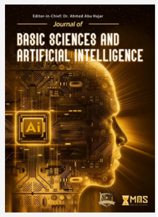
Journal of Basic Sciences and Artificial Intelligence (JBSAI)

DOI: 10.65098/jbsai.01.2026.01.07



RESEARCH ARTICLE

Bridging Educational Inequities Through Digital Twin Technology: A Data-Driven Framework for Standardizing and Enhancing STEM Learning in Universities

Cosmas Knowen[1,*], Duncan Kodhek[1], Henry Kinya[2]

[1] Zetech University, Ruiru, 00200, Kenya
[2] Rongo University, Rongo 40404, Kenya
[*] Corresponding Author E-mail: cosmasknowen@gmail.com

ARTICLE DETAILS

Article History:
Received 05 May 2026
Accepted 13 Aug 2026
Available online 31 Aug 2026

Online Article Code

ABSTRACT

The rapid advancement of artificial intelligence and data-driven technologies presents unprecedented opportunities to reimagine university education, particularly to address persistent challenges in educational equity and pedagogical standardization in Science, Technology, Engineering, and Mathematics (STEM) disciplines. This paper proposes a novel Digital Twin (DT) framework designed to revolutionize STEM teaching and learning by creating virtual replicas of educational environments, learner profiles, and knowledge ecosystems. DTs' dynamic, real-time virtual representations of physical systems offer transformative potential to equalize access to high-quality STEM education across diverse institutional contexts and to bridge uncertainties inherent in traditional pedagogical approaches. By leveraging continuous data collection from multiple sources, including learning management systems, student interaction patterns, assessment outcomes, and cognitive engagement metrics, the framework constructs personalized digital representations of learners and adaptive teaching environments. By simulating various instructional scenarios, the system enables evidence-based pedagogical decision-making, predictive intervention for at-risk students, and standardization of learning outcomes without sacrificing pedagogical flexibility. The paper addresses critical challenges in STEM education: resource disparities between institutions, inconsistent teaching quality, limited access to specialized laboratory equipment, and the need for personalized learning pathways that accommodate diverse learning styles and paces. Through feedback loops and predictive analytics, the DT framework facilitates proactive identification of learning gaps, optimization of curriculum delivery, and creation of equitable learning experiences regardless of geographical or institutional constraints. Virtual laboratory simulations within the DT environment provide students with unlimited access to experimental scenarios, reducing dependency on physical infrastructure while maintaining pedagogical rigor. Furthermore, the framework supports continuous professional development for educators by providing data-driven insights into teaching effectiveness and student engagement patterns. This research contributes to the growing discourse on rethinking university education in the age of artificial intelligence by demonstrating how DT technology can catalyze educational transformation, promoting both excellence and equity in STEM learning outcomes across the higher education landscape.

KEYWORDS

Digital Twin Technology, STEM Education, Data-Driven Learning, Personalized Pedagogy

1. INTRODUCTION

In modern society, Science, Technology, Engineering, and Mathematics (STEM) education plays a very important role. STEM helps to drive innovation, economic development, and improve the general social well-being of a given community. Learning Institutions are increasingly integrating Artificial Intelligence into their teaching and learning. This comes in the form of intelligent systems, analytical systems, and digital platforms that form the basis for improved teaching and decision-making based on data-driven evidence (Alghamdi & Alghizzi, 2025). For STEM, these technologies present the opportunity to address the pedagogical gaps that have been continuously identified regarding the provision of quality learning (Man et al., 2026; Tate & Warschauer, 2022). However, even with the advancement in technologies to this extent, there is still a gap in pedagogy in higher learning institutions. These challenges range from disparities and infrastructural access issues to difficulties accessing laboratory equipment and facilities, quality teaching supported by digitized tools, and the unavailability of digital resources in the learning environment.

The issue of educational inequity in STEM subjects is still a major issue in most universities around the world. The effects of the differences in institutional resources, technological infrastructure, as well as access to special facilities have been reported in many studies to create unequal learning opportunities among students. Indicatively, empirical surveys in the geosciences have found that academic research may be limited to a great extent by funding and access to analytical facilities, with a high percentage of students reporting that inability to access facilities prevented them from following some research directions (Man et al., 2026). Besides the deficiencies in the laboratory, low-income students often encounter some issues with poor internet access, inadequate access to suitable computing equipment, and the prohibitive nature of subscription-based digital learning platforms to conduct STEM learning. Remote laboratories, virtual learning environments, and high-tech digital learning devices that are increasingly carrying the weight of STEM education can be limited by these technological and financial barriers for students (Castle et al., 2024).

Moreover, the use of conventional pedagogies based on labs usually implies that institutions with insufficient infrastructure are disadvantaged, as they do not have the possibility of practical experimentation and learning through practice. Although there are other solutions like remote labs, mobile learning technology, and virtual laboratories, which are suggested to increase access to practical learning experiences, they usually require secure connectivity, sufficient digital devices, and institution-level support systems to work (Liljaniemi & Paavilainen, 2020). Therefore, a solution to inequities in STEM education would not only be a technological solution but also comprehensive structures that can help lessen the disparity of resources, facilitate inclusive education, and allow equitable access to quality STEM education experiences in a variety of institutional settings.

2. LITERATURE REVIEW

Inequality in STEM education remains a persistent issue in institutions of higher learning. This is reflected in the inequality in access to essential learning materials, disparities in digital access, and imbalances in instruction support that team up to determine student interactions, retention, and access to opportunities. A digital divide study on higher education indicates that unequal access to devices, good internet connectivity, and support of technology in institutions still remains a barrier to students accessing digital learning environments and online STEM resources in ways that maximize their potential. This strengthens the idea that there are wider socioeconomic inequalities in education participation and achievement (Man et al., 2026; Tate & Warschauer, 2022).

For instance, the research on the impact of digital inequality in the university context shows that poor access, lower digital abilities, and poor socioeconomic status are linked to a higher rate of dropouts, decreased involvement in technology-mediated learning, and decreased chances of academic achievement (Man et al., 2026). Also, studies on digital inequity show that learners in rural, remote, or underdeveloped areas tend to face greater disadvantages. This is attributed to unstable infrastructure and reduced reliability of the internet, which disproportionately affects students with low-income or marginalized backgrounds (Tate & Warschauer, 2022). In addition to access, a lack of institutional support in the development of digital competencies and integration of technology into the pedagogical process increases these differences for students. The lack of both resources and support systems makes students have difficulties engaging in digitally rich STEM pedagogy (Man et al., 2026). Such constraints not only curtail access to online learning tools and research resources but also curtail students' participation in collaborative activities, which are key to the success in STEM careers of the modern age. This is the reason why frameworks that address not only resource inequities but also pedagogical integration should be developed (Man et al., 2026).

The issue of resource inequity and pedagogical barriers also contributes largely to unequal STEM higher education results. It also shows up in the systemic drawbacks that have been demonstrated as existing in a variety of institutions and student groups. The system limitations are differences in the level of income and the race and ethnicity of the students. Castle et al. (2024) examined over 200,000 STEM course enrollments in six research-intensive institutions and discovered that students who had more systemic advantages kept on getting higher grades. The findings underscore the ability of structural inequities to define STEM outcomes in any institution (Castle et al., 2024). The findings then inform the idea that students who have better access to technology are likely to perform better. Greater surveys of STEM education in higher learning institutions find more complex issues with implementing digital technologies and pedagogical innovation. This issue is more pronounced where there are resource constraints and hesitation to change (Meng, 2024). Also, a study on equity-oriented education as a teaching practice demonstrates that educators have numerous forms of inclusive instruction. These include differentiated instruction and culturally responsive pedagogy so as to help reduce disparities. However, the scarcity of resources and the lack of institutional support to fully implement the interventions often pose challenges (Meng, 2024). Empirical and theoretical research also indicates that an unequal distribution of infrastructure, support systems, and learning conditions remains a factor in participation and achievement in STEM fields. The studies therefore highlight that there should be development of frameworks that take into account material and pedagogical constraints (Sedebo et al., 2025).

Solutions of remote and digital learning have become more popular to reduce inequities in STEM education. There is considerable evidence that they can be equal, or in most instances even superior to more conventional face-to-face methods when applied considerately (Schmid et al., 2023). According to meta-analyses, the results of purely online learning are quite similar to face-to-face learning, whereas the effects of blended and flipped models are much more powerful in terms of their impact on achievement, engagement, and self-efficacy (Schmid et al., 2023). Virtual laboratories, simulations, inquiry-based and computer-based tools are effective in conceptual learning, as well as practical skills acquisition. This is achievable without the physical infrastructure in STEM in particular (Flegr et al., 2023). Recent reviews also point to the fact that technology-enhanced learning alongside learning analytics can be used to provide learners with personalized, adaptive STEM experiences and to use data-driven interventions that can be beneficial to various learners (Qushem et al., 2025).

Such developments, however, have not successfully reduced structural barriers to equity. The systematic reviews of remote learning during the pandemic era highlight that the success of remote learning depends on a number of factors. These include: instructional design, efficient access to technology, digital literacy, teacher readiness, and institutional support. The disadvantage is even more pronounced in disadvantaged communities, such as low-income students, rural students, and marginalized students (Meng et al., 2024). New technologies such as immersive virtual reality and extended reality can improve the experiences and knowledge in STEM. However, there will be challenges, including high costs, technical complexity, infrastructure needs, and inconsistent adoption in equitable pedagogical models (Santilli et al., 2025). Widening analyses bring to focus perennial digital disparities based on socioeconomic status, geography, gender, and intersectional inequalities that expand access gaps, as well as access outcomes, especially in low-resource or remote environments (Nedungadi et al., 2026).

3. THE DIGITAL TWIN

The Digital Twin (DT), an application-focused and more interactive approach to STEM education, is proposed. It is a technology that builds real-time virtual models of physical systems. DT integration has been found to be highly promising for facilitating experiential learning through safe, real-time simulation. This bridges theory and practice, increases student motivation and conceptual learning (Liljaniemi & Paavilainen, 2020). On the same note, DT significantly enhances practical skills, interaction, and project-based performance. This is based on simulated activities provided through immersive, feedback-based simulation (Zhang et al., 2024). Additionally, the results show that DT-enhanced programming teaching improves general interest and proficiency gains, especially among inexperienced learners, by providing them with interactive and contextual experiences (Lu & Hu, 2025).

A review indicates that DTs with virtual learning environments support simulation-based, problem-based, and gamified learning in smart manufacturing education (Karanam & Hartman, 2025). This results in high problem-solving scores, enhanced knowledge retention, and improved theory-to-practice bridges, which are all advantageous in remote STEM environments that are limited by available resources (Karanam & Hartman, 2025). A review reveals that the tools became integrated into cornerstone and capstone courses to prepare students for Industry 5.0 tools. The study finds that it offers the benefits of immersive interaction, risk-free experimentation, and workforce readiness.

However, it needs scalable and cost-effective implementations in various global settings. The future development of technologies such as DTs in STEM learning further supports the idea of how these technologies can be used to improve equity and SDG4 objectives by allowing adaptive and personalized learning in low-resource settings and developing countries (Nedungadi et al., 2026).

However, it remains associated with several challenges, including technical complexity and infrastructure requirements. Other challenges are reliable connectivity in low-resource locations, interoperability, and educator training, which slow down the mass adoption (Liljaniemi & Paavilainen, 2020; Lu & Hu, 2025; Zhang et al., 2024).

Although advanced digital solutions like DT technologies have a transformative potential, there still remains a considerable set of challenges to the equitable and successful implementation of such technologies in STEM education. The first obstacle is a lack of equal access to the basic digital infrastructure such as reliable high-speed internet access and appropriate devices (Van De Werfhorst et al., 2022). This significantly restricts the capabilities of students to participate in interactive, simulation-based, and data-driven learning environments. Digital readiness comparisons across multiple countries after the pandemic indicate that there have been consistent socioeconomic and migration-related disparities in digital capabilities among students. This is also true in educational institutions in terms of Information and Communications Technology (ICT) resources, and this directly limits the use of advanced technologies in online and hybrid settings of STEM courses(Van De Werfhorst et al., 2022).

The second important dimension entails digital literacy and meaningful use of technology. Students who do not have the underlying competence to navigate complex digital tools have difficulty gaining value out of immersive platforms. The lack of skill thus continues to create second- and third-level digital divides and empowerment (Kim et al., 2026). The access, participation, and benefit of technology-enhanced STEM learning also become even more intersectional due to gender disparities, socioeconomic status, and geographic location. Thus, implying that equity interventions necessitate culturally responsive and not one-size-fits-all interventions (Kim et al., 2026).

Although the literature and studies on digital learning grow and the advantages of DT technologies in STEM education become more significant, there is still a gap in the integrated and equity-related frameworks in higher education. Current literature focuses on digital tools, virtual laboratories, or DT systems as separate entities. They pay little attention to the way in which these methods may be systematized and joined to provide both personalized learning and educational results standardization (Schmid et al., 2023; Zhang et al., 2024).

In addition, literature demonstrates that digital learning has the potential to enhance student achievement and engagement. However, little focus has been on the possibility of digital learning in solving institutional structural inequity. This is particularly noticeable in the resource-constrained contexts (Meng et al., 2024). Recent research also has a tendency to emphasize technological enhancement more than pedagogical consistency and equity. This has led to a large number of solutions that are still disjointed and do not focus on the differences in access, quality of instruction, and infrastructure. It is thus necessary to have a detailed, data-based model that incorporates real-time simulation, adaptive learning, and institutional standardization. This review fills this gap by suggesting a framework for a DT that can be implemented to promote equity, streamline the process of learning in STEM, and standardize the educational experience in different university settings.

3.1 The Proposed Solution

There have been many significant changes across sectors since the pandemic, and education was no exception. The extreme changes in digital and Artificial Intelligence (AI)-driven technologies have initiated the reconsideration of pedagogical approaches in STEM education. Although the literature shows that digital tools, virtual laboratories, and custom-tailored learning platforms can be effective in improving engagement, equity, and learning outcomes, the challenge remains of translating these findings into a multifaceted, working system. The proposed conceptual framework of the study fills this gap by providing an approach to the implementation of DT technology in higher education STEM courses in a structured, multi-layered manner.

The framework will help operationalize the principles of adaptive learning, real-time feedback, and predictive analytics. It will also turn raw educational data into actionable insights for both the instructor and the learner. The framework will enable personalized, equitable, and scalable learning by linking learners' individual profiles with course material, institutional resources, and simulated experimental settings. It also provides a basis for evidence-based pedagogical choices, allowing instructors to predict learning gaps, optimize instructional plans, and sustain standardized learning without restricting pedagogical adaptability.

In the next section, the interconnected layers of the structure will be outlined. Their roles, relationships, and efforts towards an effective STEM education will be detailed. The combination of the layers makes the findings of the peer-reviewed studies in the field of engineering and programming education evidence-based and practically applicable to the framework (Liljaniemi & Paavilainen, 2020; Lu & Hu, 2025; Zhang et al., 2024).

The first layer proposed is the data acquisition layer. This Layer lies at the core of the proposed DT framework of STEM education. Its main role is to comprehensively gather and assimilate a variety of learner and environmental information. This layer is necessary to ensure the digital representation accurately reflects the actual educational processes in the real world. Learning platform digital footprints, including assignment submissions, interaction history, navigation, and assessment data, can be used to gather important data on student engagement, progress, and performance (Zhang et al., 2024). In addition to interactions through the platform, sensor-based and contextual data, including physiological responses, classroom environments, and device use, provide more detailed insights into student behavior and learning environments (Zhang et al., 2024). The introduction of internet of things gadgets and interconnected sensors also significantly expands the reach of the information so that the physical and virtual environment could be synchronized in real time (Yağcı, 2022). Stringent measures to ensure the quality, consistency, time correlation, and reliable treatment of data are necessary. Such processes also ensure that the steps that follow, such as analytics, predictive modeling, and simulation, utilize trustworthy and valid inputs (Yağcı, 2022). The layer will enable the DT to facilitate the adaptation of pedagogical approaches and informed decision-making in STEM education. This is because it will enable the DT to capture a complete and precise picture of learner activity and the environment (Figure 1).

The second layer in this system is the Representation Layer, which transforms the raw data obtained in the first layer into a structured virtual model. The virtual model is a reflection of real-world learning. It establishes a dynamic counterpart in digital form where the state and behavior of learners and learning environments are dynamically aligned with incoming data streams. It helps to maintain their fidelity and relevance over time. DTs are conceptually perceived as continually updated models that allow reflecting the real system physically in the virtual environment and support the correct representation and decision-making based on the changing conditions (Kukushkin et al., 2022; Wu et al., 2023). At this layer, the connection of real-time sensor and interaction data with real-time models will make sure that the virtual representation is up-to-date, and meaningful interpretations and analyses of patterns and trends can be made (Jedermann et al., 2023). The organization of complex and multidimensional data into a consistent model thereby allows the data to be visualized, interpreted, and ready to undergo functions of higher order. The functions include predictive modeling and adaptive feedback. Ongoing revision of the representation also facilitates a smooth transition to simulation and scenario testing at the layers that follow and sets the pace for adaptive pedagogical interventions.

The third layer of the proposed framework is the learning analytics, also known as the Predictive Modeling Layer. It is a layer that operates on the dynamically updated digital representations to obtain some useful insights and predict the future outcomes of learners. Learning analytics

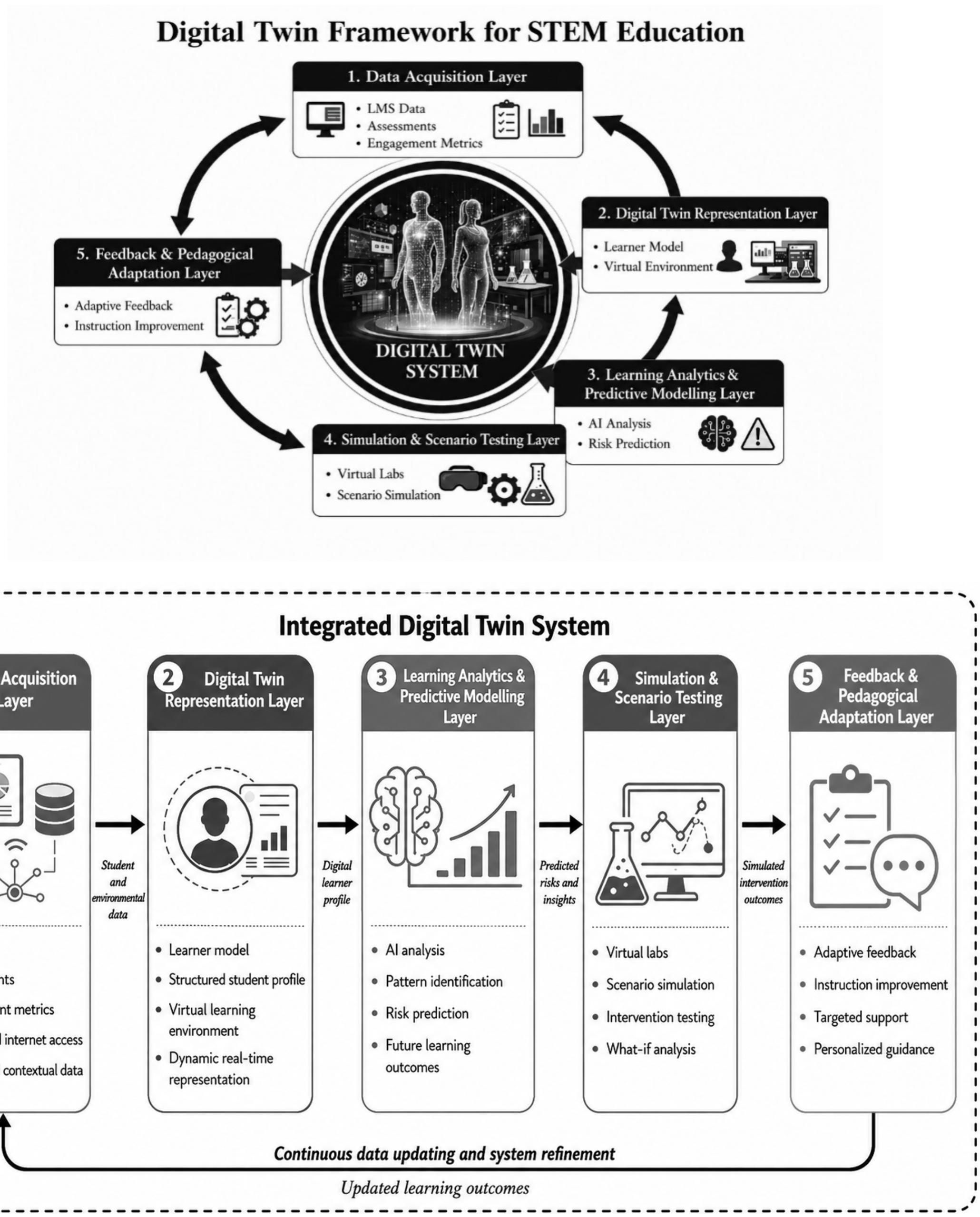


Figure 1 Proposed DT Framework for STEM Education

is a planned method to measure, collect, and analyze learner data in a systematic way to identify patterns in engagement, performance, and behavior to make instructional decisions and educational planning (Lampropoulos & Evangelidis, 2025). Practically, predictive modeling uses statistical and machine learning models to forecast the performance of students and define the at-risk students based on past and current data to predict future learning progress (Yağcı, 2022). As an illustration, educational data mining studies indicate that decision trees, logistic regression, and support vector machines can be used to predict final course grades. The prediction is based on interaction and assessment data using machine learning and proves useful in early-intervention strategies (Yağcı, 2022). The systematic reviews of predictive models also point to the fact that one of the significant areas of learning analytics research is the ability to predict the success and engagement of learners. These early predictions help to implement more specific support and pedagogical adaptations (Lampropoulos & Evangelidis, 2025). A DT ecosystem consists of predictive models that are constantly updated with incoming data to make predictions. These predictions can be further adapted and act in advance of anticipated learning requirements. This analytics and predictive modeling supply chain means that systems and educators can support the underperforming learners prior to failure and optimize learning pathways based on learner behavior and performance-based evidence.

The fourth layer is the simulation layer. Simulation and Scenario Testing Layer applies the structured digital data on representations and analytics outputs of lower layers to design interactive learning environments, tasks, and hypothetical scenario simulations. Simulation models in this layer can be used to explore what-if conditions, and educators and learners can test various strategies, interventions, or instruction sequences without putting real learners at risk. The complex problem of space exploration and pedagogical variation experimentation supported by simulation has been demonstrated to enhance the understanding of the STEM disciplines through experiential and inquiry-based learning (Radianti et al., 2020). In a DT setup, scenario testing uses real-time and predictive information to estimate how variations in behaviors of learners, parameters of tasks, or support systems could affect results, helping to make sound decisions and instructional planning (Grieves & Vickers, 2017). These types of environments also help to point out adaptive learning pathways. They point out possible bottlenecks, misconceptions, or barriers to engagement before they emerge fully in real classroom or online environments. With its integration into the general architecture, the DT allows refining learning designs continuously and assisting the stakeholders in predicting the impact of pedagogical changes in different conditions.

The fifth layer is the Feedback & Pedagogical Adaptation Layer, which is the interface where feedback and predictions are learned and provided as actionable instructional responses, and these suit learners and educators. The personalized and adaptive feedback systems occur in this layer, which will assist learners in tracking their progress and reflecting on their performance, as well as adjusting their strategies. The layer enhances self-regulated learning and involvement in STEM content. Learning analytics-based feedback systems have been found to enhance perceptions of feedback usefulness and deeper self-reflection and control of learning behavior among students (Weidlich et al., 2025). The systematic reviews of personal feedback in online learning also record the steady improvement of learning outcomes in the case of personalized feedback on their individual needs, both cognitive and emotional aspects of engagement (Fougour & Erradi, 2025; Maier & Klotz, 2022). Moreover, AI-based feedback systems are under investigation, which could offer timely and personalized feedback to supplement human teaching and help achieve scalability in courses with a high number of enrollees. The AI systems would also address the continued worries about data privacy and pedagogical suitability (Alghamdi & Alghizzi, 2025). By allowing real-time, personalized instructions and letting instructors modify pedagogical approaches depending on the responses of the learners, this layer guarantees that the DT is an adaptive system. The DT refines pedagogical strategies until they lead to better personal and group learning outcomes.

The proposed DT framework acknowledges that many institutions dealing with educational disparities face constraints in their technological environment, such as unreliable internet access, outdated computing equipment, and low digital competency. Thus, the framework is not a must-have for advanced technologies but is a model that is scalable and adaptable. Initial implementation can use existing institutional data sources, offline data collection methods, or periodic data synchronization before moving to more sophisticated predictive analytics and simulation. Furthermore, digital representations can be light, and centralized processing can minimize hardware needs for individual users. The framework introduces digital readiness factors, like the availability of infrastructure, staff capacity, and technical support, to offer a realistic route for institutions to progressively integrate DT capabilities, addressing the potential challenges that lead to educational inequalities.

3.2 Critical Evaluation of the Proposed Framework

Although the DT framework provides an interesting solution to the promotion of teaching and learning in STEM education, its theoretical basis, feasibility, and pedagogical consequences present both strengths and shortcomings. Recent studies on learning analytics and artificial intelligence draw attention to an increase in the movement towards data-driven, adaptive learning contexts that can serve the needs of personalized instruction on scale (Wu et al., 2023). In the context of this changing environment, DTs build on the methods of the past and allow the immediate coordination of physical and virtual learning spaces, which in turn facilitates ongoing monitoring, simulation, and data-driven decision-making (Wu et al., 2023).

The DT framework is strong and innovative for the development of STEM education. This is because it can integrate real-time data, simulation, and adaptive learning processes. Another major advantage is its ability to support personalized, competency-based education through constantly updated digital representations, enabling customized learning processes based on individual performance and learners' needs (Kabashkin, 2025). It is also consistent with the modern literature on learning analytics, which emphasizes the power of data-driven solutions to improve learner engagement and to fine-tune instructional decision-making (Bachmann et al., 2024).

Moreover, the framework presents an influential capability of high-fidelity simulation and experiential learning. The better learning opportunity enables learners to work with realistic, risk-free settings, which combine theoretical learning and practical practice. The recent research focused on DT systems highlights the capability of establishing dynamic and real-time virtual environments that help to gain a better insight into complex systems and facilitate experiential learning in the engineering and STEM fields (Matjie et al., 2026; Wu et al., 2023). These simulation-based environments were found to enhance critical thinking, problem-solving, and engagement among the learners, especially when used with interactive and immersive technologies (Radianti et al., 2020).

Another important innovation is that the framework would combine predictive analytics and continuous feedback loops to provide early detection of learning difficulties and provide pedagogical intervention on time. The literature on AI-based educational systems proves that predictive modeling and adaptive feedback can be implemented to a greater extent and lead to improvement in learning outcomes through the support of proactive and personalized instructional strategies (Kabashkin, 2025). Furthermore, DT convergence with artificial intelligence and learning analytics generates a comprehensive and scalable educational model, which can be used to support both personalized learning and learning optimization at the system level (Wu et al., 2023).

3.2.1 Challenges of Technology-Driven Methods in STEM Education

Although the use of digital and data-driven technologies in STEM education has become increasingly popular, the lack of structural, pedagogical, and technological support continues to limit their effectiveness in achieving equitable learning outcomes. These obstacles are not singular but structural, and they reflect broader differences in accessibility, institutional capacity, and policy enactment.

The digital divide is one of the most complex issues hindering the opportunities presented by STEM. Researchers indicate that disadvantaged students have significant barriers to accessing quality internet, digital tools, and online learning systems, which makes them vulnerable to the exclusionary situation in the digital environment of learning (Matsieli & Mutula, 2024). These inequalities are even more pronounced in developing areas, where poor infrastructure and insufficient institutional investment prevent the efficient implementation of digital learning solutions. Consequently, the transition towards online and distance STEM education will contribute to, instead of decreasing, the existing disparities in education.

Besides the problem of access, another essential obstacle to the successful adoption of technology in STEM education is the digital literacy gap among students and educators. A systematic review of universities in Sub-Saharan Africa revealed that inadequate digital skills, training, and unfavorable institutional environments are major barriers to the acquisition of competencies of the 21st century (Kafile et al., 2025). Equally, the teaching staff tends to be deficient in the pedagogical and technical skills to incorporate high-end technology like virtual labs and AI-based systems in the educational environment, resulting in a lack of use of the accessible technologies (Kafile et al., 2025).

The other significant issue is pedagogical integration and design of instruction. Although digital tools and distance learning platforms can be incredibly promising, their usefulness is largely determined by the integration of these tools into the learning and teaching activities (Bond et al., 2019). The research has shown that poorly constructed online learning platforms may result in decreased engagement, surface-level learning, and unfair results, especially among those students who need extra attention (Bond et al., 2019). Moreover, the utilization of conventional pedagogical frameworks in the digital setting does not tend to use the interactive and adaptive opportunities of new technologies because of a limitation on their transformational potential.

Funding and infrastructure limitations are also major constraints, especially in institutions that have limited resources. To launch the use of the latest STEM technologies that include virtual laboratories, AI systems, and DT environments, a lot of investment in hardware, software, and maintenance is needed. Nevertheless, not all institutions have access to sufficient funding, which means that they do not succeed in obtaining modern tools and may not implement them consistently in various educational settings (Mwansa et al., 2025). This establishes inequalities among the countries as well as among the institutions within the same region.

Moreover, new technologies like artificial intelligence and the development of more sophisticated digital systems create new types of inequality, commonly known as the AI divide (Matjie et al., 2026). Although these technologies allow a highly personalized and data-driven learning process, their advantages are not equally available to under-resourced institutions (Matjie et al., 2026). This creates issues concerning the fair allocation of technological gains and the possibility of sophisticated systems increasing the disparities in education.

Lastly, there is the limitation of institutional and policy preparedness, which is a major factor in achieving success in introducing digital innovations in STEM education. Research indicates that incoherent ICT policies, the absence of institutional support, and resistance to change are the main reasons that restrict the use of digital learning solutions (Mwansa et al., 2025). Integration of advanced systems like DTs, with the absence of strategic alignment between technology, pedagogy, and policy, may not have an easy ride during Implementation.

3.2.2 DT Framework Comparisons with Other Frameworks

Current models like Substitution, Augmentation, Modification, and Redefinition (SAMR) offer a scale of the technology integration in terms of substitution or enhancement of existing learning activities to redefinition (Bicalho et al., 2023). Although SAMR offers useful suggestions for categorizing the extent of technological contribution, it does not directly address adaptive, real-time learner modeling or how to combine multiple data streams to inform pedagogical choices. Likewise, Analysis, Design, Development, Implementation, and Evaluation (ADDIE) provides a methodical approach to instructional design, which includes analysis, design, development, implementation, and evaluation, and stresses the alignment among learning goals, teaching plans, and evaluation (Castle et al., 2024). Nonetheless, ADDIE is still less linear and not very responsive in real-time, which restricts its ability to direct interventions on the basis of constantly updated information about the learners. Technological, Pedagogical, and Content Knowledge (TPACK) and related models anticipate the overlap between technological, pedagogical, and content knowledge, with a primary focus on teacher competency around the successful and effective adoption of technology in the disciplinary content. However, they lack ways to integrate large-scale, data-driven personalization or to model complex learning ecosystems.

In contrast, the suggested DT framework will incorporate the key aspects of these known models and address their weaknesses. Its real-time simulations, data-driven feedback loops, and a scaffold can be mapped to SAMR levels and ADDIE stages, allowing formative adaptation as well as transformative learning. Through the integration of adaptive modeling and pedagogical design, the framework translates the concepts of TPACK into practical application, as well as relating the technology affordances to content delivery and teacher intervention. Besides, it builds classical structures with an integrated assessment measure and scaling, enabling active assessment of learning outcomes, engagement, and equity across various institutional settings. The DT framework offers a comprehensive, active, and practical framework for STEM education, which helps simultaneously support personalization, pedagogical standardization, and institutional scalability as compared to isolated or linear applications of SAMR, ADDIE, or TPACK (Karanam & Hartman, 2025; Weis et al., 2025; Zhang et al., 2024).

3.2.3 Recommendations for Future Research

Although the suggested DT framework elevates the cause of pedagogical consistency, methodical assessment, and scalability in STEM education, there are areas that need further research. First, it is important to validate the framework empirically. To determine the rigor of the impact of the framework on learning outcomes, knowledge retention, skill transfer, and long-term progression of the STEM pathways in a wide range of disciplines, student demographics, and settings, large-scale, multi-institutional, and longitudinal studies are required. These studies will enable generalization of findings (Karanam & Hartman, 2025).

Second, pedagogical processes and integration of educators should be more thoroughly researched. The research projects are expected to operationalize TPACK, ADDIE, and SAMR. Additional studies on faculty professional development are also imperative. This will involve identification of relevant training models, barriers to adoption, and dashboard-mediated changes in the teaching practice to make the implementation sustainable.

Third, there is the need to pay specific attention to equity, accessibility, and technological refinement. Low-cost and cloud-based variants of DT should be tried in comparative tests in under-resourced or geographically differentiated areas to lower digital disparities. Simultaneous studies should also come up with governance models that encompass data privacy, algorithm bias, consent, and accountable AI usage in learner modeling. Also, the implementation of the framework in pure science and mathematics would determine its flexibility to diverse pedagogical requirements. Research on novel features, including edge computing as a latency minimization technique, more virtual reality/augmented reality immersion, and human-centered design, can be used to compare the framework with new models. These guidelines will enlighten the hybrid solutions of maximized change, scalability, and inclusivity.

REFERENCES

Alghamdi, L. H., & Alghizzi, T. M. (2025). Educators' reflections on AI-automated feedback in higher education: A structured integrative review of potentials, pitfalls, and ethical dimensions. *Frontiers in Education, 10*, 1704820. https://doi.org/10.3389/feduc.2025.1704820

Bachmann, J. E. C., Silveira, I. F., & Martins, V. F. (2024). Digital twins for education: A literature review. *Simpósio Brasileiro de Informática na Educação (SBIE)*, 722–736. https://doi.org/10.5753/sbie.2024.242288

Bicalho, R. N. D. M., Coll, C., Engel, A., & Lopes de Oliveira, M. C. S. (2023). Integration of ICTs in teaching practices: Propositions to the SAMR model. *Educational Technology Research and Development, 71*(2), 563–578. https://doi.org/10.1007/s11423-022-10169-x

Bond, M., Zawacki-Richter, O., & Nichols, M. (2019). Revisiting five decades of educational technology research: A content and authorship analysis of the *British Journal of Educational Technology*. *British Journal of Educational Technology, 50*(1), 12–63. https://doi.org/10.1111/bjet.12730

Castle, S. D., Byrd, W. C., Koester, B. P., Pearson, M. I., Bonem, E., Caporale, N., Cwik, S., Denaro, K., Fiorini, S., Li, Y., Mead, C., Rypkema, H., Sweeder, R. D., Valdivia Medinaceli, M. B., Whitcomb, K. M., Brownell, S. E., Levesque-Bristol, C., Molinaro, M., Singh, C., & Matz, R. L. (2024). Systemic advantage has a meaningful relationship with grade outcomes in students' early STEM courses at six research universities. *International Journal of STEM Education, 11*(1), 14. https://doi.org/10.1186/s40594-024-00474-7

Fougour, W. E., & Erradi, M. (2025). Personalized Feedback in Computer-Based Learning: A Systematic Review of Its Cognitive, Emotional, and Educational Impacts. *International Journal of Technology in Education*, *8*(3), 825–848. https://doi.org/10.46328/ijte.1192

Flegr, S., Kuhn, J., & Scheiter, K. (2023). How to foster STEM learning during COVID-19 remote schooling: Combining virtual and video experiments. *Learning and Instruction, 86*, 101778. https://doi.org/10.1016/j.learninstruc.2023.101778

Grieves, M., & Vickers, J. (2017). Digital twin: Mitigating unpredictable, undesirable emergent behavior in complex systems. In *Transdisciplinary perspectives on complex systems: New findings and approaches* (pp. 85–113). Springer International Publishing. https://doi.org/10.1007/978-3-319-38756-7_4

Jedermann, R., Singh, K., Lang, W., & Mahajan, P. (2023). Digital twin concepts for linking live sensor data with real-time models. *Journal of Sensors and Sensor Systems, 12*(1), 111–121. https://doi.org/10.5194/jsss-12-111-2023

Kabashkin, I. (2025). AI-based digital twins of students: A new paradigm for competency-oriented learning transformation. *Information, 16*(10), 846. https://doi.org/10.3390/info16100846

Kafile, M., Ninana, A., & Makhetha, P. (2025). The digital divide and e-learning participation: A mixed-methods study of Extended Curriculum Programme students in South Africa. *International Journal of Learning, Teaching and Educational Research, 24*(9), 769–784. https://doi.org/10.26803/ijlter.24.9.37

Kim, Y., Beland, S. E., & Subramaniam, M. (2026). Crossing the third-level digital divide through digital literacy programs. *Journal of the Association for Information Science and Technology, 77*(2), 397–413. https://doi.org/10.1002/asi.70032

Kukushkin, K., Ryabov, Y., & Borovkov, A. (2022). Digital twins: A systematic literature review based on data analysis and topic modeling. *Data, 7*(12), 173. https://doi.org/10.3390/data7120173

Karanam, S. A. K., & Hartman, N. W. (2025). A systematic review of Digital Twin (DT) and virtual learning environments (VLE) for smart manufacturing education. *Manufacturing letters*, *44*, 1597–1608. https://doi.org/10.1016/j.mfglet.2025.06.179

Lampropoulos, G., & Evangelidis, G. (2025). Learning analytics and educational data mining in augmented reality, virtual reality, and the metaverse: A systematic literature review, content analysis, and bibliometric analysis. *Applied Sciences, 15*(2), 971. https://doi.org/10.3390/app15020971

Liljaniemi, A., & Paavilainen, H. (2020). Using digital twin technology in engineering education: Course concept to explore benefits and barriers. *Open Engineering, 10*(1), 377–385. https://doi.org/10.1515/eng-2020-0040

Lu, M., & Hu, Z. (2025). Digital twin-enhanced programming education: An empirical study on learning engagement and skill acquisition. *Computers, 14*(8), 322. https://doi.org/10.3390/computers14080322

Maier, U., & Klotz, C. (2022). Personalized feedback in digital learning environments: Classification framework and literature review. *Computers and Education: Artificial Intelligence, 3*, 100080. https://doi.org/10.1016/j.caeai.2022.100080

Man, R., Li, J., & Tan, K. M. (2026). Educational disparities in STEM during COVID-induced distance learning and a potential strategy to address them. *Nature Communications, 17*(1), 3239. https://doi.org/10.1038/s41467-026-69925-9

Matjie, M. A., Nethavhani, A., & Matlakala, M. (2026). AI and the digital divide in education. *Frontiers in Computer Science, 8*, 1759027. https://doi.org/10.3389/fcomp.2026.1759027

Matsieli, M., & Mutula, S. (2024). COVID-19 and digital transformation in higher education institutions: Towards inclusive and equitable access to quality education. *Education Sciences, 14*(8), 819. https://doi.org/10.3390/educsci14080819

Meng, X. (2024). Teaching for social justice: How educators address inequalities in STEM education. *Journal of Education and Educational Policy Studies, 2*(1), 18–23. https://doi.org/10.54254/3049-7248/2/2024010

Meng, W., Yu, L., Liu, C., Pan, N., Pang, X., & Zhu, Y. (2024). A systematic review of the effectiveness of online learning in higher education during the COVID-19 pandemic period. *Frontiers in Education, 8*, 1334153. https://doi.org/10.3389/feduc.2023.1334153

Mwansa, G., Ngandu, M. R., & Mkwambi, Z. (2025). Bridging the digital divide: Exploring the challenges and solutions for digital exclusion in rural South Africa. *Discover Global Society, 3*(1), 54. https://doi.org/10.1007/s44282-025-00189-2

Nedungadi, P., Thushara, M. G., Veena, G., Tang, K. Y., & Raman, R. (2026). Emerging technologies for STEM education: Global evidence on learning, equity, and SDG4. *Humanities and Social Sciences Communications, 13*(1), 522. https://doi.org/10.1057/s41599-026-06565-w

Qushem, U. B., Christopoulos, A., Kaliisa, R., Khalil, M., Salakoski, T., & Laakso, M. J. (2025). Technology-enhanced Learning and Learning Analytics for personalized STEM learning: A scoping review. *International Journal of Educational Research*, *134*, 102827. https://doi.org/10.1016/j.ijer.2025.102827

Radianti, J., Majchrzak, T. A., Fromm, J., & Wohlgenannt, I. (2020). A systematic review of immersive virtual reality applications for higher education: Design elements, lessons learned, and research agenda. *Computers & Education, 147*, 103778. https://doi.org/10.1016/j.compedu.2019.103778

Santilli, T., Ceccacci, S., Mengoni, M., & Giaconi, C. (2025). Virtual vs. traditional learning in higher education: A systematic review of comparative studies. *Computers & Education, 227*, 105214. https://doi.org/10.1016/j.compedu.2024.105214

Schmid, R. F., Borokhovski, E., Bernard, R. M., Pickup, D. I., & Abrami, P. C. (2023). A meta-analysis of online learning, blended learning, the flipped classroom and classroom instruction for pre-service and in-service teachers. *Computers and Education Open, 5*, 100142. https://doi.org/10.1016/j.caeo.2023.100142

Sedebo, G. T., Shafi, A. A., Muchie, M., & Shatalov, M. Y. (2025). Inclusive STEM education to fight poverty and inequality: The case of South Africa. *African Journal of Science, Technology, Innovation and Development, 17*(1), 56–64. https://doi.org/10.1080/20421338.2024.2417779

Tate, T., & Warschauer, M. (2022). Equity in online learning. *Educational Psychologist, 57*(3), 192–206. https://doi.org/10.1080/00461520.2022.2062597

Van De Werfhorst, H. G., Kessenich, E., & Geven, S. (2022). The digital divide in online education: Inequality in digital readiness of students and schools. *Computers and Education Open, 3*, 100100. https://doi.org/10.1016/j.caeo.2022.100100

Weidlich, J., Fink, A., Frey, A., Jivet, I., Gombert, S., Menzel, L., Giorgashvili, T., Yau, J., & Drachsler, H. (2025). Highly informative feedback using learning analytics: How feedback literacy moderates student perceptions of feedback. *International Journal of Educational Technology in Higher Education, 22*(1), 43. https://doi.org/10.1186/s41239-025-00539-9

Weis, P., Bašťovanský, R., & Vereš, M. (2025). A web-based digital twin framework for interactive e-learning in engineering education. *Computers, 14*(10), 435. https://doi.org/10.3390/computers14100435

Wu, H., Ji, P., Ma, H., & Xing, L. (2023). A comprehensive review of digital twin from the perspective of total process: Data, models, networks and applications. *Sensors, 23*(19), 8306. https://doi.org/10.3390/s23198306

Yağcı, M. (2022). Educational data mining: Prediction of students' academic performance using machine learning algorithms. *Smart Learning Environments, 9*(1), 11. https://doi.org/10.1186/s40561-022-00192-z

Zhang, J., Zhu, J., Tu, W., Wang, M., Yang, Y., Qian, F., & Xu, Y. (2024). The effectiveness of a digital twin learning system in assisting engineering education courses: A case of landscape architecture. *Applied Sciences, 14*(15), 6484. https://doi.org/10.3390/app14156484