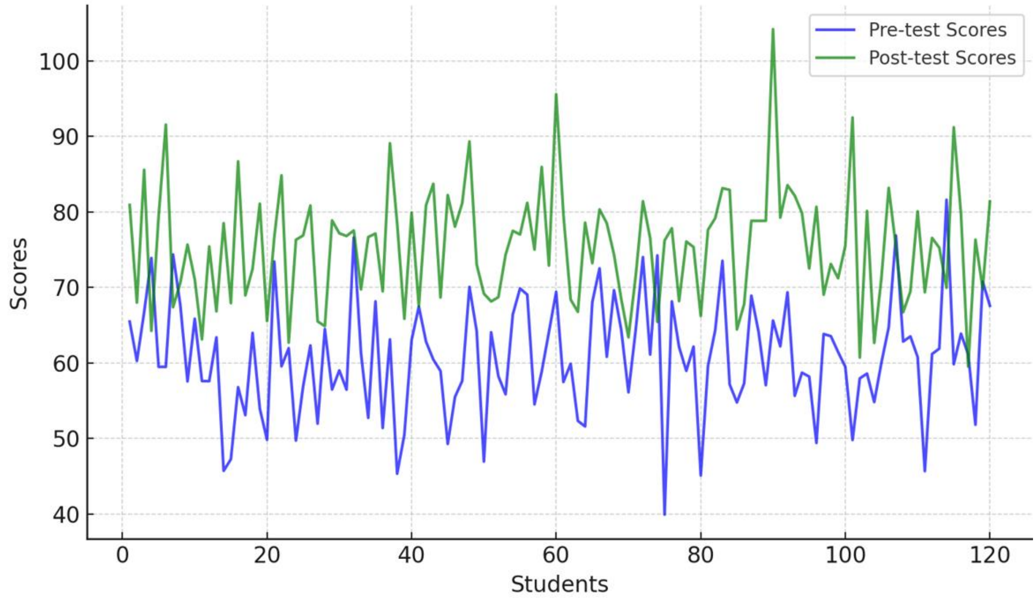

Figure 2.
Pre-test vs. Post-test scores of EFL students.

Figure 2 shows the comparison between pre-test and post-test scores of EFL students. The graph illustrates a marked improvement in performance after the integration of AI-powered learning analytics. The upward shift in the post-test line compared to the pre-test line highlights that students, on average, achieved higher scores, suggesting that AI-driven support contributed to enhanced learning outcomes.

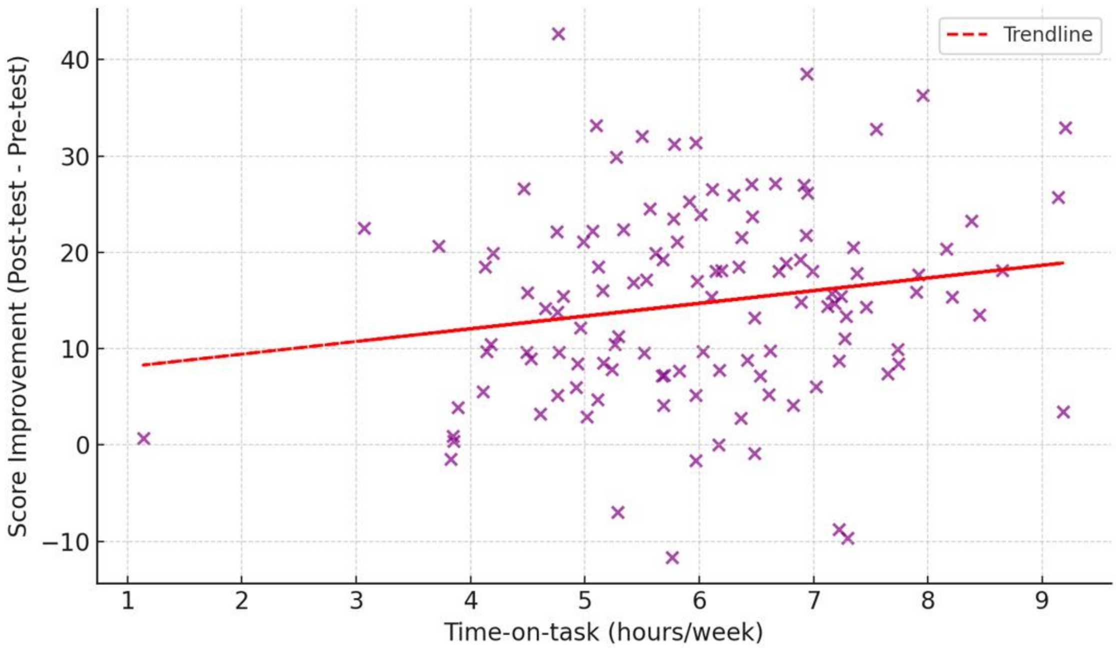

Figure 3.
Relationship between time-on-task and improvement in test scores.

Figure 3 shows the relationship between time-on-task and improvement in test scores. The scatterplot demonstrates a positive correlation: EFL students who invested more hours engaging with the platform showed greater score improvements. The upward trendline confirms that increased engagement with digital learning resources was a strong predictor of academic success.

4.1.3. Predictive Value of Analytics Indicators

One of the most valuable contributions of AI-powered analytics lies in its ability to identify "at-risk" EFL students early in the semester. The data revealed that learners who spent **less** than 3 hours per week on the LMS and scored below 60% in early quizzes had a 70% probability of underperforming in the final exam. These insights provide actionable intelligence for instructors and administrators, enabling timely interventions before performance declines become irreversible.

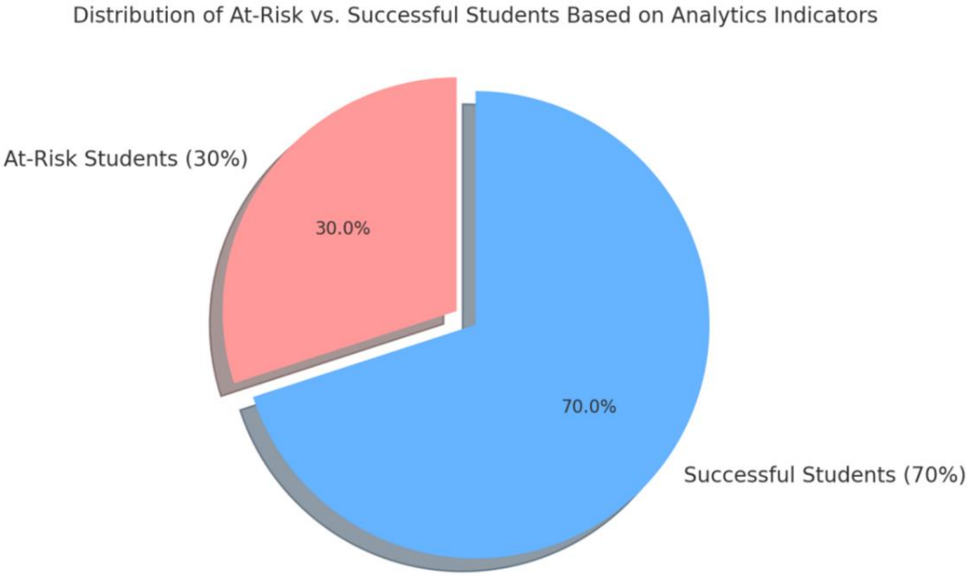

Figure 4.
Distribution of at-risk vs. successful EFL students based on analytics indicators.

Figure 4 displays the distribution of EFL students who were identified as "at-risk" and "successful" based on the AI-powered learning analytics indicators: The chart shows that about 30% of the EFL students were identified as at-risk, mostly because they spent less than three hours per week on the LMS and scored below 60% on early quizzes. In contrast, 70% of the EFL students were deemed successful as they showed consistent engagement, and satisfactory performance at the beginning of the year. As we can see, this predictive model of AI-driven analytics can identify EFL students who might need early interventions, and provide faculty and administrators with an evidence-based tool to provide targeted academic support and improve overall student success.

4.2. Qualitative Results

4.2.1. Student Perspectives

Focus group discussions indicated that for EFL students, AI-enabled learning analytics were viewed as an extremely valuable addition to their learning experience. The system-generated personalized feedback was reported as one of the most motivating features of the system consistently. The dashboards, according to EFL students, enabled them to track their learning in real-time, thus motivating them to engage actively with course content. Many learners said that having access to instant feedback about their strengths and weaknesses was a motivating way to become more self-directed and strategic about their study practices. For instance, one of the participants said: "The dashboard made it very clear to me where I was lagging behind." Instead of waiting for the results from my midterm exam, I could work on improving my quiz performance right away." This quote echoes a general theme running through the participants: the feeling that learning analytics promoted a sense of agency, accountability and ownership over learning. EFLstudents also reported that the focused recommendations (e.g., go back and review certain readings or take another practice quiz) helped them more efficiently use their time, especially on areas where they previously struggled.

However, there were also areas of concern highlighted during the focus groups. Some EFL students who were monitored commented on the amount of monitoring, explaining that it created a feeling of "constant surveillance" and contributed to the pressure of school. Others were concerned about data privacy, and were unsure about how their information would be stored and used outside of the classroom context. These views underline the importance of balancing the power of personalised feedback with ethical considerations surrounding student data.

4.2.2. Faculty Members Insights

EFL Facultymembers' interviews further inform the understanding of the role of AI-powered analytics in the development of pedagogical practices and curriculum delivery. Many EFL instructors stated that the system provided them with insightful actionable information about performance at both the class and the student level. For example, after analytics uncovered a persistent area of struggle in some modules - academic writing –EFL faculty members were able to make changes to the design of the course by added workshops and other instructional materials. The solution provided a way for teachers to proactively address the needs of EFL students instead of reacting after poor performance in the exams.

In addition, EFL faculty members reported that access to real-time information allowed them to better pace their instruction. By catching EFL students who were falling behind early in the semester, EFL instructors were able to intervene with targeted remediation, such as remedial exercises, peer tutoring sessions, or one-on-one feedback. These changes were perceived as critical to closing performance gaps and improving learning outcomes in general. In addition to these benefits, EFL faculty members mentioned challenges. Several EFL instructors noted challenges in interpreting complex analytics dashboards, especially in understanding what statistics are meaningful and what are "*noise*". This indicates that although the analytics were a source of valuable knowledge, there is an urgent need for data literacy professional development and training in order for faculty to gain the most of these systems. Additionally, some faculty expressed concerns that institutions may become overly reliant on quantitative measures and warned against a system that, as it currently stands, would essentially replace holistic judgment about student learning with a set of quantitative measures.

4.2.3. Integration of Findings

Overall, the combination of quantitative and qualitative outcomes points to meaningful gains in EFL student (learning) and teaching effectiveness due to AI-powered learning analytics. EFL students showed measurable academic improvement and showed a greater involvement in learning activities. Qualitatively, EFL students self-reported increased motivation, self-awareness, and confidence in their ability to manage their studies, and faculty were able to use the data to revise curricula and improve instructional strategies.

Yet, both these results also indicate open problems. Students' concerns about data privacy and the psychological strain of being monitored constantly remind us of the ethical aspect of AI adoption. Improving institutional investment in faculty training and professional development to address challenges in data interpretation. Taken together, these findings demonstrate that although AI-powered learning analytics offers transformative potential for higher education, its successful delivery is conditioned by the need to address ethical, pedagogical, and professional capacity building issues.

5. Discussion

The purpose of this study was to examine the role of AI-powered learning analytics in enhancing curriculum design and improving learning outcomes in higher education. Drawing on data collected from undergraduate students, the discussion addresses three main objectives: (1) evaluating the impact of AI-powered learning analytics on student learning outcomes, (2) assessing its role in informing curriculum design and instructional practices, and (3) exploring student and faculty perceptions of its effectiveness.

5.1. Impact on EFL Students Learning Outcomes

The results of this study demonstrate that AI-powered learning analytics can have a transformative impact on enhancing student learning success. Analysis of the pre- and post-test found that there was a statistically significant increase in the mean scores by over 13 points. This sizable leap highlights the power of analytics systems to offer learners the kind of personalized help that many classroom-based methods do not. This finding is congruent with previously published research that learning analytics leads to better outcomes through individualized learning trajectories and timely interventions based on students' specific needs [17, 25].

Another interesting aspect of the study is how well early engagement indicators predict outcomes. Time on task and frequency of online engagement turned out to be powerful predictors of student achievement. In doing so, AI-based systems showed the ability to serve as reliable "early warning systems" based on these early markers. This can help educators and institutions evaluate risk in EFL students before their academic struggles spiral out of control, so that intervention can be proactive (as opposed to reactive). The predictive aspect of analytics is especially relevant in higher education, where being able to intervene early can make the difference between a student continuing their studies and dropping out.

In addition, the visibility of these engagement indicators to learners themselves had an empowering effect. When EFL students were able to see how their level of activity correlated with their learning outcomes, many reported being motivated to adjust their study habits. This finding resonates with prior research that confirms student engagement metrics—particularly active participation and time-on-task—as robust predictors of academic success [5, 34]. By rendering these patterns transparent, AI-powered systems not only supported academic monitoring but also promoted self-regulation, accountability, and sustained engagement across the semester.

5.2. Role in Curriculum Design and Instructional Practices

In addition to the benefits realized on a student-by-student basis, the study also points to the influence learning analytics can have on curriculum planning and teaching practices. Faculty interviews showed that the information gleaned from analytics helped instructors make informed changes to curriculum. For instance, consistently poor student performance on academic writing courses led faculty to reorganize content presentation and incorporate add-on workshops.

Such adaptations echo the general argument that analytics constitute a dynamic "feedback loop" between learners and instructors [14]. This cycle helps to ensure that curricula are adaptive, changing based on student needs and performance trends, rather than being static. Not only was analytics able to identify which areas of difficulty needed improvement, but it provided educators with actionable data that can be applied to further refine instruction. This is in line with emerging scholarship that stresses the potential of learning analytics to move beyond descriptive reporting of student data to become an enabler of pedagogical innovation [21]. With an understanding of student performance both areas of strength and areas of weakness, analytics can be used to inform better decisions around course pacing, assessment development and integration of supplemental resources.

However, the study also identified issues around faculty capacity. While instructors agreed that analytics could be useful in informing curriculum and instruction, most reported obstacles to interpreting complicated data outputs. This is an important limitation, as the pedagogical value of analytics can only be realized if learners have the appropriate training in data literacy. As argued in prior scholarship, professional development programs are needed to help faculty learn to analyze, interpret, and apply analytics findings in ways that make sense [12]. If support for analytics is lacking, there is a risk that analytics data will be underutilized or misinterpreted, which will compromise its transformative power.

Taken together, the results of this study indicate that AI-driven learning analytics not only enhances measurable learning outcomes, but indeed engenders an iterative process of curriculum design and instructional refinement. By improving student learning and faculty pedagogy, analytics is a promising tool to transform higher education into a more responsive, data-driven, and student-focused business.

5.3. EFL Students and Faculty Members Perceptions

The qualitative aspect of this research provided insight into the complex views of both EFL students and faculty about the incorporation of AI-enabled learning analytics within higher education. From the students' perspective, the system was assessed positively in general, especially in terms of its ability to give individual feedback and enhanced transparency in the monitoring of academic progress. Several EFL students expressed that seeing their own patterns of learning and receiving corrective feedback in a timely manner had decreased their sense of uncertainty of their academic standing. This rings true with evidence found in previous literature where increased learner agency, learner motivation, and academic confidence have been linked to the use of AI-enhanced analytics by empowering EFL students to track their progress and to make independent changes to their study habits [35].

At the same time, however, students also expressed concern about the psychological and ethical implications of constant monitoring. The fact that everything they clicked, submitted, or delayed was monitored caused some EFL students to feel pressured, which led to an increase in anxiety about how they performed. These issues mirror wider discussions in the learning analytics literature, where issues of data privacy, student consent, and the psychological burden of being under surveillance have been extensively raised [20]. Thus, in addition to expressing appreciation for the system, EFL students emphasized the importance of institutions setting clear data governance policies and ensuring that analytics did not jeopardize their wellbeing.

From the standpoint of faculty members, learning analytics' most important value was seen to be its diagnostic value. Instructors were grateful for the system's ability to identify at-risk EFL students early in the semester, and to help identify areas in which EFL students struggled. This information enabled faculty to revise teacher strategies, reorganize modules, and add additional workshops to address the needs of learners. However, faculty also expressed a concern about being overdependent on quantitative measures. Although analytics was a valuable source of information, it was not always able to address contextual or affective aspects of learning such as student motivation, external challenges, or classroom dynamics. This tension emphasizes the need to strike a balance between data-driven decision making and human judgement, which is also a theme in the literature that warns against the danger of using analytics as a substitute for holistic pedagogic practices.

5.4. Implications

Taken together, the perspectives of EFL students and faculty bolster the argument of the study that AI-powered learning analytics is not an inspection system, but a transdisciplinary pedagogical tool. Its dual nature—as a means to empower EFL students by providing them with their own personalized learning pathways, while also giving faculty the actionable insights they need to refine their curriculum—simply highlights its potential to transform higher education into a more adaptive, student-centric enterprise. By improving transparency, facilitating timely intervention and supporting curriculum design informed by data, analytics contributes directly to the study's goals of improving learning outcomes, engagement, and educational practices.

However, the findings also pointed out that the important challenges to be overcome for sustainable uptake. Respect for the privacy of EFL students and the potential psychological impact of constant monitoring, in addition to informed consent and anonymization requirements, requires consideration of ethical guidelines and sensitivity to learner well-being. Similarly, faculty need to develop data literacy skills to effectively use analytics to improve instruction, so appropriate professional development efforts are needed to help faculty interpret complex analytics outputs. Without such support there is potential for the data generated to be mistranslated or under-used. These implications reflect global trends in higher education where integration of AI and analytics is increasingly perceived as part of a digital transformation agenda [22, 25]. However, this case study showed that the success of such initiatives is not just dependent on technological sophistication, but also on institutional readiness, faculty preparedness and infrastructural support. As such, while there are exciting opportunities related to the adoption of AI-powered learning analytics, its sustainability is dependent on institutional contextual realities.

6. Conclusion

This study examined how AI-supported learning analytics can be used to improve student learning outcomes, engagement, and curriculum design. Through both quantitative and qualitative research, the findings revealed how artificial intelligence-powered systems are powerful tools in the development of higher education practices. Quantitatively, EFL students made significant academic gains, with students' post-test scoring significantly higher than pre-test. Time-on-task and online participation measures were shown to be good predictors of success, and the predictive models were able to flag learners at risk early in the semester. These findings illustrate the potential of analytics in not only monitoring but also predicting student performance and enabling educators to plan timely and targeted interventions. Qualitative findings provided the color to this picture. EFL students reported that they found the personalized, real-time feedback from AI tools to be motivating and that it increased their accountability and ability to self-regulate learning. Faculty also used analytics to gain actionable insights into student performance, enabling them to make changes to course pacing, include supplementary materials, and fill ongoing gaps in learning, including weaknesses in academic writing. However, constraints were found. EFL students expressed concern over data privacy and the psychological burden of ongoing data collection while faculty highlighted the need for data literacy education to ensure the analytic system is most beneficial pedagogically. Taken together, these results highlight the transformative power of AI-powered learning analytics in higher education. Far from a technological bolt-on, analytics can transform the educational experience by driving adaptive learning pathways through early interventions and evidence-based, rather than intuition-led, curriculum design. However, unlocking this potential will necessitate that ethical issues are addressed, faculty are prepared, and that analytics are used as a complement to, not a substitute for, human judgment in instruction and learning.

7. Recommendations

The results of this study suggested some important recommendations for the effective rollout of AI-enabled learning analytics in higher education. First, institutional leadership needs to prioritize faculty members learning about data literacy. Professional Development: Providing professional development workshops and ongoing support programs is crucial to ensure that teachers are equipped to interpret analytics dashboards accurately and translate insights into their instructional strategies. Without capacity building, analytics will not be fully exploited. Equally important is the creation of data policies centered around students. Concerns about surveillance and misuse should be countered by being transparent with learners about how and when data is collected, who can access it and how it is used. Privacy and consent mechanisms and anonymization can further support student trust, which is important for the long-term sustainability of analytics adoption. Therefore, a healthy balance of AI is also encouraged. While quantitative measures give important information, excessive use of measures can cause reductive interpretations of learning. A combination of analytics-driven evidence, qualitative assessments and teacher judgment will provide a more holistic view of student needs. Second, institutions are recommended to set up formal early intervention programs for EFL students identified as at risk. Mentorship programs, supplemental workshops, or peer tutoring can offer the kind of specific attention that is needed to prevent academic regression from becoming permanent. Finally, information gleaned through analytics should inform curriculum improvement. Persistent or low performance in certain areas (such as academic writing) is an incentive for systematic curriculum adjustments. Adding competency-based modules to courses would embed competency-based learning within curricula, ensuring that curricula are responsive to changing student needs and enhancing EFL students overall academic success.

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