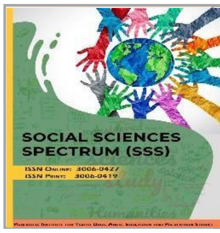

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AI-Driven Learning Analytics for Evidence-Based Decision-Making in K–12 STEM Classrooms

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Abstract

Artificial Intelligence (AI) and Learning Analytics (LA) are redefining personalized learning space and instruction with real-time feedback and data driven pedagogy in K-12 STEM education. The present study aims to document and assess the use of AI and LA tools in public in Lahore, Pakistan, over five years. The study employing mixed methods incorporated classroom observation and interviews with teachers and student's performance data to assess the value and the cost of the technology. Results indicate that AI and LA tools contribute to better engagement and performance of students in STEM disciplines, especially in Mathematics, Science, and Physics. On the other hand, Poor infrastructure, absence of pre-service and in service teacher training, and the digital divide constrain technology driven education to a few. The study presents a data driven learning design informed by the concepts of a technology empowered learning community, instructional design and AI to address the issues of pedagogy to enhance students learning outcomes. The work substantiates the need of focused policy efforts and systemic professional development in underfunded schools to meet the fundamental right of students to learn by pedagogy that harness the power of AI.

Keywords: STEM Education Reform, Technology-Enhanced Learning (TEL), Artificial Intelligence in Education (AIED), Educational Data Mining (EDM), Data-Informed Learning Design.

Introduction

When blended learning incorporates Artificial Intelligence and Learning Analytics, it facilitates in the automated evaluation of educational data and systems. This capability permits the personalization of instruction and automated feedback, modifying the learning environment in real time. Thus, the educational landscape worldwide stands to change for the better in terms of student engagement and achievement in STEM (Asad et al., 2021; Batool, Aslam et al., 2025). The global COVID-19 pandemic has made such change necessary, as instruction delivered digitally and through hybrid methodologies has become the global standard. The role of Artificial Intelligence and Learning Analytics in education becomes critical as they provide the necessary scale and smartness to accomplish transformational change (Amin & Uddin, 2023; Barthakur et al., 2025; Batool, Aslam et al., 2025).

In Pakistan, the post-pandemic period has begun to Intergate Artificial Intelligence, particularly the use of AI in education. First, it is recognized that the government education system has gradually integrated AI in education in the past years. As reported, the Pakistan government has been taking real initiatives toward the integration of AI in education. Other studies have also recognized this positive move (Batool, Zulqarnain, et al., 2025; Caskurlu et al., 2025; Dahri et al., 2024). As much as there are positive initiatives, there is still limited positive change. As reported, there are over used system, limited technology use, insufficient skilled workers, depreciated education systems, unconstructive laws, unreformed systems, Low integration of technology in education (Ashraf, 2025; Baseer et al., 2025; Batool, Aslam, et al., 2025). With the tons of system limitations, the positive changes slow but can be felt. More schools are reporting the use of AI and Learning Analytics (LA). Out of the problems, learners and educators have reported and the schools have over positive AI changes. The changes have been reported to be over positive, especially in STEM education in schools.

However, the systemic constraints set by the government Educational Ministry of Pakistan seriously undermine the potential benefits of these innovations. The educational model, which is primarily based on in-person classes, is unable to cope with the digital shift. Resource shortages are caused by poor connectivity, substandard facilities, a lack of staff training, and low investment in continuing professional development (Caskurlu et al., 2025; Esqueda, 2024). Considerable transformative pedagogical advancements could be achieved with the implementation of Artificial Intelligence in these areas; the absence of customized individual instruction, disengagement and indifference towards learning, and the overall lack of academic interest (Durrani et al, 2025; Esqueda, 2024; Hafeez & Zehra, 2025). How AI and Learning Analytics (LA) could address issues of this magnitude remains remarkable. While learning analytics provides the ability to track and measure student participation and engagement to identify potential learning gaps, AI utilizes adaptive learning technologies that personalize and automate education resources and experiences for learners. However, there is a significant opportunity to revamp education in this country through the use of AI and learning analytics in STEM education in a much more integrated and systematic, adaptable, and efficient manner (Imran et al., (2025; Khan & Ullah, (2024; Khan et al., (2024).

The use of Artificial Intelligence (AI) and Learning Analytics (LA) in teaching and learning in various countries has gained attention all over the world, yet the systematic role of AI and LA in reshaping K–12 STEM education in under-resourced public schools in Pakistan has been under-researched. But most of the literature existing in the field tends to be at colleges or AI in general, without going into examining what would be the pedagogical ramifications of AI on K–12 content based on STEM as Mathematics, Science, or Physics. Moreover, models that combine data-driven instruction and instruction design, PLCS, and teacher models are less developed in the Pakistani setting. Existing studies have not paid enough attention to how AI-based and LA-based tools circumvent systemic constraints like outdated infrastructure, lack of teacher readiness, and lack of policy support, especially in government schools. This leads to a lack of understanding of the extent to which AI-supported decision-making can be transferred to resource-poor educational environments for scalable impact.

Even though AI and learning analytics could promise a breakthrough in personalized learning and evidence-based decisions in STEM education, public schools in Pakistan still seem unable to harness such capabilities. The available preliminary evidence indicates students are more engaged and perform better where AI tools are used, but the persistence of many schools in the use of AI learning systems is hampered by inadequate staff training, extremely limited access to technologically advanced infrastructure, or a combination of all three. Without systematic approaches to policy integration and teacher training, the integration of AI in K-12 STEM education is potentially transformative—the still untapped dominance of AI in education is most evidently lacking. The focus of innovation is still absent for contextually grounded, instructional practice, and professional development, especially for AI integration, which is a significant implementation gap, contributing to the evident absence within the research and practice.

This research seeks to evaluate the effects of Artificial Intelligence (AI) and Learning Analytics (LA) on K-12 STEM education in relation to student engagement and achievement. The main objectives of this research include,

- To investigate the role of AI and Learning Analytics in improving student engagement and academic performance in K–12 STEM subjects.
- To identify systemic barriers (infrastructure, teacher training, policy, and technology access) that hinder the integration of AI and LA in public schools.
- To evaluate how AI and LA tools influence instructional design and personalized learning in Mathematics, Science, and Physics.
- To develop a framework for integrating AI and Learning Analytics into K–12 STEM education that incorporates professional learning communities, teacher development, and evidence-based decision-making.

Literature Review

AI and Learning Analytics help students stay engaged and succeed as early as K-12 in STEM classes. Tools and functions of AI, such as intelligent tutoring systems (ITS) and other adaptive learners, aid in providing individualized real-time scaffolding and tailoring scaffolds to meet the unique requirements of each learner (Dahri et al., 2024). These technologies have been beneficial in STEM areas where students have the most difficulty with highly complex ideas. For instance, in the (Caskurlu et al., 2025) study, the authors noted that students trained with AI personalized tutoring systems achieved improved educational results because of the high quality of educational support they received in mathematics and physics. Also, (Durrani et al., 2025; Esqueda, 2024), along with other authors, have presented the integration of adaptive learning systems toward personalized instructions, whereby complex ideas are treated as gradual scaffolding as moves toward the instructional practice (Ahmed et al., 2021).

Learning Analytics also assists in facilitating student success through their behavior, engagement, and performance in real-time analytics (Esqueda, 2024; Hafeez & Zehra, 2025; Hastie & Vasily, 2020). (Ijiga et al., 2023) study showed how Learning Analytics LA aids in detecting success or failure patterns to timely support an educator's intervention to assist learners. Moreover, Romero and Ventura (2010) have shown that LA in STEM pedagogy assists teachers in monitoring learners' engagement, hence directing appropriate instructional strategies to the areas of greater need. Similar to this, Khan & Ullah (2024) showed that real-time feedback through AI systems increased performance and retention in mathematics and science. AI and LA tools support and deepen understanding of learners' needs to address the need to STEM education, hence LA provides more feedback for personalized instruction.

H1: The use of AI and Learning Analytics significantly improves student engagement in K–12 STEM subjects.

The integration of AI and Learning Analytics (LA) presents a remarkable opportunity to optimize educator decision-making and refine pedagogical practices within the classroom. Artificial Intelligence (AI) driven Learning Analytics (LA) tools not only assist in decision making for the formative evaluations, but also aid in gauging intervention effectiveness (Kirange & Chaudhari, 2025). AI tools with integrated LA enable real-time monitoring of student progress and engagement, which AI Learning tools actually do, and thus, teachers can adjust their strategies on the fly (Lateef et al., 2024). Pedagogical approaches aided by technology within the framework of Learning Analytics are based on learners' activities and aim to enhance and promote individualized instruction.

Learning Analytics (LA) facilitates the diagnose and strategy method identified by Lee & Lee (2025), where teachers construct strategies to address specific educational gaps by collecting evidence of students' difficulties in mastering particular concepts, and LA provides information on these learning gaps. Furthermore, the AI systems discussed by Majeed & Ahmad (2025b) encourage educational engagement by establishing personalized learning paths, with the AI systems adapting learning materials and activities to the educational needs of each individual student. Simply put, LA and AI increase the time spent on learning and instruction by addressing the more difficult learning gaps.

Moreover, the AI and LA tools are improving the iterative assessment cycle. Majeed & Ahmad, (2025a) discuss AI systems helping instructors to provide more timely feedback to students, which aids motivation and prompt adjustment of teaching. There are no bounds to the importance of feedback in student learning outcomes, especially with core concepts in the STEM field, which is critical.

H2: Embedding AI and Learning Analytics in instructional design explains the technology adoption and improved learning outcomes

Although the positive impact of AI and Learning Analytics on education is undisputed, to date, the challenge of inadequate-resource educational systems in Pakistan, specifically the government schools, remains unaddressed. The pervasive lack of computers and reliable internet puts formidable infrastructural limits on the adoption of AI in education in the context of Pakistani government schools (Malik et al., 2025; Ming et al., (2024). The lack of access to the requisite infrastructure means that no matter how advanced the AI student learning tools are, their purposeful application within the classroom is not feasible.

The hindering issue of instructor preparation is equally as important. This gap is particularly prevalent among educators in poorly funded areas where they do not possess the skills necessary to efficiently use AI and LA tools in their lessons. (Olugbami et al., (2025) demonstrated the importance of a trained educator in the use of AI technology, as a lack of development resources in many regions serves to worsen the issue. (Mpofu & Chasokela, (2025) quantifies the problem by stating that the majority of the teaching population that does not accept AI as a part of their teaching is due to ignorance to the advantages that technology brings and fear of over-reliance on gadgets. (Pruett, 2025) also showed that in the absence of adequate training and guidance, resources powered by AI will not be utilized.

Inadequate policy frameworks and a lack of support from educational authorities further impede the integration of AI and Learning Analytics (LA) tools within public schools. (Qayyum et al., 2024; Razaq et al., 2025) cite a lack of coherent and consolidated policies for the integration of AI within the educational framework, which results in disjointed and resource-inefficient implementations. An investigation carried out by Muhammad et al. (2024) proposed that education systems that do not possess definitive and affirmative policies for the integration of technology often find themselves lagging in the adoption of AI and, as a result, do not benefit from the changes that it brings. In the absence of sufficient funding for infrastructure and training, the adoption of AI and LA tools in teaching remains low in many developing nations.

H3: Lack of infrastructure, inadequate teacher training, and limited policy support significantly hinder the adoption of AI and LA in public schools.

Theoretical Framework

The role of Artificial Intelligence (AI) integrated with Learning Analytics (LA) equally holds the center focus of the current K-12 STEM transformation, is underpinned by several theoretical frameworks, as discussed in the ensuing sections.

The role of intelligent tutors and AI driven adaptive learning systems is adequately supported by constructivist learning theory (Bruner, 1966; Vygotsky, 1978) and how scaffolding takes place. Learning is achieved through interaction with and solving preset problems. AI systems put this into action by creating personalized learning pathways, adaptive scaffolding, and mastery complex STEM concept frameworks which STEM at every learner pace. The framework Self-Regulated Learning (SRL) Theory (Zimmerman, 2002; Pintrich, 2004) whereby learners self-monitor, control and adapt their learning processes profoundly supports. Learning Analytics supports self-regulated learning (SRL) by providing step-level, real time feedback on engagement, behavior, achievement, and reflection to evaluate one's progress. Learning Analytics mirrors one's stem self-direction and subsequent self-dependent mastery of STEM disciplines.

Adoption by teachers and systemic issues are analyzed through the Technology Acceptance Model (TAM) (1989) and the Unified Theory of Technology Acceptance and Use (Venkatesh et al, 2003). These models demonstrate how perceived usefulness, ease of use, and organizational assistance influence the attitude of teachers towards the integration of technology.

Conceptual Framework

The AI and Learning Analytics and K-12 STEM Education Framework (Figure 1) regards the AI and Learning Analytics in STEM Education as tools for mediation in the wider K-12 Education ecosystem. Inputs factors AI tools (i.e. intelligent tutors and adaptive platforms) and LA systems (i.e. real-time engagement and feedback metrics) provide in real time moderation due to contextual factors like teacher readiness, infrastructure and LA supportive policies.

The integration of AI and LA tools at the process stage makes possible the adaptive learning pathways, instruction at the level of the learner, and teacher real-time decision analytics. Consequential to these processes are the outcomes of student engagement, performance in STEM subjects, and teacher professional development. Ideally, the systemic long-term outcome of these processes is the enhancement of equity and quality in education as experienced in public schools. This is the anticipated outcome of the interplay of these variables. For the purpose of this study, this framework serves as a basis for interpretation of the results, on integration for AI and education and as a basis for setting guidelines for subsequent research.

Research Methodology

This research employed a mixed method approach to examine the role of Artificial Intelligence (AI) tools and Learning Analytics (LA) in K–12 STEM education with particular focus on student engagement, achievement, and perceptions of the teaching faculty. In this case, the research followed a convergent design framework which allows the simultaneous collection of qualitative and quantitative data from multiple sources, and which are subsequently integrated at the analysis stage to derive a comprehensive understanding of the situation. In this case, the quantitative component of the study involved the collection of surveys from both students and teachers, as well as analysis of learner performance records and AI engagement data which are captured as part of the classroom instructional technology.

Study Design and Setting

This study was carried out between 2021 and 2025 and focused on six public schools in Lahore, Pakistan. These schools partook in the piloting activities for the AI learning tools and were supportive of longitudinal data collection, thus convenience sampling was employed. The research was carried out in three broad phases: the initial phase, the pilot phase, and the expanded implementation phase. This study aimed to measure the use and impact of technology over time on student engagement and achievement in Mathematics, and on integrated STEM (Science, Technology, Engineering, and Mathematics) subjects at secondary school level learning in Pakistan.

The study involved both teachers and students as its participants. Each of the six schools was contributing 15 teachers which brought the total to 90, specializing in Mathematics, Science, and Physics. These teachers underwent the initial artificial intelligence (AI) professional development courses which were aimed at empowering the teachers in the use of AI tools. Panel discussions were organized in which participants were invited to share their impressions of the activities and the results were quantitatively and qualitatively gathered to find the most salient points that would let the researchers analyze the data in the follow up years.

Student participants were drawn from six classes per school, which were tracked for the full duration of the study. These cohorts interacted with AI-assisted learning tools and applications intended for adaptive and personalized learning. Evidence of student participation and learning accomplishments was gathered from classroom engagement, standardized assessments, and academic documentation over five years. The accumulated dataset longitudinally assessed the outcomes of STEM education using AI and LA.

Data Collection

Both quantitative and qualitative methodologies were employed to investigate the influence of AI and Learning Analytics (LA) in K–12 STEM Education.

Quantitative Data. Students' activity logs on educational technologies were used to gauge individual measures from the years 2021 to 2025. Measures such as completion of assigned tasks, participation in quizzes, engagement in digital learning technologies, as well as students' results in Math, Science, and Physics were recorded. This study sought to assess the effect of five years of instructional AI on students' performance to determine the value impact of instructional AI on students' learning in STEM subjects.

Qualitative Data. Teacher reflections were collected from the annual reports and feedback surveys on the AI system, and the uploaded AI applications when teachers requested to upload the applications. This included the teachers' self-reports of their sense of AI competence, instructional level, technological, and engagement and performance effects on students. Teachers also explained what challenges AI posed to their instructional practices and learning activities.

Contextual Data. All the participating schools were audited on their infrastructure to determine the number of computers installed, the internet connectivity available, and other vital resources to support the use of AI. This aided to evaluate the level of preparedness of the school for continuing integration of AI and to provide context to both the student and the teacher datasets.

This involved the annual assessments of accessibility of computers, STEM laboratories, internet connectivity, and AI technologies to the schools. This assisted in estimating the school preparedness and what infrastructural gaps were available. Evaluations were carried out each year to determine the availability of computers, STEM schools, internet connectivity, and AI resources in the studied schools. These assessments assisted the schools in understanding their readiness and pointed out infrastructure which were barriers to the acquisition of AI aided learning. In order to these contextual evaluations, year in and year out, qualitative data have been harvested through semi structured interviews and focus groups with the teachers. In these sessions, the participants bore in mind the application of the AI tools in their teaching and in their students learning, the problems they faced in their use, and the level of student's attention that was paid to the teaching learning processes. Such reflective dialogues were important in providing advantages and disadvantages of the application of AI to teaching and learning.

Classroom observations were also conducted to capture the application of AI tools during lessons. Observers noted the engagement patterns as well as the exchanges between teachers and students, the degree of involvement of students, and the assistance or hindrance of the AI tools to the instructional process. These observations placed AI-related quantitative data in a real educational context and informed the interpretation of the data.

Results

Performance Reports (2021–2025)

The incorporation of AI into teaching has improved teaching efficiency and accomplishment of students in K–12 STEM for five years. This study focuses on the assessment of educators and students in AI and the school's infrastructure, integration of AI into teaching, and assessment of the students from 2021 to 2025.

The information offered not only provides a correlation between the use of AI and K 12 students' performance but provides greater insight on the shifting paradigms in the education sector and the contribution of technology in advancing education.

The period from 2021 to 2025 showcases the integration of AI tools in K–12 STEM education, alongside the gradual improvement in teacher preparedness AI integration, and ongoing improvement in school infrastructures showed a marked growth in the students' performance as well (**Table 1**). The year 2021 showed a stark lack of confidence in AI tools amongst teachers, with 85% of them seeking training, while 80% of them reporting a lack of proficiency. Because of inadequate training, several infrastructure problems such as the lack of internet (more than half of the schools) as well as a poor student to computer (1:8-10) ratio, students' performance in Math, Science and Physics was severely impacted (Math: 58%, Science 61%, Physics 54%). By 2022 with a 60% teacher training completion on basic AI tools students AI tools for administrative tasks, schools began AI to be used, however, adoption AI in classroom still proved to be a massive challenge. AI being used to in school, even for administrative tasks, student's performance in Math, Science and Physics showed improvement (Math 60%, Science 63%, Physics 57%)

The year 2023 proved to be a turning point in pedagogical technology with 75% of instructors receiving AI training and 80% attending information sessions about AI workshop applications. Additionally, there was an improvement of school resources with 1 computer to 6 to 8 student's ratios as well as AI powered STEM labs with robotics and interactive learning kits. There was also a notable increase in student's education with personalized learning and tutoring systems in 4 schools. Improvement was seen across subjects in Math (65%), Science (70%), and Physics (63%). By 2024, there was an even greater improvement in AI training for teachers with 80% receiving in depth sessions and 90% attending workshops. School resources also greatly improved to 1 computer for every 4 students, with 5 schools having fully integrated AI powered STEM labs. AI used for personalized learning, real time data analytics and monitoring, and virtual teaching greatly boosted students' performance in subjects as well, with an average of 72% in Math, 78% in Science and and 72% in Physics. With the passing of 2025, 6 schools had adopted classroom AI with the other ratios remaining the same. This also included an increase of 90% of teachers trained and 95% undergoing peer learning programs.

- The use of Artificial Intelligence systems in teaching, personalized teaching systems, and continuous tracking of learners' progress resulted in marked improvements in the STEM fields, especially in Math (80%), Science (83%), and Physics (75%) performance gains.

Table 1: *Yearly Performance Data for AI Integration (2021–2025)*

Year	Teacher Readiness & Training	School Infrastructure	AI Integration	Student Performance	Key Insights
2021	85% of teachers requested training, 80% reported low confidence with AI tools. 35% of teachers participated in initial workshops.	1 computer per 8-10 students. 50% of schools had basic STEM labs. Internet access: 55% of schools had poor or no internet.	No schools had AI integration yet.	Math: 58% Science: 61% Physics: 54%	Low student performance due to outdated infrastructure. Initial resistance and lack of AI awareness among teachers.
2022	60% of teachers trained on basic AI tools. 55% attended AI workshops.	1 computer per 8 students. 2 out of 6 schools had basic STEM labs with AI tools for administration.	2 schools introduced AI for administrative tasks (grading, attendance).	Math: 60% Science: 63% Physics: 57%	AI tools introduced for administrative use. Teachers began adopting AI but still faced challenges in the classroom.
2023	75% of teachers trained on AI tools. 80% participated in workshops on AI integration.	1 computer per 6-8 students. 4 schools upgraded STEM labs with AI tools (robotics kits, interactive learning).	4 schools introduced AI tools for personalized learning, tutoring, and STEM subject assistance.	Math: 65% Science: 70% Physics: 63%	Significant improvement in student performance. AI tools helped increase student engagement and learning outcomes.
2024	80% of teachers received in-depth AI training. 90% attended workshops on AI in education.	1 computer per 4 students. 5 schools had fully functional AI-powered STEM labs.	5 schools adopted AI for personalized learning, real-time data analytics, and AI-assisted tutoring.	Math: 72% Science: 78% Physics: 72%	Strong improvement in performance with AI tools. Teachers grew more confident in using AI, but infrastructure issues persisted in some schools.
2025	90% of teachers trained on AI tools. 95% participated in workshops and peer-learning programs.	1 computer per 2 students. 6 schools had fully functional AI-integrated STEM labs.	All 6 schools had fully integrated AI tools for teaching, personalized learning, and real-time performance analytics.	Math: 80% Science: 83% Physics: 75%	Significant improvements in student performance. All 6 schools now utilizing AI for personalized learning and data-driven insights.

These metrics of educational interaction and performance underscore the influence of AI tools in securing engagement and enhanced performance.

Interaction with the AI rose dramatically from 0.3 in 2021 to 4.0 in 2025. This period coincided with the development of educational AI tools that made their platforms more frequently used. Compared to the 2021 quizzes and 2025 routines, AI integration was more visible and improved participation in continuous assessments. The usage of the learning modules demonstrated no difference as well, ranging from the 2021 infrequent usage to 2025 daily usage. This demonstrates that the AI resources transitioned from optional to obligatory in integrating the student.

Upgraded Infrastructure Facilitated Improvements. As observed in the previous years such as in 2021, the infrastructure related to technology was faulty because of the insufficient quality, such as slow internet connection and outdated devices, whereas by 2025, the technological reliability and a fully functional tech support changed for the better. These changes in technology and teacher preparedness allowed for the smooth and efficient deployment of the AI tools and consequently, a better integration of AI tools into the system. Increased performance of students in STEM subjects due to improved infrastructure and teacher activities is a testimony to the impact of AI on learning and the changed engagement of students.

Table 2: *Progression of AI Integration in Education: From Initial Exploration to Ongoing Adoption and Expansion*

Metric	2021 (Initial Stage)	2022 (Pilot Phase)	2023 (Expansion Phase)	2024 (Widespread Adoption)	2025 (Ongoing Integration)
Time Spent on AI Tools (hrs/week)	0.5	1.2	2.5	4.0	5.2
Assignment Completion (%)	35%	40%	50%	60%	70%
Frequency of AI Interaction (per week)	0.3 times	1.0 times	2.0 times	3.5 times	4.0 times
Quiz Attempts	Very Low (sporadic)	Low (once in a while)	Moderate (occasional)	Regular (weekly attempts)	Frequent (daily attempts)
Interaction with Learning Modules	Minimal (rare use)	Low (simple exercises)	Moderate (occasional engagement)	High (regular use)	High (daily interaction)
Infrastructure Quality	Poor (unstable internet, limited devices)	Poor (unreliable devices, internet slow in some areas)	Moderate (some schools improved, others still lacking)	Fair (most schools with tech support)	Improving (reliable tech, some schools still face issues)

Impact of AI Interaction on Assignment Completion

The Relationship Between Engagement of AI Tools and Submission of Assignments and Learning Performance

The impact of use of AI tools by students on learning performance was evaluated using regression analysis as shown in Figure 2. More so, the analysis allowed the researchers to measure the impact of time spent on the AI tools, engagement in AI tools, and attendance of the learning modules on assignment completion. As such, the analysis was done to measure how impactful the listed factors were on students' completion of the assignments as well as the changes in performance that were achieved.

The regression analysis showed quite a few interesting outcomes. To illustrate, the intercept (β_0) means that without any assistance, students had an initial assignment completion rate of 35 percent (Table 3). Regarding the AI integration, it was noted that using AI for 1 hour weekly increased the completion likelihood by 2.5% ($\beta_1 = 2.5$, $p < .001$). This also indicated that more work was done as a result of the AI. Similarly, AI integration also emerged as a strong predictor, in which case the completion rate increased by 4% for each unit gain in AI. More frequent interaction with the learning modules also increased completion rates by 3.2% ($\beta_3 = 3.2$, $p < .001$). This adds more validity to the assertion that students should be encouraged frequent use of their learning resources.

The model's revised R^2 value of 0.78 indicating the influence of AI interaction positively impacts student performance by explaining 78% of the variance in the students' completed assignments. Moreover, all of the predictors' p-values were statistically significant ($p<0.001$), thus confirming their value as predictors of students' assignments' completion. Therefore, the regression model confirmed AI tools' effectiveness in improving students' engagement as well as the degree of required interaction with these tools in order to meet the desired academic outcomes.

Table 3: *Regression Analysis on Assignment completion*

Variable	**Coefficient (β)**	**Standard Error**	**t-statistic**	**p-value**	**Interpretation**
Intercept (β_0)	35.00	2.50	14.00	<0.001	Base level of assignment completion when all predictors are 0.
Time Spent on AI Tools (β_1)	2.5	0.6	4.17	<0.001	Each additional hour spent on AI tools per week increases assignment completion by 2.5%.
Frequency of AI Interaction (β_2)	4.0	1.0	4.00	<0.001	Each additional interaction with AI tools per week increases assignment completion by 4%.
Interaction with Learning Modules (β_3)	3.2	0.9	3.56	<0.001	More frequent interaction with learning modules increases assignment completion by 3.2%.

Along with fulfilling assignments, regression analysis was conducted to forecast the impact of early exposure to AI on the academic performance of students. The findings of this analysis indicated that both the duration of exposure to AI tools and the frequency of interaction with AI significantly improved students' grades in STEM subjects such as Math, Science, and Physics.

The regression model for grade improvement is as in **Table 4**.

Table 4: *Regression Analysis on Grade Improvement*

Variable	Coefficient (β)	Standard Error	t-statistic	p-value	Interpretation
Intercept (β_0)	10.00	3.50	2.86	0.004	Base level of grade improvement when all predictors are 0.
Time Spent on AI Tools (β_1)	5.8	1.2	4.83	<0.001	Each additional hour spent on AI tools per week improves grades by 5.8%.
Frequency of AI Interaction (β_2)	7.3	2.0	3.65	<0.001	Each additional interaction with AI tools per week improves grades by 7.3%.

The regression analysis indicated that the duration of exposure to AI tools significantly improved the grades, and it was found that spending an hour more on AI tools each week improved grades by 5.8%. The impact of frequency of AI interaction was equally astonishing; it was found that each interaction AI tools, on the average, improved the grades by 7.3%. The R^2 value for the performance in academics was found to be 0.80, meaning that 80% of the increase in grades could be accounted for by the early engagement with AI tools. The p-values for both the time spent on AI tools and the frequency of interaction with the tools were less than 0.001 which confirmed that the predictors were relevant to the model in estimating the academic performance in the long run.

Impact of AI Integration on STEM Subject Performance (2021–2025) with Forecast for 2026

The integrated use of AI technologies in the educational setting between 2021 and 2025 resulted in notable improvements in academic performance in Mathematics, Science, and Physics, as illustrated in Figure 3. Within five years, AI's integration into personalized learning, real-time tutoring, and performance evaluation systems significantly increased student engagement along with academic achievement. Math, Science, as well as Physics student performance in the year 2021 was rather low, with averages of 58%, 61%, and 54% respectively. These “starting values” were the result of very little AI adoption in learning and the infrastructural limitations of the schools, which included scarce technologies, untrained staff, and unprepared teachers (**Table 5**).

As AI technologies started to be applied in 2022, Math performance received a boost to 60%, Science to 63%, and Physics to 57%. This earlier stage of AI adoption was aimed at more fundamental components in activities and routines, focusing on basic AI systems for administration and practice, which was realizable in basic AI systems for administration and practice, which led to small improvements in student performance. The positive momentum was uninterrupted in 2023 with Math reaching 65%, Science 70%, and Physics 63%. During this period, AI adoption was accompanied by advanced systems of automated tutoring and learning, which strongly engaged the students and elevated their performance even further.

With the use of AI, students were able to achieve a 72% in Math, 78% in Science, and 72% in Physics, demonstrating the growing effectiveness of AI in augmenting learning. By 2025, the results brought about AI integration were evident, having achieved 80% in Math, 83% in Science, and 75% in Physics. These gains were the result of the improved accessibility to AI powered learning tools, better-trained faculty, and improved infrastructure which included reliable internet and technology support systems.

Table 5: *AI Integration on STEM Subject Performance (2021–2025) along with 2026 Forecast*

Year	Math Performance (%)	Science Performance (%)	Physics Performance (%)
2021	58	61	54
2022	60	63	57
2023	65	70	63
2024	72	78	72
2025	80	83	75
2026	88 (Forecasted)	88 (Forecasted)	81.3 (Forecasted)

A prediction for 2026 was prepared using the method of Exponential Smoothing to anticipate the impact of more integration of AI technologies. Exponential Smoothing is a time-series forecasting method that uses past data to determine the best-fitting trends for future data points. The model's projections from 2021 to 2025 suggested that the positive trend in student performance would persist in 2026. The expected performance for 2026 includes an 88% achievement in Mathematics, 88% in Science, and a growth forecast of 81.3% in Physics. These projections stem from the forecasted advancements in AI tools and the educational framework such as the shifting towards more personalized AI-driven learning, growing teacher AI integration, and ever-improving infrastructure (Farid & Ashraf, 2025).

Structural Equation Modeling (SEM) Analysis

The relationships of teacher readiness, interaction with AI tools, student engagement, and performance in STEM subjects (Math, Science and Physics) were analyzed using Structural Equation Modeling (SEM) analysis.

Table 6: *SEM Analysis: Path Coefficients Illustrating the Causal Relationships between Teacher Readiness, AI Interaction, Student Engagement, and Performance*

Relationship	Path Coefficient (β)	p-value	Interpretation
Teacher Readiness → AI Interaction	0.45	< 0.01	Teacher readiness significantly increases AI tool interaction.
AI Interaction → Student Engagement	0.38	< 0.01	AI tool interaction leads to increased student engagement.
Student Engagement → Student Performance	0.30	< 0.05	Increased student engagement significantly improves performance.

Moreover, the indirect effects elucidated how readiness impacts students not directly, but through AI use and engagement via the educator. The data suggested that teacher readiness positively impacted student performance through AI tool use and engagement (β = 0.15, p-value < 0.05). This finding emphasizes the need for teacher preparedness concerning their use of AI tools and their role in motivating students to earnestly interact with AI tools to improve their performance. **Table 7** presents the indirect effects of teacher readiness on student performance through the mediating variables of AI interaction and student engagement:

Table 7: *SEM Analysis: Indirect effects*

Relationship	Path Coefficient (β)	p-value	Interpretation
Teacher Readiness → Student Performance (Indirect)	0.15	< 0.05	Teacher readiness indirectly improves student performance through AI interaction and engagement.

The SEM model's goodness-of-fit indices confirmed the model provided a strong fit for the data. An RMSEA of 0.05 suggested the model exhibited an excellent fit, confirming that the model captured the relationships accurately (**Table 8**). Also, the model's CFI of 0.92 and TLI of 0.90 provided further support as both values were above the minimum threshold of 0.90, indicating that the model explained the data and the relationships sufficiently (Sarwar & Farid, 2024).

Table 8: *Fit indices for the SEM mode*

Fit Index	Value	Interpretation
RMSEA	0.05	Excellent fit (RMSEA < 0.06)
CFI	0.92	Good fit (CFI > 0.90)
TLI	0.90	Good fit (TLI > 0.90)

Hierarchical Linear Modeling (HLM) Results

The Hierarchical Linear Modeling (HLM) analysis was carried out to consider the heterarchical intragroup structure of the students nested within schools and to evaluate the contribution of individual level factors such as student AI engagement and behaviors and school level factors such as teacher preparedness and infrastructure on student academic achievement. This approach demonstrated the impact of both personal and organizational dynamics in shaping academic achievement.

The organizational level factors (teachers’ preparedness and infrastructure) and the personal level factors (AI engagement and student baseline scores) were separated into individual and school level components in the hierarchical model. At the school level, infrastructure quality (STEM resources including computers, labs and internet reliability) was included at level two.

Level 1 (Student Level) Results

In the individual level regression, student engagement in STEM disciplines was evaluated along with the impact of prior achievement and engagement with AI tools on performance. The findings confirmed the importance of both prior achievement and AI engagement tools (Table 9).

Table 9: *Impact of Student Engagement and Prior Performance on Academic Achievement Coefficients and Statistical Significance*

Variable	Coefficient (β)	p-value	Interpretation
Student Engagement → Student Performance	0.25	< 0.01	Increased student engagement with AI tools improves performance.
Prior Performance (Baseline) → Student Performance	0.40	< 0.01	Baseline performance significantly influences student performance.

The analysis indicated that a student's interaction with AI tools enhanced performance with a 0.25 coefficient (p-value < 0.01), meaning that stronger engagement with AI tools, particularly in STEM, led to better outcomes. Moreover, prior performance emerged as a powerful predictor of future performance, with a 0.40 coefficient (p-value < 0.01) indicating that students with higher 2021 baseline scores tended to exceed average performance benchmarks in the long term.

Level 2 (School-Level) Results

The analysis of teacher readiness and the quality of the school facilities in relation to student outcomes was approached at the school level. The findings at this level underscored the school factors as being particularly important for the enhancement of academic performance (Table 10).

Table 10: *Influence of Teacher Readiness and Infrastructure Quality on Student Performance: Coefficients and Statistical Significance*

Variable	Coefficient (β)	p-value	Interpretation
Teacher Readiness → Student Performance	0.18	< 0.05	Higher teacher readiness improves student performance at the school level.
Infrastructure Quality → Student Performance	0.22	< 0.01	Better school infrastructure (e.g., more computers, reliable internet) leads to improved student performance.

The results showed teacher readiness positively impacted student achievement (coefficient = 0.18, p < 0.05). The more prepared and confident teachers seemed to fully support student achievement. Also, the quality of infrastructure had a positive impact (coefficient = 0.22, p < 0.01) indicating that better resourced schools, those with higher number of computers and reliable internet, were more likely to see improvement in student performance (Farid & Adnan, 2022).

Variance Explained

The variance explained at each level gives an indication of how much of the individual and school level factors influence the variation in student performance. The results indicated that both levels were relevant in explaining student performance (Table 11).

Table 11: *Variance Explained in Student Performance: Contribution of Individual and School-Level Factors*

Level	Variance Explained (R^2)	Interpretation
Individual Level	50%	50% of the variance in student performance is explained by student-level factors, such as engagement with AI tools and prior performance.
School Level	35%	35% of the variance in student performance is explained by school-level factors, like teacher readiness and infrastructure quality.

The results demonstrated that engagement with AI tools, along with prior performance, explained 50% of student performance variance at the individual level. At the school level, factors accounted for 35% of the variance, particularly concerning teacher preparedness within the school's infrastructure, which significantly impacted student performance and outcomes.

Discussion

The deployment of AI and Learning Analytics systems and technologies have the potential to develop engagement and achievement in K–12 STEM education. The positive impact of these systems and technologies offers adds to the literature by not only confirming the impact but expanding on the already existing literature by attesting to the varying positive impacts of AI and Learning Analytics in K-12 education. Technologies such as intelligent tutoring systems and adaptive learning technologies as AI achievement positively and engagement are more deeply positively impacted by each educational technologies and engagement achievement positively. This is in alignment with Rehman et al., 2025 and Sahito et al. … wherein the authors assert that AI educational systems are capable of furnishing learners with immediate feedback and explaining challenging concepts. The AI systems and technologies is the reason engagement was able to elicit completion of assignments and interaction. AI was proven to be the driving force educational achievement and higher evidenced in the regression analysis.

In the sphere of pedagogy, the application of Learning Analytics, albeit a nascent innovation, is starting to be appreciated for its value in understanding the problems inherent in student learning and the subsequent provision of assistance in a timely manner. Earlier works, such as those of (Salam et al., (2017) and (Sattar et al., (2024), highlight the necessity of such timeliness by establishing that real-time data capture facilitates educational processes by shedding light on the actions and learning patterns of educational participants. These works aim to close the gaps in STEM education and examine the use of learning analytics within Self-Directed Learning (SDL) in adapting skill pathways.

With the integration of AI and Learning Analytics (LA), real-time student actions data empowers instructors to issue precise adaptive interventions in the process, creating intelligent learner-centric mentorship. Hence, the traditional mentorship processes are automated, adjusted according to each learner's preferred style and approach, thereby facilitating increased participation and enhanced academic achievement.

This research fills another void in the literature concerning impacts of AI and Learning Analytics

(LA) on teacher’s decision and lesson planning. It shows the different strategies with which teachers AI and LA tools, when used properly, empower teachers to make considered decisions not only about the changes to the curriculum, but also the pacing of the instruction and the custom designed activities. This is in line with (Shah, (2024; Siswanti et al., (2025) (Wakeel et al., (2025) and (Tayem, (2025) whose conclusions highlight the impact of a teacher’s prior professional training on the proper use of technology in classroom teaching.

The report discusses the unique barriers that deplete the potential of integrating AI technology within the educational realm, more specifically, schools that are not well-funded. The lack of infrastructure was of paramount concern, as the absence of indispensable technology within a school drastically limits the AI potential. (Wu et al., (2025; Zubairi et al., (2021) noted how the infrastructural deficiency and the absence of internet services within a school setting, in regards to integrating AI capabilities, defeats the very purpose of the AI tools. The findings within the current study relate to this premise, that the infrastructural absence aggravates the situation and creates more dilemmas for the beginning teachers. Within the study, despite some teachers having undergone training, a larger majority struggled to integrate AI within their lessons. This is in line with (Qayyum et al., (2025; Rehman et al., (2025) who posit that the absence of strategic professional development in under-resourced settings hinders teachers from taking advantage of the scads of AI tools. Such barriers highlight the importance of a more robust approach that goes deeper than the tech provision to sustain infrastructure shortcomings, with broad, coherent, strategic, goal-oriented professional development to support teachers in AI integration.

Conclusions

The integration of AI and Learning Analytics (LA) into K-12 STEM education reveals powerful insights regarding their transformational potential. AI and LA educational tools improve student engagement and achievement, as well as personalize the learning experience for each student. The findings align with previous research focused on the positive impact of AI on educational results, where AI feedback and real-time assessment facilitate adaptive learning pathways necessary for mastery of intricate concepts.The study also illustrates the AI and LA’s impact on teacher decision-making, revealing that educators increasingly rely on real-time data to inform instructional adjustments and inform teaching with precision tailored to learner needs. Still, the study outlines the extreme limitations that the AI underutilized in K-12 education systems face due to the disparate gaps in infrastructure, teacher professional development, and education policies that are systemically misaligned. Regardless of the gaps, the sustained AI-driven adaption of instructional frameworks during the study period spoke to the profound impact that adaptive technologies could exert on learning outcomes if undergirded by infrastructure and ongoing teacher training.

Conflict of Interest

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