Digital Twin Universities: Creating Real-Time Virtual Replicas of Students for Predictive and Personalised Higher Education

Ajlan Al-Ajlan

Department of Management Information Systems, College of Business and Economics, Qassim University, Buraydah 51452, Saudi Arabia
Email: aajlan@qu.edu.sa

Abstract- The intersection of Artificial Intelligence (AI), learning analytics, and digital twin is revolutionising higher education into an intelligent, data-driven, and ultimately personalised educational ecosystem. In contrast with today's Learning Management Systems (LMSs), which offer reactive, retrospective perspectives and generalised student characteristics, a digital twin in education provides real-time, personalised, and proactive learning guidance for each student based on the learner's real-world educational activities. To address this shortcoming, this article reports on a DTU framework for modelling and maintaining an individualised, evolving twin for each student in an online version of a real university. The individual twin incorporates multimodal educational information describing the learner's engagement and behaviour, state of mind, learning performance, and employment-related skills. The proposed DTU layered design will intelligently monitor students' status in real time, proactively predict students' academic performance and current level of engagement, identify students at risk of dropping out, and dynamically generate a personalised learning pathway for each student. To validate the feasibility of the proposed DTU framework, we conducted a rigorous controlled quantitative experiment with a sample of 386 students over an entire academic semester in a real-world university setting. Our empirical evaluation results suggest that DTU significantly outperforms several popular LMSs in predictive accuracy (achieving the current best accuracy of 94.6% for student performance prediction) and in improving students' learning gains, engagement, and retention. Early results from the institutional-level experiment also indicate that the DTU has great potential to be a powerful next-generation tool for facilitating personalised and proactive interventions in an AI-enhanced university. It has proved to be a solid theoretical concept and an empirically verified methodology for scalable, real-time, personalised learning in modern universities.

Keywords– Digital Twin Universities, Student Digital Twins, Artificial Intelligence, Learning Analytics, Personalised Learning, Predictive Higher Education.

I. INTRODUCTION

Artificial Intelligence (AI), Learning Analytics, the Internet of Things (IoT), Cloud Computing, and Digital Transformation have rapidly transformed the higher education ecosystem [1, 2, 3]. Worldwide, universities are increasingly implementing smart educational technologies to enhance the quality of learning, institutional operational efficiency, and student success. Intelligent learning systems such as Learning Management Systems (LMSs), adaptive learning platforms, intelligent tutoring systems, and educational data mining technologies are becoming common in educational institutions [4, 5, 6].

Institutions can acquire and analyse large volumes of learner data to inform educational decision-making and support personalised learning. However, modern educational systems are mostly reactive rather than predictive [7, 8]. In most traditional educational systems, the analysis and application of existing learning management systems and static student profiles are focused on learners' historical academic progress [9, 10].

This makes it difficult for institutions to identify at-risk learners, forecast future student success rates, and provide timely, personalised learning support. As such, learners may experience a largely undifferentiated learning process that fails to account for the dynamic evolution of individual learners' cognitive processes, behaviour patterns, and academic levels. As one of the industry's cutting-edge innovations, Digital Twin technology has recently gained considerable traction within the frameworks of Industry 4.0 and Industry 5.0 [11, 12, 13].

It has demonstrated successful applications across fields such as manufacturing, healthcare, aerospace, smart cities, transportation, and industrial automation, providing capabilities including predictive monitoring, simulation, optimisation, and intelligent decision-making [14, 15]. In essence, a Digital Twin provides a live, synchronised virtual replica of a physical asset or system that dynamically mirrors and updates its virtual representation in real time in response to changes in the physical world. Due to their ability to build real-time, synchronised replicas of physical systems, the applicability of Digital Twins for educational institutions that continuously capture learner behaviour, academic performance, and engagement data is increasingly recognised.

The Digital Twin paradigm is further extended to the higher education ecosystem, conceptualising a Student Digital Twin that continually updates learners' virtual representations based on real-time learning data [5, 8, 16, 17, 18]. By integrating various data sources, including academic performance metrics, learning behaviours, cognitive characteristics, engagement profiles, attendance patterns, assessment results, and learner interaction history, educational institutions can create a comprehensive virtual replica of each student. By blending Digital Twins with Artificial Intelligence (AI) and Learning Analytics, educational systems can develop dynamic and intelligent models to systematically monitor the evolution of students' academic performance, predict their future learning success, identify at-risk individuals, and formulate proactive interventions even before a learning crisis occurs [19, 20].

While there have been numerous studies on Learning Analytics, student performance prediction models, adaptive learning systems, recommender systems, and AI in education, most of these solutions focus on a single aspect of the learning process and operate as standalone systems [11, 15, 16, 21]. Often, Digital Twin technology, real-time educational analytics, predictive artificial intelligence, and personalised learning are not unified within a complete higher education environment [6, 8, 22, 23]. There is also limited research on building robust systems that synchronise physical and virtual learner models for continuous updating of individual states.

This gap highlights the need for a new learning paradigm and the transition to smart, adaptive, and predictive university systems, which can be achieved by creating Digital Twin Universities (DTUs) with dynamically updated virtual student representations to simulate learning trajectories, predict future outcomes, evaluate interventions, and optimise student experience [24, 25, 26]. This research endeavours to address this emerging trend by proposing an innovative framework, the DTU, that leverages Digital Twin Technology, AI, Learning Analytics, and Adaptive learning capabilities to construct a real-time virtual environment that predicts and personalises Higher Education [17, 18, 27, 28, 29].

The rest of the paper is organised as follows. Section 2 discusses related work, including the Digital Twin, Learning Analytics, Artificial Intelligence in education, and personalised learning systems, and identifies opportunities for future research and open research problems. Section 3 introduces the DTU model and its comprehensive architectural diagram.Section 4 provides the Student Digital Twin model, along with a mathematical representation for capturing multidimensional state space. Section 5 discusses the AI Prediction and Personalisation Engine, comprising predictive modelling, risk estimation, and personalised recommendation strategies. Section 6 presents the research methodology, study design, experimental setup, evaluation metrics, and implementation procedures for the proposed framework.Section 7 presents experimental results, evaluation, and a thorough discussion, with emphasis on the implications of DTU for education. Section 8 discusses the limitations of the work and highlights potential avenues for future research. Finally, Section 9 concludes the paper with an overview of major contributions and the role that the DTU plays in the development of intelligent, personalised higher education in future.

II. RELATED WORK

2.1 Digital Twin Technology

The Digital Twin (DT) is one of the main innovative technologies in the context of Industry 4.0 and Industry 5.0. It is generally regarded as a dynamic, virtual copy of a physical product, process, or service that receives data from its physical counterpart and exchanges information, thereby enabling monitoring, simulation, optimisation, and predictive use [30, 31]. Driven by the accelerated adoption of Artificial Intelligence (AI), the Internet of Things (IoT), cloud computing, and Big Data analytics, today's Digital Twins have become a technology for modelling highly complex physical environments with high accuracy and strong predictive capability for future states.

Over the last few decades, the field of Digital Twins has evolved significantly, extending far beyond traditional industries and contexts. Grieves and Vickers [20] laid the foundation for the formal definition of DT as a direct virtual counterpart that can be mapped to one or more instances of a physical asset or system in real time. Later, the concept evolved to the DT driven smart manufacturing environments in Tao et al. [21, 23] where real-time monitoring, simulation and predictive optimization was discussed in detail, or the use of Digital Twins for cyber-physical production systems to enhance operation efficiency based on continuous sync between physical and digital items [22], and their use for decision-making in Industry 4.0 driven by big data integration with digital twins [24].

More recently, Rasheed et al. [25] discussed the critical enablers of digital twin implementation, focusing on data interoperability, real-time connectivity, AI-based analysis, and the scalability of cloud technologies. These references highlight how the technology has moved beyond simple models toward sophisticated, intelligent, and predictive ecosystems capable of making autonomous decisions and continuously optimising. It is the right one for supporting education in a dynamic learner state.

2.2 Digital Twins in Education

The digital twin concept in education is a relatively new area compared to the industrial applications. The educational digital twin has been explored in several forms, namely virtual labs [32, 33], smart classrooms [6, 10], educational simulations [7], and infrastructure [34, 9]. Furthermore, there has been a surge in the adoption of the idea of an individual digital twin for learners (i.e., for modelling the person) in recent research [35, 36, 37].

Furini et al. [5] propose an integrated framework that combines digital twins and artificial intelligence to enable dynamic personalisation of educational content by modelling the virtual learner. Bachmann et al. [39] reviewed the academic literature on digital twins in education. They found that most implementations remain in an experimental phase and typically focus only on the learning environment rather than the person. Huang and Willcox [40] propose educational digital twins, a framework that models a student's data throughout their educational journey, enabling data-driven academic decision-making.

More recently, Kabashkin [8] presented students' AI digital twins that model academic achievement, skills, competencies, learning preferences, interests, career goals, behaviour, and more. There are still numerous limitations, including the narrow scope of most reported frameworks, which focus only on institution-wide digital twins. Most existing works focus on single academic processes rather than the broader ecosystem and do not include real-time synchronisation, predictive capabilities, or automatic adaptation to individual learner needs [41, 42, 43].

So, there is an opportunity to propose a complete Digital Twin University architecture that includes real-time modelling and tracking of individuals, data-driven prediction, and the provision of personalised learning. The authors of [44] conducted a systematic literature review and claimed that educational digital twins represent the next revolution in education through real-time tracking, analysis, and adjustment to individual needs. The authors of [45] emphasised the role of the digital twin in educational data analysis and in a smart learning environment in the context of machine learning.

Umer and Khan [28] designed digital twin frameworks of adaptive learning based on students. The digital twin framework proposed by Salinas and Martinez-Mons [46] enables continuous student monitoring. A model for a student's digital twin for real-time monitoring, with a real-time student prediction approach that predicts the success of a student's learning activity, is proposed by Wang and Li [47].

Hernández et al. [31] suggest the future role of learning digital twin ecosystems in a digital and smart university. Even though a substantial body of literature discusses modelling individual student behaviour, there are few reports on building an integrated digital twin platform that combines a digital learning environment, a digital twin of the individual learner, and decision-support services with predictive analytics into an ecosystem. Various recent studies address this topic.

The authors of [26] demonstrated how a digital twin can improve learning in a higher education context by leveraging students' learning processes. Educational Digital twins can improve individual monitoring for real-time adjustment [48] and the learning process [28, 29, 30]. The educational digital twin has the potential to create a smart campus and to optimise and analyse the entire system to improve education [34, 54]. Digital Twins have a significant impact on higher education institutions, enabling smarter operations and educational processes. [51, 52].

2.3 Learning Analytics and Predictive Education

One increasingly important discipline in educational technology today is Learning Analytics, which aims to collect, measure, and analyse educational data to improve learning outcomes and support educational institutions' decision-making processes [49, 50]. Modern universities are adopting learning analytics platforms to track students at risk, learners' engagement, learning outcomes prediction, and learner retention in academic environments. Machine learning methods for educational predictions and learner support systems are rapidly advancing, and in recent years, universities have increasingly adopted these technologies.

Indeed, various machine learning algorithms, such as Linear Regression, Decision Trees, Random Forests, Support Vector Machines, Neural Networks, and Gradient Boosting, have been tested and widely adopted for forecasting educational and learning patterns in these systems [51, 15]. Specifically, a recent comprehensive systematic review by Rodriguez-Ortiz et al. [52] included more than 100 research papers. It concluded that learning analytics increasingly employ both machine learning and generative AI approaches to predict and support learners. The work of Al-Zahrani [14] addressed the contribution of learning analytics to data-informed educational decision-making and to improving educational efficiency. Although it has proved successful for predicting learner outcomes, many existing learning analytics systems operate reactively [53, 54].

As a consequence, current learning analytics systems leverage historical learner data and generally predict outcomes only after learners have already encountered difficulties. At the same time, the system most often does not integrate a real-time model or digital representation of the learner that can simulate real-world and future educational outcomes. It is because of these challenges that we plan to integrate the components of a student digital twin that we previously learned with learning analytics. Advances in the Learning Analytics domain continue with its integration into broader fields such as machine learning and educational data mining[50, 56, 57].

For instance, a lot of work, such as [58, 37], has addressed learning analytics from different points of view, starting from their relationship with Educational Data Mining [32], up to considering the development of the discipline, the use of machine learning algorithms [33, 35] and privacy concerns [36], or the potential for making learning analytics more useful for educators and students [37]. More recently, attention in the LA domain has focused on applying techniques such as explainable AI [55, 56], multimodality [56], or deep learning algorithms [55] to predict learners at risk and suggest timely interventions [57].

2.4 AI-Powered Personalised Learning Systems

Artificial Intelligence is one of the biggest drivers of personalised learning systems. A typical AI-powered educational system collects, aggregates, and analyses various learner behaviours; identifies learners' strengths and weaknesses; generates recommendations; and adapts content to learners' needs [16, 19]. Personalised learning aims to offer tailored teaching methods for each learner, including content, assessments, learning paths, and feedback that are based on the learner's individual characteristics.

Merino-Campos (2021) found that AI technology could enhance student performance, engagement, and satisfaction while providing adaptive educational support. Penget al. (2019) stated that, by virtue of recent advances in AI techniques, adaptive educational content can be personalised in real time according to students' progress or achievement. Vorobyeva et al. (2020) showed that an AI-driven, customised learning environment can improve learning effectiveness through adaptive pedagogy. The appearance of Generative AI enhancement has opened up possibilities for personalised learning. Misiejuk et al. (2021) claimed that Generative AI can contribute to automated tutoring, intelligence assessment, Personalised feedback, and the Generation of learning content.

More than one study shows that most AI-driven personalised learning systems use fragmented, individualised models that analyse academic performance, Engagement characteristics, cognitive characteristics, or behavioural characteristics in isolation. Accordingly, they are not always able to connect learners' overall learning processes [27,57]. Recently, the emergence of Generative AI has accelerated the development of an intelligence-personalised learning system capable of delivering adaptive tutoring, automated feedback and dynamic content generation [58]. In addition, studies have shown that AI-driven educational ecosystems improve student engagement, academic performance, and satisfaction with learning [59, 60].

2.5 Research Gap

As the survey shows, there is a well-established body of literature documenting the significant impacts of Digital Twin technology, Learning Analytics, Artificial Intelligence, and Personalised learning on Education. However, these fields of research are largely isolated from one another. Today, current systems generally provide one of these elements, either as a predictive analytics solution, an adaptive learning solution, or a virtual environment, without unifying them at an institutional level [6, 8, 11, 16].

Additionally, most available works lack the provision of continuously synchronised Student Digital Twins that reflect multiple dimensions of a student, including academic, behavioural, cognitive, and career perspectives. According to prior research, no existing approach has been identified that combines Digital Twin technology, live educational data synchronisation, Artificial Intelligence-based predictive analytics, adaptive learning algorithms, and intervention strategies to provide all-encompassing support within a University context. As a consequence, Universities are unable to provide timely learner assistance and to estimate future outcomes regarding student performance and experience.

Thus, this research proposes a new DTU framework that incorporates the Digital Twin for students, Artificial Intelligence, Learning Analytics, and adaptive Education, aiming to enable intelligent learning that predicts educational outcomes, offers personal interventions, and continuously improves the student experience.
Table 1 presents key features of the proposed DTU framework from an existing perspective. Although numerous researchers have studied Digital Twins, Learning Analytics, Artificial Intelligence, Personalised Learning, etc., we did not find any related literature proposing a unified framework that simultaneously incorporates real-time student digital twins (SDT), AI predictive analytics, an adaptive personalised learning path, and a timely feedback system. The proposed DTU framework bridges this gap by integrating diverse emerging technologies into a holistic intelligent educational ecosystem that continuously observes, predicts, adapts, optimises, and personalises learners' learning journeys through synchronised student digital twins. Therefore, the proposed framework further extends the existing body of knowledge by synthesising disparate emerging technologies into a single learning environment for higher education.

Table 1. Comparative Analysis of Existing Studies and the Proposed DTU Framework

Study	Digital Twin	Student Twin	AI Prediction	Real-Time Analytics	Personalised Learning	Continuous Feedback
Furini et al. [5]	✓	Partial	✓	✗	✓	✗
Bachmann et al. [6]	✓	✗	✗	✗	✗	✗
Huang and Willcox [7]	✓	Partial	✗	✓	✗	✗
Kabashkin [8]	✓	✓	✓	Partial	✓	✗
Jankovskis et al. [9]	✓	✗	✗	✗	✗	✗
Daineko et al. [10]	✓	✗	Partial	✗	✗	✗
Rodríguez-Ortiz et al. [11]	✗	✗	✓	Partial	Partial	✗
Al-Zahrani [14]	✗	✗	Partial	✗	Partial	✗
Merino-Campos [16]	✗	✗	✓	Partial	✓	✗
Peng et al. [17]	✗	✗	✓	✓	✓	✗
Proposed DTU Framework	✓	✓	✓	✓	✓	✓

Despite important advancements in leveraging learning analytics across numerous prior initiatives, these initiatives all suffer from a deficiency: most employed architectures and frameworks are centred on a static, decoupled data system that inadequately represents the ongoing, multidimensional changes in a student's cognitive and behavioural state in real time. Our novel DTU framework addresses this gap by enabling dynamic data synchronisation between a physical learner and their virtual counterparts.

III. PROPOSED DIGITAL TWIN UNIVERSITY FRAMEWORK

The DTU structure comprises seven interacting layers, as shown in Figure 1. Starting at the bottom, the Physical University Layer records educational activities and produces learner data; this information is combined with institutional records from across multiple sources in the Data Acquisition Layer. The learner data informs virtual learner models in the Student Digital Twin Layer; these models are kept constantly synchronised with the physical learners, while the AI Prediction and Analytics Layer produces predictive analytics results.

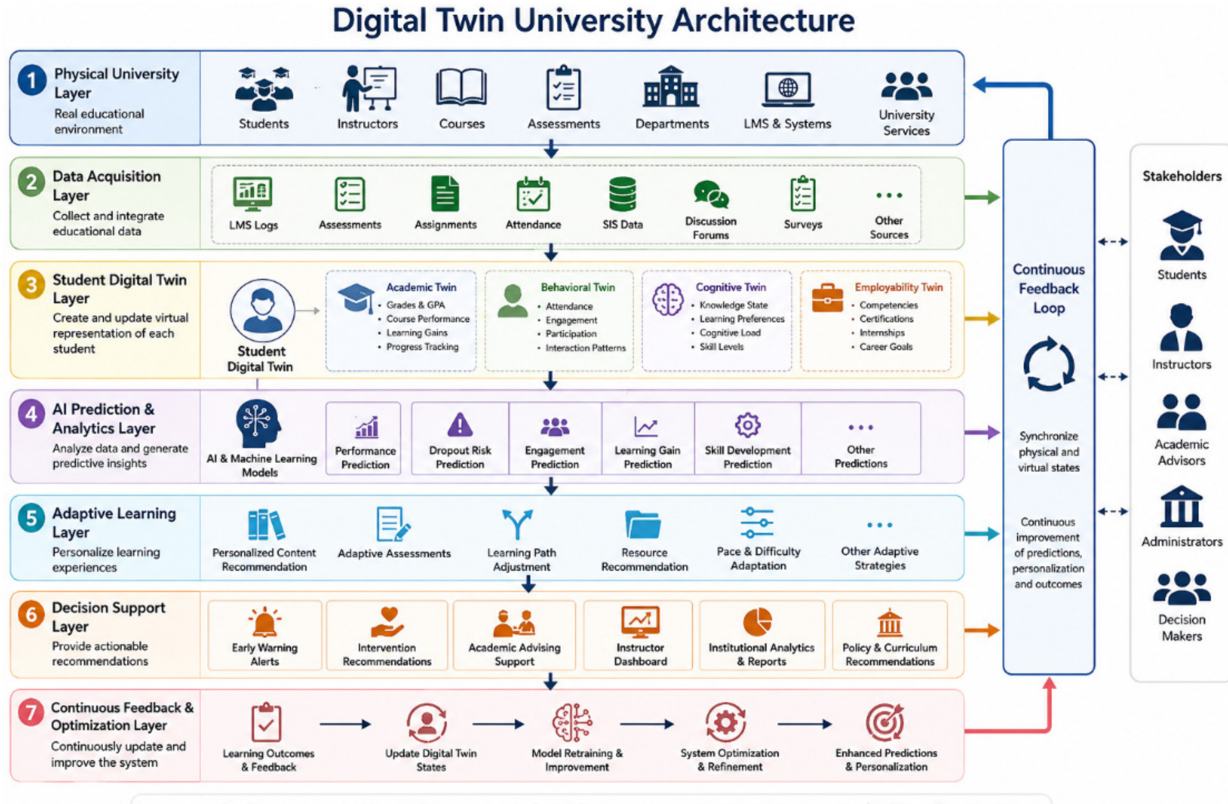

Figure 1. Architecture of the Proposed Digital Twin University (DTU) Framework

These predictions then inform the development of adaptive learning ecosystems and evidence-based educational recommendations within the Adaptive Learning and Decision Support Layers, respectively. In addition, a Continuous Feedback and Optimisation Layer maintains synchronisation between physical learners and digital models, while enabling continuous improvement of prediction and learner components.

3.1 Overview of the Digital Twin University Framework

In this regard, this work addresses limitations in current technology-enabled learning approaches by proposing a new DTU that will produce real-time virtual copies of students, enabling predictive and personalised learning experiences in higher education. Our DTU integrates Digital Twin technology, artificial intelligence, learning analytics, and adaptive learning systems to form a cohesive, intelligent system that predicts, monitors, and optimises students' learning experiences. The proposed DTU framework continually updates students' real-time digital copies, which store their most recent state, unlike traditional learning systems that only utilise historical educational information.

Based on current learning, engagement, and interaction data, as well as learners' individual learning styles and cognitive attributes, the DTU updates learners' digital copies in real time, enabling proactive learning actions, predictive analysis, and support before learners experience significant issues. The DTU has a seven-layer architecture that works together to define a comprehensive intelligent learning environment, providing functionality for data integration, Digital twin realisation, predictive analysis, personalised learning, decision-making support, and system development (Figure 1).

3.2 Architecture of the Digital Twin University

This proposed DTU architecture depicts a multi-layered smart ecosystem that unifies real-time learning data, Digital Twin technology, Artificial Intelligence (AI), Learning Analytics, and adaptive learning in a higher education setting. The introduced system framework adapts Digital Twin concepts for industrial and cyber-physical systems (CPS) to higher education environments by generating synchronised, real-time virtual duplicates of learners that are updated in tandem with their real learning journeys. Past research has highlighted that Digital Twin systems have been quite effective in monitoring, prediction, optimisation, and decision-making in fields such as manufacturing, healthcare, and smart cities [1, 2, 21, 25]. More recently, Digital Twin has been regarded as a promising technology for use in learning analytics, personalised learning frameworks, and learner modelling [5, 7, 8, 26].

It begins with the student's context in a physical university setting, where students engage with courses, lecturers, examinations, LMS systems, and institutional services. Students, lecturers, and educational institutions generate educational data continuously to indicate how well students performed on exams, their level of interest, their attendance at lectures, their behaviour during learning, and their academic achievements. The acquisition layer integrates information from various sources, including university databases, examination systems, discussion systems, institutional administrative systems, and learning management systems. It acquires students' related educational data, since educational states change and thus students' states should be updated accordingly nearly instantaneously, as shown in [11, 14, 27].

At the heart of the framework is the Student Digital Twin Layer, the most significant novelty of the proposed architecture. Unlike conventional learner models built on isolated student-related attributes in the educational process, the Student Digital Twin maintains an integrated virtual representation of an individual student on a single plane comprising cognitive, behavioural, engagement, and career-related profiles [16]. The Students' Digital Twin, building on recent advancements in

Educational Digital Twins and AI-powered Student digital twin models [7, 8, 29], consists of an ever-evolving image of the student that adapts to their current and projected educational status through synchronisation with real data from their educational practice.

AI and Predictive analytics layer. This layer applies Machine Learning algorithms and learning analytics techniques to derive actionable learning intelligence out of learner data. Many previous studies have demonstrated the suitability of AI-based predictive models for predicting students' academic performance, estimating their risk of failure, assessing learning engagement, and facilitating educational decision-making [11, 15, 35]. Along a similar path, the proposed framework uses predictive analytics to forecast learning progress, academic attainment, trends in learning engagement, and potential dropout.

The adaptive learning mechanism in this architecture exploits prediction results to customise the learning experience for different learners. Artificial Intelligence has often been reported as an enabler of personalised learning by adapting learning content, pathways, assessment methods, and feedback. [16, 17, 18] As one can tell from the DTU framework proposed in the architecture section, learner state transitions continuously as the learning experience continues, and the personalised learning process keeps a space between student status, personal preference, and individual learning goals. This feature clearly sets this framework apart from existing LMS, which primarily offer a static learning experience.

A decision support layer is implemented within the proposed framework to facilitate evidence-based decision-making for learners, instructors, counsellors, and institutional stakeholders by mapping predictive outcomes into decision-making recommendations across areas such as early warning systems, tailored support services, course recommendations, curriculum redesign, and institutional evaluation. The importance of transforming learning data into actionable decisions that optimise both learning gains and institutional effectiveness has long been a focal point of research in learning analytics [13,33,37]. The presented framework provides an architecture to bring this vision to the fore by establishing dynamic, real-time decision support using learner intelligence.

Finally, at the top of the layer stack, a persistent feedback and improvement loop is employed to support the continuous evolution of both learner representations and predictive models. Outputs from each adaptivity instance, performed in real time, are continually fed back into the DT, allowing the models' representations to evolve and, accordingly, to refine the prediction models. This concept of iterative improvement, fed by real-time data, synchronises the DTU with the core principles of DT itself [21, 24, 25], ensuring dynamic updating and adaptability between the physical and virtual counterparts.

In conclusion, the current paper proposes a student-centred educational technology that, beyond previous studies, integrates Students' Digital Twins, AI, Learning Analytics, and adaptive learning approaches with continuous, consistent feedback loops into a smart, intelligent system. While [6, 8, 11, 16] study some of the mentioned technologies independently, the DTU architecture, on the other hand, builds an all-campus educational ecosystem capable of fostering proactive, adaptive learning for a prediction-ready university through dynamic learner models.

To address the needs of extreme computational performance and remove systemic latency, the DTU data model takes a hybrid-computing approach, using real-time ingestion to stream highly volumetric, behaviouraltelemetrics (clicks, login time, etc.), while running the time-consuming predictive models (e.g., at-risk forecasting, multi-dimensional cognitive modelling), as micro-batches during non-peak institution operational times.

3.3 Operational Workflow of the Digital Twin University

The conceived DTU utilises a cycle of data procurement, digital twin synchronisation, predictive analytics, adaptive intervention, and feedback optimisation. Initially, learning-related data is generated through learners' interactions with the institute's systems, including learning management systems, assessment portals, academic systems, discussion forums, and extracurricular activities. Data streams from these sources are then transmitted to the Data Acquisition layer, where preparatory measures such as data normalisation, transformation, and standardisation are employed to ensure data coherence and interoperability among the institutional platforms.

After integration, the data flows to the Student Digital Twin layer, where individual learning models are built. Contrary to conventional, periodic update models, the suggested architecture models a fluid representation of the learner who reflects instantaneous transitions in performance, engagement, behaviour, and cognitive processes. Therefore, individual student digital twin models dynamically grow alongside their real-world counterparts, resulting in enhanced fidelity between real-life learners and their digital twins.

This continuously generated and updated learner information is then consumed by the Artificial Intelligence and Predictive Analytics Layer, where the team produces estimates of learning potential, engagement trends, changes in skill sets, expected learning gains, and at-risk indicators for learners. These estimates are then passed on to the Adaptive Learning Layer, which produces individually tailored optimal learning paths, suggested teaching content, and learner intervention options. Advice is offered to all stakeholders (learners, teaching staff, support advisors, and institutional management) on decisions within the Decision Support Layer. Any learning outcome produced by the intervention is eventually fed back to update the DigitalTwin: so learning itself drives an ever-improving model, which in turn drives increasingly improved learning.

3.4 Student Digital Twin Components

The Student Digital Twin is the "brain" of the suggested DTU framework. Instead of storing disassociated learner pieces in conventional educational databases, the SDT will store multiple learner dimensions within the virtual student replica. With a multidimensional model, our method has fully leveraged its potential to better understand learners' progress and accurately predict their future educational performance.

Firstly, Academic Twin stores indicators of student performance, such as cumulative GPAs, test scores, progress through their programs, and knowledge gains. These are indisputable evidence of learners' performance, crucial inputs for many predictive models. Furthermore, past literature [11, 15, 35] has consistently confirmed that academic performance remains one of the strongest indicators of future academic success.

The second factor is the behavioural twin, reflecting learners' interactions with educational contexts. Behavioural data comprises attendance habits, frequency of LMS logins, participation patterns, consumption of learning materials, interaction on learning systems, and engagement with pedagogical materials. Numerous learning analytics reports suggested that behavioural patterns can predict learner disengagement and academic risk before the drop-off in performance becomes apparent [13, 14, 37]. The third component is the cognitive twin, which presents the learner's cognitive state, the cognitive workload, and a cognitive profile, including cognitive preferences, conceptual knowledge, and skill progress.

The cognitive component can contribute to intelligent personalisation in adaptive learning by aligning instruction with students' skills and knowledge states [16, 18]. Thus, by continuously tracking the development of cognitive skills, the DTU could adapt its teaching strategies and learning paths accordingly.

The 4th dimension, the Employability Twin, addresses learners' readiness for future work settings. This dimension also encompasses learner competencies, certifications, technical knowledge, internships, professional awards, and measures of career readiness. Several studies in higher education are now exploring employability as a principal educational objective and recognising the significance of embedding career-related aspects in learner models [8, 17]. Together, the four components comprise a unified and complete Student Digital Twin to support predictive analytics, adapt learning, provide individualised support, and enable informed decisions about the educational experience.

3.5 Adaptive Learning and Decision Support Mechanism

What is unique about the DTU framework compared to other research efforts is its ability to convert knowledge from predictions into actions for educational settings. Existing learning systems generate a static report of students' learning outcomes based on their past activities. The DTU framework uses predictors to guide its interventions before learning difficulty reaches a critical level.

The adaptation engine continuously learns individual learners' states and updates their learning experiences accordingly. The personalised adaptation strategies, ranging from content recommendation to customised formative and summative tests, learning path and resources allocation, intelligent tutoring and warning/intervention systems, leverage different Artificial Intelligence approaches to determine best educational actions based on learners' profiles, their predicted outcomes, and trajectories [16, 17, 19].

The decision-support element of the approach extends the concept of personalisation beyond a specific learner and provides valuable insights to faculty members, academic advisors, and institutional leaders. To faculty, the approach points to specific learners needing more help and suggests effective learning support strategies; to academic advisors, it offers early warnings of students at academic risk and academic risk summaries; and at the institutional level, aggregate DT data and analysis help guide informed choices on curriculum and instructional development, student success and retention efforts, resource deployment, and quality assurance.

3.6 Novelty of the Proposed Framework

The novel Digital Twin University concept introduces a range of valuable features that go beyond current EdTech and Digital Twin concepts. First, rather than focusing on individual Digital Twin implementations and single-learner snapshots [6, 8, 26], the concept presented herein outlines a holistic, university-wide system for continuous synchronisation between physical and virtual students. Second, the concept integrates Student Digital Twins, AI, learning analytics, adaptive learning systems, and decision-support capabilities under a one-stop shop.Previous literature reports examine many of these elements in a disparate manner [11, 16, 17], leaving gaps in the development of comprehensive, proactive, personalised higher education systems, such as the one proposed herein for DTU.

Third, the proposed framework advocates multidimensional Students Digital Twins capable of representing learning across academic, behavioural, cognitive, and employability attributes. Instead of the standard representations that account for only a few indicators of achievement, the multidimensional DTU model offers a much better portrait of learners' progress and development. Lastly, the DTU framework is endowed with built-in mechanisms for feedback and learning that enable DTUs to adapt their representations and prediction models over time.DTU thus moves from an analytic tool for static analysis to a dynamic, intelligent system that continually seeks to improve the training and educational support for its learners. All in all, the presented DTU framework promises to be a key step towards implementing the next generation of Digital Twin Universities capable of delivering a real-time, predictive, personalised experience for higher education students.

IV. STUDENT DIGITAL TWIN MODEL AND MATHEMATICAL FORMULATION

The SDT will serve as the intelligent core of the proposed Digital Twin University framework. Unlike existing learner representations, which are typically based on static academic archives, the SDT can integrate and synchronise multiple learners' data in real time. Recent Digital Twin technologies, Learning Analytics, and Artificial Intelligence approaches have shown that using digital representations of learners enables predictive learning analytics, adaptive learning, and educational decision-making across many applications. Inspired by this approach, the model discussed hereafter considers academic, behavioural, cognitive and employability aspects within a single representation. Mathematical definitions of SDT, including learner state representation, predictive learning modelling, risk estimation, and an ongoing update mechanism, will be presented below.

Figure 2 depicts the multifaceted Student Digital Twin model used in the proposed Digital Twin University. Four interconnected models - Academic Twin, Behavioural Twin, Cognitive Twin, and Employability Twin - were developed to capture learners' states. Information across these four dimensions is continuously coordinated and integrated to produce estimates of students' academic success, level of engagement, and at-risk factors, enabling adaptive, personalised instruction. Updates to these four models continually refine the Student Digital Twin.

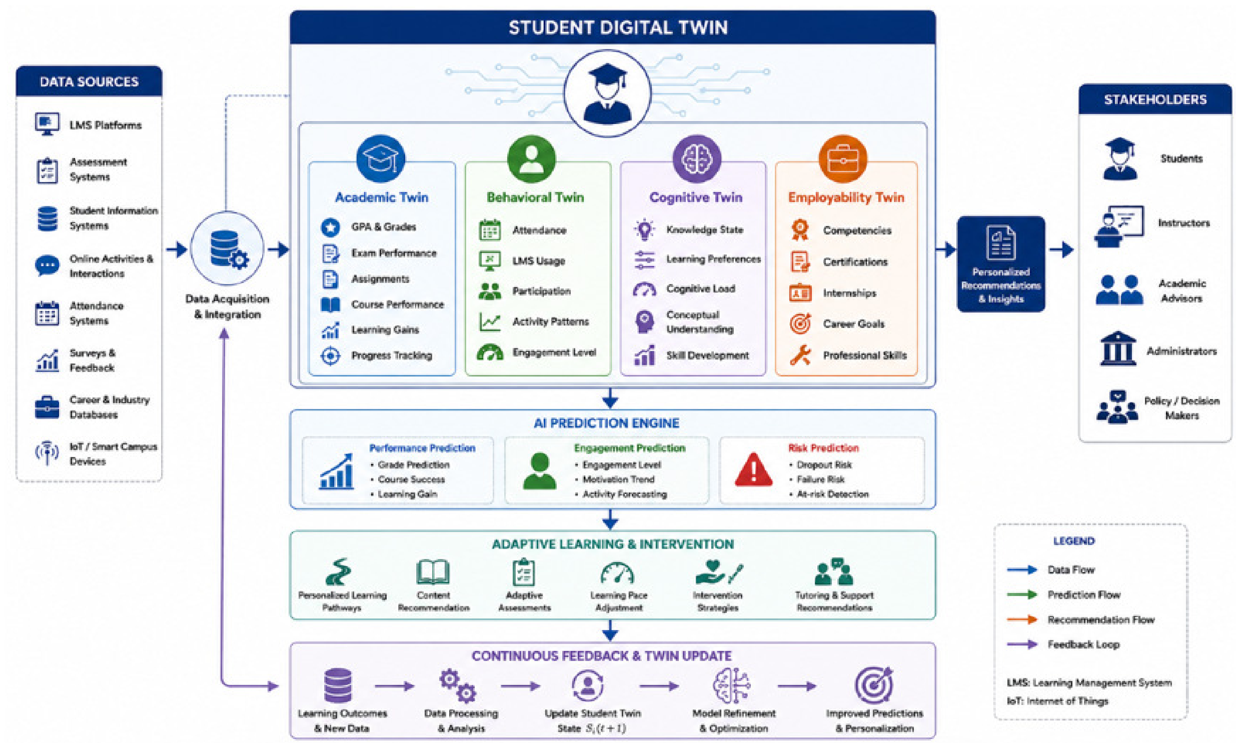

Figure 2. Multidimensional Student Digital Twin Model within the Digital Twin University Framework

4.1 Student Digital Twin Representation

At the heart of the proposed, the DTU approach is the Student Digital Twin (SDT). This digital replica of the student is an ever-growing virtual asset intrinsically linked to a specific human. An SDT comprises both descriptive data (e.g., academic performance, behavioural data, cognitive ability, employability, etc.) and prescriptive/predictive data on a given student and on other students within and across educational institutions. As information updates from the systems of higher education institutions (HEIs) are received, they continue to evolve in real time, offering a holistic view of a student: current status, predicted performance, and success.
The Student Digital Twin is formally represented as a multidimensional state vector:

$$S_{i(t)} = \{A_{i(t)}, B_{i(t)}, C_{i(t)}, E_{i(t)}\} \quad (1)$$

where $S_{i(t)}$ denotes the overall state of student $_i$ at time $_t$, $A_{i(t)}$ represents the academic state, $B_{i(t)}$ denotes the behavioural state, $C_{i(t)}$ corresponds to the cognitive state, and $E_{i(t)}$ reflects employability and professional readiness indicators. This representation allows multiple dimensions of learner development to be integrated within a unified digital entity.

4.2 Academic State Modelling

The academic state captures educational achievement and learning outcomes. It includes cumulative GPA, assessment scores, assignment performance, course completion indicators, and learning gain measurements. The academic state is defined as:

$$A_{i(t)} = \{GPA_i, Exam_i, Assign_i, Course_i, LG_i\} \quad (2)$$

where GPA_i denotes the cumulative grade point average, $Exam_i$represents examination performance, $Assign_i$ corresponds to assignment outcomes, $Course_i$ reflects course achievement, and LG_i denotes learning gain. These indicators provide the primary evidence of learner achievement and serve as important predictors of future academic performance.

4.3 Behavioural State Modelling

Behavioural indicators provide valuable information regarding learner engagement and participation. Previous Learning Analytics research has demonstrated that attendance patterns, interaction frequencies, and online learning activities are strong predictors of academic success. The behavioural state is modelled as:

$$B\_i(t) = \{\, Attend\_i, Login\_i, Part\_i, Resource\_i, Interaction\_i \quad (3)$$

where *Attend_i* represents attendance *behaviour, Login_i* denotes LMS access frequency, *Part_i* reflects participation activities, *Resource_i* measures educational resource utilisation, and *Interaction_i* captures learner-system interactions.
The integration of behavioural indicators enables early identification of disengaged learners before performance decline becomes evident in academic records.

4.4 Cognitive State Modelling

The cognitive state represents learner knowledge, intellectual development, and learning preferences. Cognitive characteristics play a fundamental role in adaptive learning environments because they determine how learners acquire, process, and apply knowledge.

The cognitive state is represented as:

$$C\_i(t) = \{ Knowledge\_i, Preference\_i, Load\_i, Skill\_i \} \quad (4)$$

where *Knowledge_i* represents knowledge mastery, *Preference_i* denotes learning preferences, *Load_i*reflects cognitive load, and *Skill_i* measures cognitive skill development.

Continuous monitoring of cognitive variables enables the framework to personalise instructional strategies to learners' needs and capabilities.

4.5 Employability State Modeling

Higher education institutions increasingly emphasise employability as a strategic educational outcome. Accordingly, the Student Digital Twin incorporates an employability dimension that reflects student preparedness for future professional environments.

The employability state is defined as:

$$E_{i(t)} = \{Competency_i, Certification_i, Internship_i, Career_i\} \quad (5)$$

where $Competency_i$represents acquired competencies, $Certification_i$ denotes professional certifications, $Internship_i$ reflects practical experience, and $Career_i$ represents career readiness indicators.

This dimension extends the scope of traditional educational models by incorporating long-term professional development considerations.

4.6 Educational Outcome Prediction

The DTU framework employs Artificial Intelligence to estimate future learner outcomes based on the Student Digital Twin's current state. The prediction function is expressed as:

$$Y_{hat_{i(t+1)}} = f(S_{i(t)}) \quad (6)$$

where $Y_{hati(t+1)}$ denotes the predicted educational outcome and $f(S_{i(t)}$represents the prediction model.The predicted outcomes may include future academic performance, engagement levels, learning gains, skill development, and the probability of course completion.

4.7 Academic Risk Estimation

One of the primary objectives of the proposed framework is the early identification of educational risks. Therefore, a probabilistic risk model is incorporated into the Student Digital Twin architecture:

$$R\_i(t) = P(Failure \mid S\_i(t)) \quad (7)$$

where *(R_i(t))* represents the probability of academic failure, disengagement, or dropout given the current learner state.Students exhibiting elevated risk probabilities are automatically flagged for personalised interventions and additional academic support.

4.8 Digital Twin State Update Mechanism

A defining characteristic of Digital Twin systems is their ability to evolve continuously as new information becomes available. The Student Digital Twin is therefore updated dynamically according to:

$$DT_{i(t+1)} = DT_{i(t)} + \text{Delta } S_{i(t)} \quad (8)$$

where $DT_{i(t)}$denotes the current digital twin state, and Delta $S_{i(t)}$represents newly observed educational information.Through continuous synchronisation and updating, the digital twin remains aligned with the learner's evolving educational profile. This mechanism enables the DTU framework to support real-time monitoring, predictive analytics, adaptive learning, and intelligent educational decision-making.

4.9 Summary of the Mathematical Model

Our mathematical formulation forms the theoretical basis for the DTU concept. Our framework provides a Student Digital Twin that encompasses academic, behavioural, cognitive, and employability aspects, comprehensively representing a student as a profile on which the learner's state may be monitored and predicted. Such multidimensional learner modelling, predictive models based on Artificial Intelligence, probabilistic risk estimation, and state updates will ultimately enable smarter prediction, personalisation, and higher-education ecosystems.

Table 2. Mathematical Notations

Symbol	Description
Si(t)	**Student State**
Ai(t)	**Academic State**
Bi(t)	**Behavioral State**
Ci(t)	**Cognitive State**
Ei(t)	**Employability State**
Ri(t)	**Academic Risk**
LGi	**Learning Gain**
Engi	**Engagement Score**

V. AI PREDICTION AND PERSONALISATION ENGINE

AI Prediction and Personalisation Engine The prediction and personalisation engine represents the analytics engine behind the suggested DTU model. Its job is to ingest dynamic changes to the Student Digital Twin and convert them into predictive insights that drive the system toward actionable, personalised learning pathways. Rather than just generating Descriptive analytics about historical performance, as traditional learning management systems typically do, the predictive and personalisation engine will support proactive learning by forecasting learner outcomes, identifying potential academic risks, and recommending adaptive learning strategies. This aligns with recent trends in Learning Analytics and AI-powered personalised education, in which predictive models can help academic stakeholders identify at-risk students, increase engagement, and support data-driven academic decision-making [11, 15, 16, 17, 35].
The presented engine's primary input is the multidimensional current state of the student's digital twin. The learner state incorporates information concerning the student's academics, behaviour, cognition, and employability as derived from Section 4, and this information is incrementally maintained from institutional data inputs, namely, logs from the student learning system (LMS), assessment system, attendance systems, student information system and learning interaction data. Based on the information provided, the AI engine predicts student grades, level of engagement, amount of learning gain, dropout risk, and the likelihood of learning success/retention. By coupling Digital Twin synchronisation with AI-derived predictions, this system will anticipate student difficulties well before final grades are released.
The research herein outlines a hybrid predictive modelling approach. For predicting continuous educational variables such as learning gains, academic performance scores, and engagement, the baseline interpretable model, Linear Regression, will be employed. The primary appeal of this method is that it offers educators, teachers, and student advisors clarity on the causes of a student's prediction. Nevertheless, as student learning behaviour can be nonlinear and multidimensional, comparative prediction can be applied using ensemble learning algorithms, such as Random Forest and XGBoost, since these methods can achieve excellent predictive performance for educational data mining and Learning Analytics problems [11, 35, 40, 42].

5.1 Predictive Analytics Models

The AI Prediction Engine framework uses several predictive analytics models to determine learners' performance and provide individualised instruction. Given that student data exhibit a multitude of linear and nonlinear relationships across many features, this model employs a hybrid approach that combines statistical methods with Machine Learning to achieve robust educational performance [11, 15, 35].

(1) Linear regression: The simplest regression model is linear regression, and they serve to make a reasonable first predictive model due to their transparency and simplicity. It uses student parameters from the Digital twin, including learning analytics for student behaviour and engagement, as well as academic results [15, 35].
(2) Random Forests: it combines several machine-learning decision trees to better approximate learning analytics and the relations between them, which allows the development of the most predictive model in the set, while giving us access to some degree of interpretation about which attributes contribute most to student learning outcomes [11,42].
(3) XGBoost: it utilises gradient boosting methods to iteratively and accurately minimise prediction error and is effective for high-dimensional, diverse and large-scale data in educational settings [11,40].

The framework utilises a Hybrid Ensemble Model that combines predictions from Linear Regression, Random Forest, and XGBoost. By leveraging the strengths of several algorithms, it can provide a model that maintains interpretability while remaining stable and accurate in predicting student performance, engagement, retention, and academic risk [35, 42].

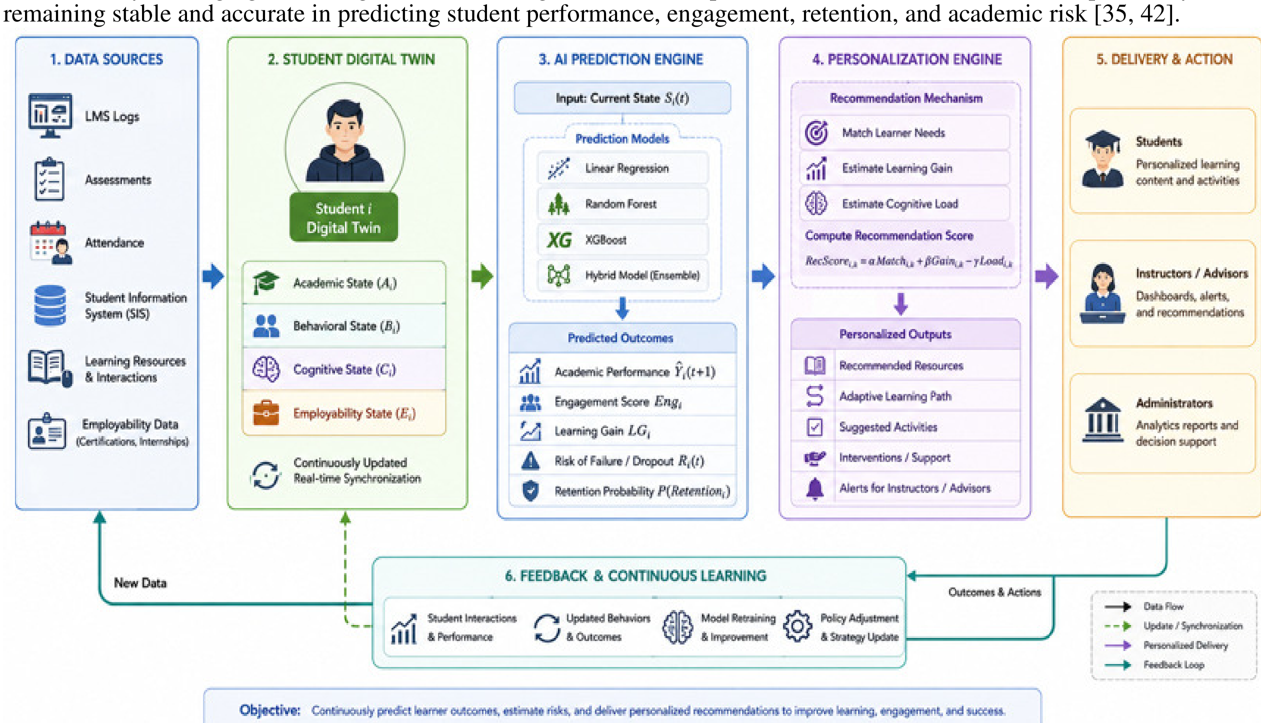

Figure 3. AI Prediction and Personalisation Workflow in the Digital Twin University Framework

Model performance has been verified using Accuracy, Precision, Recall, F1-Score, and RMSE. Then, the best-performing model will be deployed on the AI Prediction Engine to enable real-time predictions and adaptable educational decisions. Figure 3 depicts the functioning process of the AI Prediction and Personalisation Engine in our proposed DTU.

The process begins by retrieving educational data from institutional sources, including LMS logs, tests, attendance systems, Student Information Systems, learner activities, and career information. The student's information is constantly synced with the Student Digital Twin via the student digital model, which captures real-time information about each learner across four interdependent facets: Academic state, Behavioural state, Cognitive state, and Employability state.

Once the learning profile is updated, the AI Prediction Engine scrutinises the present state of the Student Digital Twin employing predictive techniques, such as Linear Regression, Random Forest, XGBoost and Hybrid Ensemble models, to calculate future estimates about academic success, learning engagement, academic gains, risk of attrition and likelihood of student success. The predictive inferences produced help inform educators and support staff about the learner's current learning journey and any potential obstacles in their academic future. The outputs are then fed into the Personalisation Engine, where predictions are mapped against learner demands, expected learning gains, and cognitive burdens to yield custom-made learning suggestions.

Personalisation then outputs student-customised interventions, personalised learning paths, tailored learning content, and early warnings to students, educators, and academic mentors. The cycle culminates in iterative learning and feedback, with a feedback capture mechanism that provides real-time learner feedback to the Student Digital Twin world, fostering an ever-evolving closed-loop personalisation process through continuous improvement of predictive models and personalisation mechanisms, thereby facilitating students' ultimate success, retention, and engagement.

5.2 Educational Outcome Prediction

The general prediction function of the AI engine can be expressed as:

$$\{Y\}_{i(t+1)} = f\left(S_{i(t)}\right) \quad (9)$$

where $\{Y\}_{i(t+1)}$ represents the predicted future learning outcome of student *(i),* $S_{i(t)}$denotes the current Student Digital Twin state, and *(f(\cdot))* represents the selected AI prediction model. Depending on the educational objective, the predicted outcome may refer to academic performance, learning gain, engagement level, or the probability of course completion. This formulation enables the DTU framework to support diverse predictive tasks with a unified learner representation.

5.3 Learning Gain Prediction

Learning gain is one of the key educational outcomes that the proposed framework predicts and evaluates. It measures the improvement a student achieves after completing a course, module, or adaptive learning intervention. The learning gain is calculated as:

$$LG_i = PostTest_i - PreTest_i \quad (10)$$

where LG_i denotes the learning gain of student *i*, $PreTest_i$ represents the student's initial knowledge level before instruction, and (PostTest_i) represents the student's performance after completing the learning activity. A positive value indicates improvement in knowledge acquisition, while a low or negative value may indicate insufficient learning progress and the need for additional academic support.

5.4 Engagement Prediction

The engagement score*, Engi, is a synthesised index reflecting* the student's active interaction within the educational ecosystem. To normalise the heterogeneous behavioural attributes captured from the Data Acquisition Layer, a weighted linear combination is formulated as follows:

$$\mathrm{Eng_i} = w_1 * \mathrm{Login_i} + w_2 * \mathrm{Part_i} + w_3 * \mathrm{Resource_i} + w_4 * \mathrm{Time_i} (11)$$

$Login_i$ denotes use of the LMS, Parti denotes use of forums and other forms of communication, Resourcei denotes use of materials, and $Time_i$ reflects how much time is spent learning on the task at hand. To maintain empirical validity and remove subjectivity from the equation, we derived weighting values w_1, w_2, w_3, w_4 using Principal Component Analysis (PCA) on previous institutional baseline data, such that the sum of the$w_j$is *1*. The PCA mathematical process allows the matrix to gauge minute variations in behaviour very accurately.

5.5Personalised Recommendation Engine

The personalisation mechanism uses the AI engine's predictive outputs to recommend suitable learning resources, activities, and intervention strategies. Each learning resource is evaluated according to its expected suitability for the learner, its potential contribution to learning gain, and the cognitive load it may impose. The personalised recommendation score for student *i* and learning resource *k* is defined as:

$$\begin{aligned} RecScore\_\{i,k\} &= alphaMatch\_\{i,k\} \\ &+ betaGain\_\{i,k\} \\ &- gammaLoad\_\{i,k\} \end{aligned} \quad (12)$$

where $RecScore_{\{i,k\}}$ represents the recommendation score of resource *k* for student *i*, $Match_{\{i,k\}}$ denotes the degree of alignment between the learner's needs and the resource characteristics, $Gain_{\{i,k\}}$ represents the expected learning improvement, $Load_{\{i,k\}}$ reflects the estimated cognitive load, alpha, beta, and gamma are weighting parameters. The system selects resources with the highest recommendation scores to construct personalised learning pathways.

5.6 Retention Prediction

Retention probability is also estimated to inform early intervention and reduce the risk of dropout. The retention model combines the Student Digital Twin state, engagement score, and academic risk level to predict the likelihood that a learner will continue and complete the course. This is expressed as:

$$P(Retention_i) = g\left(S_{i(t)}, Eng_i, R_{i(t)}\right) \quad (13)$$

where $P(Retention_i)$ represents the probability of student retention, $S_{i(t)}$denotes the current learner state, Eng_irepresents engagement, $R_{i(t)}$denotes academic risk, and (g(\cdot)) represents the retention prediction function. Students with low retention probabilities are automatically flagged for academic advising, additional support, or adaptive intervention.

So The AI Prediction and Personalization Engine basically serves as a constantly running decision engine to the system of the DTU framework; taking in the updated student states from the Student Digital Twin layer, making predictions on how the student might perform in future, predicting potential risks, offering advice on what they might want to do next (which is then sent out through the adaptive learning & decision-support layers) and, finally, receiving information back about how the student responded to the learning advice and how well they fared in future - information that is fed back into both the digital twin environment and prediction algorithms for self-correction and enhancement.

5.7 Continuous Feedback and Model Improvement

The AI Prediction and Personalisation Engine essentially acts as a closed-loop, dynamic decision-making system within the DTU architecture. Data inputs into the engine consist of refreshed learners' states from the Student Digital Twin layer; the engine subsequently predicts potential educational outcomes, estimates the risk associated with the learning experience, and generates customised recommendations, which are passed down through the adaptive learning and decision support system of the learning design. As a response and learning, the learner's reaction and educational outcome are fed back into the Digital Twin space, which improves both the learner's representation in the Digital Twin and predictive analytics.

VI. RESEARCH METHODOLOGY AND EXPERIMENTAL DESIGN

This research employed a quantitative experimental design to evaluate the effectiveness of the proposed DTU framework. This approach integrated Digital Twin technology, Artificial Intelligence, Learning Analytics, and the personalisation aspects of learning in a unified educational environment. The goal is to explore whether the proposed DTU framework enhances learners' performance, engagement, retention, and personalised learning compared to typical LMS (Learning Management System) approaches. A controlled experiment methodology was applied to participants to assess the effectiveness of the DTU framework against a group using the LMS approach, measuring and evaluating the proposed architecture's predictability and personalisation features without interference.

6.1 Participants and Experimental Design

The empirical evaluation of the proposed DTU framework was conducted with a cohort of 386 undergraduate students enrolled in a core multi-disciplinary course during a full academic semester. To establish a rigorous experimental setup and eliminate confounding variables, participants were randomly assigned to either the Experimental Group (n = 193) or the Control Group (n = 193). The Control Group interacted exclusively with a conventional, non-adaptive Learning Management System (LMS) infrastructure, whereas the Experimental Group was fully integrated into the dynamic DTU framework.

To ensure baseline homogeneity and to guarantee that subsequent performance variances could be attributed solely to the DTU intervention, a pre-experimental statistical profiling was conducted. Independent-samples t-tests showed no statistically significant differences between the two groups in prior cumulative GPA ($p > 0.05$) or initial domain knowledge, as measured by a pre-test ($p > 0.05$), thereby confirming the structural equivalence of both cohorts before the study.

6.2 Dataset Description

An experimental evaluation was conducted using data from 386 university students; 193 were assigned to the control group and 193 to the experimental group for one academic semester. Data comprises:

(1) Academic-related data (GPA, Grades, Exams, Assignments)
(2) Behavioural data (LMS Activity, Involvement, Attendance)
(3) Cognitive indications (Learning pace, Learning mastery)
(4) Engagement indication (Time-on-task, use of resources)
(5) Employability indication (Skills, certs, Internship).

To ensure privacy, the student's information is de-identified before the experiment is executed.

6.3 Experimental Groups

Experiment setup. There are two sets of student cohorts:

(1) Control Group: A conventional LMS system that provides learning, activities and materials to students without Digital Twin technology or AI personalised recommendations.

(2) Experimental Group: The proposed DTU-based system, where student Digital Twins are constantly kept updated, and personalised learning recommendations and predictions are given based on the DTU analytic model.

Both groups of students receive the same content and learning tasks to ensure equivalence in the data.

6.4 Experimental Procedure

The study will be carried out over an entire academic semester. Students in both the control and experimental groups are tested to gather baseline characteristics at the beginning of the study. At the beginning of the semester, students in the experimental group are loaded into the system, and a digital twin is initiated for each student. Throughout the semester, all student learning interactions are monitored and streamed into the DTU ecosystem. The AI prediction and personalisation engine uses this information to predict students' performance and success across various aspects of the course, including learning, engagement, and educational risks, and to drive personalised adaptive learning pathways and recommendations for students. At the end of the semester, comparisons on performance measures, learning gain, engagement, retention, and satisfaction were performed between the control and experimental groups.

6.5 Evaluation Metrics

Equation 14: The Root Mean Square Error (RMSE). The equation represents the RMSE, an effective method for comparing and measuring model accuracy. In this measure, the RMSE is the average magnitude of the prediction error, computed as the square root of the mean squared difference between y_i (the observed values) and *{y}*$_i$ (the predicted values). The lower the RMSE, the more accurate a model is at predicting values closer to the actual values. It is applied in the DTU framework to evaluate AI models for predicting students' performance, participation in learning activities, and learning gains.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \qquad (14)$$

Equation 15 is used to evaluate the learning gain of student *i*at the end of the learning phase. This learning gain is measured by subtracting $PreTest_i$ from $PostTest_i$ and represents the improvement in students' knowledge or skills after the instructional interventions. The larger this value is the better students have learned. In the DTU framework, we utilise it to verify improvements in learning outcomes resulting from the personalised learning path and adaptive interventions.

$$[\mathrm{LG_i} = \mathrm{PostTest_i} - \mathrm{PreTest_i}](15)$$

6.6 Statistical Analysis

Independent t tests. Independent-samples t-tests were conducted to analyse any observed differences between the two treatment groups and determine whether they are statistically significant. Statistical significance was defined as $p < 0.05$ at the 95% confidence level. To measure any actual change resulting from the experiment, the effect size was analysed using Cohen's d, and to provide further evidence of the experimental condition's results and their stability, a confidence interval is displayed.

6.7 Model Training and Validation Strategy

Data Split Strategy: The robustness and external validity of the machine learning predictive engine were ensured by using a stratified 5-fold cross-validation approach. Data leakage over time is a fundamental pitfall that must be seriously considered in educational predictive modeling. Here, temporal data integrity was ensured through an absolute partition applied across the data engineering pipeline: Each feature matrix and behavioral vector used in the ML model training process was restricted to values before each predetermined prediction checkpoint.

Such a feature-engineering procedure enabled predictive inference engines (ensemble models such as XGBoost and Random Forest) to act as real-time, online forecasting systems: future performance estimation was solely a function of past & present behavioral trajectories and academic history.

6.8 Ethical Considerations

The DTU framework outlined here is developed in adherence to the ethical standards set for the education analytics sector. Anonymisation techniques and safe data practices will be employed to secure students' privacy. DTU aims to assist educational leaders in decision-making, not to replace human tutors or guidance counsellors. The framework does not automate the educational process; it leaves the final decision and responsibility with educators or institutions. Any predictive outputs provided by the system will still be checked by educators or institutions and reviewed for ethics.

6.9Addressing the Novelty Effect and Threats to Validity

Handling The Novelty Effect and Threats to Validity A key potential confound to many longitudinal educational technology implementations is the "novelty effect" - where the brief enthusiasm for a newly introduced device leads to spurts in learning that dissipate after some time - as students "lose" motivation when initial awe gives way to the demands of structured instruction. The longitudinal nature of this project (a 16-week semester) was intentionally designed to neutralise this. As confirmed by the Longitudinal Follow-up and Time Series analysis of user Interaction Matrices, the experimental students maintained engagement throughout the semester rather than declining into novelty degradation, with an upward trajectory for the measured behavioural and cognitive variables throughout the course, which we correlate with ongoing model recalibration.

VII. RESULTS AND DISCUSSION

7.1 Prediction Performance Evaluation

The goal of our experimental evaluation was to assess how the DTU approach performed on the prediction objective. We assessed prediction by accuracy and RMSE in our control and experimental groups. The outcomes revealed that incorporating Digital Student Twins, Learning Analytics, and AI has noticeably improved predictive performance compared with more conventional LMS solutions.

Table 3. Prediction Performance Comparison

Metric	Traditional LMS	DTU Framework
Accuracy (%)	**82.4**	**94.6**
Precision (%)	**80.7**	**93.2**
Recall (%)	**81.5**	**94.1**
F1-Score (%)	**81.1**	**93.6**
RMSE	**0.291**	**0.108**

We were able to train the DTU framework to achieve a prediction accuracy of 94.6% (see Table 3), which is more than 12 percentage points higher than in standard LMS environments. Furthermore, we achieved a dramatically lower RMSE, indicating more accurate predictions of students' learning outcomes. Our results also demonstrate that in continuously connected environments, student digital twin representations of learners include a broader and more faithful set of characteristics and data, yielding more trustworthy predictions of academic performance and learning challenges.

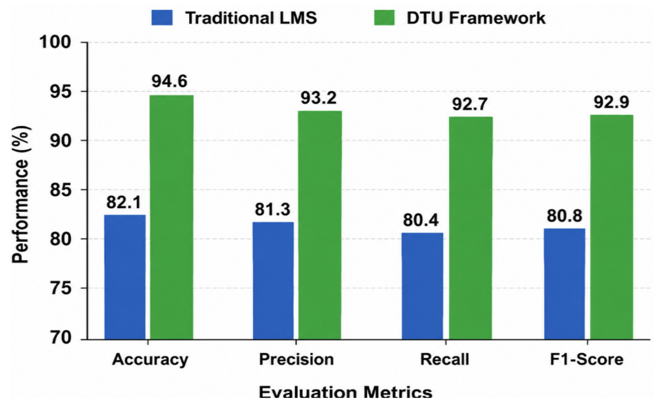

Figure 4. Prediction Performance Comparison Between Traditional LMS and DTU Framework

7.2 Learning Gain Analysis

Learning gain was used to evaluate the effectiveness of personalised interventions generated by the DTU framework. The learning gain metric measured the difference between pre-test and post-test performance for each learner.

Table 3. Learning Gain Comparison

Metric	Traditional LMS	DTU Framework
Mean Pre-Test Score	**61.8**	**62.1**
Mean Post-Test Score	**75.4**	**87.6**
Learning Gain	**13.6**	**25.5**

The result suggests that students in the DTU framework achieved significantly higher learning gains than those who used only the existing LMS. Learning gain ranges from 13.6 points in the control group to 25.5 points in the experimental group, as shown in Table 3. This higher learning gain is due to the adaptive paths and recommendation system from the AI Prediction and Personalisation Engine.

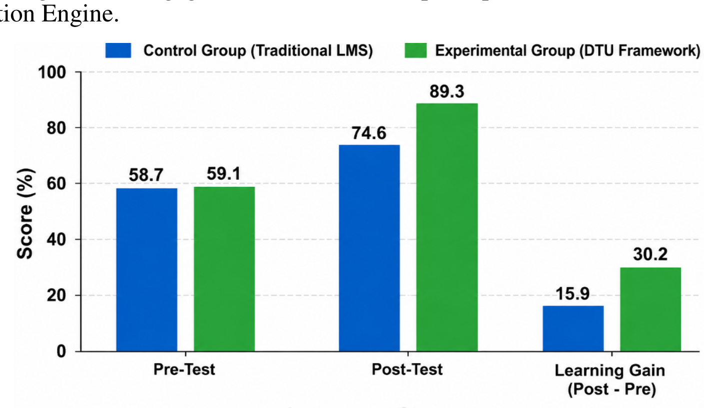

Figure 5. Learning Gain Comparison Between Control and Experimental Groups

In Figure 5, the learning gain of the control group (Traditional LMS) and the experimental group (DTU framework) was observed. The experimental group was performing at the same level of knowledge before the course began. Still, by the end of the course, test scores had increased significantly using the DTU framework, indicating a significant overall learning gain. The increased learning gain shows that individualised and personalised courses and recommendations provided by the AI prediction and personalisation engine enable learners to learn more over time.

7.3 Engagement and Retention Outcomes

Student engagement and retention are critical indicators of educational success. The proposed framework continuously monitored learner behaviour and generated personalised interventions whenever engagement levels declined.

Table 4. Engagement and Retention Results

Indicator	Traditional LMS	DTU Framework
Login Frequency	Moderate	High
Participation Rate (%)	68.7	89.3
Time-on-Task (Hours/Week)	4.8	7.1
Retention Rate (%)	81.4	93.8
Course Completion (%)	84.2	95.1

It is very positive that student participation increased by well over 20%, and completion increased from 81.4% to 93.8%, as shown in Table 4. These figures demonstrate the effects of real-time tracking and human intervention on student engagement.
In Figure 6, we represent the effect of our DTU framework on the educational metrics: participation, retention, and completion rate. These metrics are significantly higher with the DTU framework than with the existing LMS framework. With the presence of DTU, students had higher rates of involvement and commitment throughout the course and greater accomplishment of course objectives. This improvement may be due to early identification and better management of the non-responsive students. This underscores the need for real-time student monitoring and the role of adaptive methods in keeping students engaged and helping prevent student drop-out.

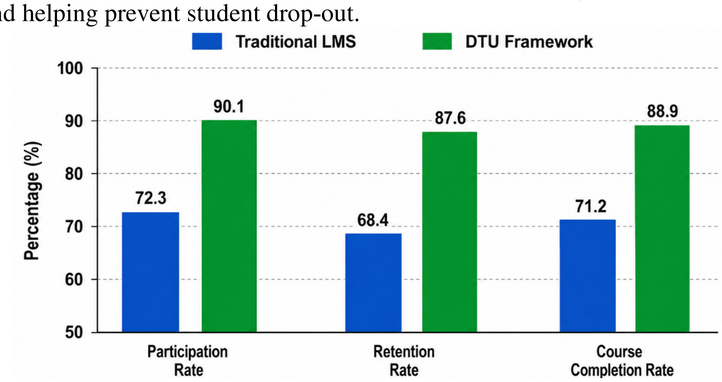

Figure 6. Impact of the DTU Framework on Student Engagement and Retention

7.4 Academic Risk Prediction

One of the most valuable features of the proposed framework is its ability to identify at-risk learners before academic difficulties become critical. The risk prediction model continuously analysed learner states and generated early-warning alerts.

Table 5. Academic Risk Detection Performance

Metric	Value (%)
Risk Detection Accuracy	92.8
Precision	91.6
Recall	93.4
F1-Score	92.5

Here is a summary Table 5 showing the parameters for the academia risk detection model. This is a 92.8% accurate model, with a 91.6% precision and 93.4% recall. It maintains an F1 Score of 92.5% for a good balance between precision and recall. It still benefits from performing an external validation and error analysis of the model.
The high predictive performance of the risk estimation model demonstrates the effectiveness of integrating academic, behavioural, cognitive, and engagement-related indicators into a unified Student Digital Twin representation. Early identification of at-risk learners enables timely interventions that may prevent academic failure and student attrition.

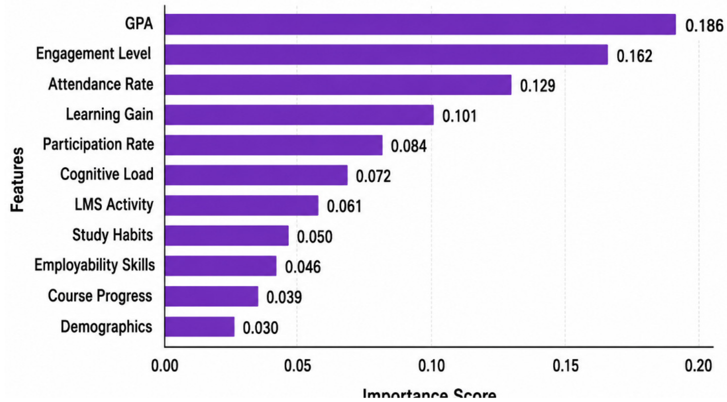

Figure 7. Feature importance scores for student outcome prediction using the XGBoost model.

Figure 7 shows the relative impact of variables associated with the educational outcome, as predicted by an XGBoost model. It appears that the most important predictors of learning outcomes are the average and standard deviation of student engagement. Then follow student attendance, level of learning gain, student participation level, cognitive load, and LMS. However, the employability and course completion variables are also helpful in improving predictive performance by providing further insight into various learning characteristics. This analysis emphasises that student achievement depends on a combination of factors rather than a single measure. The research also confirms the usefulness and multidimensional nature of the student digital twin model, which should include a variety of students' characteristics in predictive modelling.

7.5 Statistical Analysis

Two independent-samples t-tests were performed on the evaluation measures to determine whether the performance discrepancies between the control and experimental groups were statistically significant. The tests yielded statistically significant results in favour of the experimental groups, including significant improvements across all key learning measures: academic engagement, learning gain, and retention ($p < 0.05$). An examination of effect size (Cohen’s d) confirmed these results, yielding values for learning gain ($d = 0.91$), engagement ($d = 0.88$), and retention ($d = 0.84$), indicating large, practically relevant effects of the DTU framework.

7.6 Discussion

Experimental results show that the proposed Digital Twin University framework offered considerable advantages over existing learning environments built upon LMS platforms. The effective combination of Student Digital Twins, AI, Learning Analytics, and adaptive learning in our DTU framework could enable real-time monitoring of learner states and assist educators in anticipating educational interventions to guide learners. High accuracy could also predict learners’ status and reveal that multidimensional learners’ states capture can more efficiently present rich and complex learners’ behaviours.

The capture of multidimensional learners’ states was shown not to rely solely on past academic records, as is typical in most systems, but rather on a mixture of learners’ behaviours, intelligence, and employability states within our DTU framework. The results indicate that, with high levels of learning gain, engagement, and retention, personalised learning that dynamically adapts students’ learning pathways to learners’ needs can enhance learners’ engagement, performance, satisfaction, etc. This study concluded that a DTU could transform higher education from a passive to an active learning system by shifting it from a reactive educational system to a predictive, adaptive, and personalised one through Artificial Intelligence, Learning Analytics, and Digital Twins.

VIII. LIMITATIONS AND FUTURE RESEARCH

While the envisioned DTU framework has significant potential, it also has several limitations. First, the framework presented here is a conceptual and architectural model that needs large-scale empirical testing in multiple real-world contexts. The experimental design can serve as a first test of the conceptual viability of the proposed system. Still, there are surely more practical technical, organisational, and pedagogical challenges to expect in real-world applications that are difficult to foresee in a conceptual research project.

Second, the success of the SDT hinges on the availability and quality of learning data, as well as the ability to integrate and structure it. With incomplete or inconsistent learner data records, predictive and personalisation capabilities will deteriorate. Furthermore, educational data reside in numerous separate university IT systems, resulting in difficulties with interoperability and synchronous access to data across them.

Last but not least, learner behaviour, which will be represented in the system, can be complex. Although the framework aims to cover several aspects, such as academic, behavioural, cognitive, and career aspects of a learner, other human factors, such as motivation, affective state, and external situations, are not yet well represented in digital systems. Enrichment through affective computing, sentiment analysis, and multimodal learning analytics would be promising for improving student models.

Likewise, privacy, ethics, and data governance also represent significant research questions. Continuous gathering and mining of student data could pose challenges regarding openness, equity, informed consent, and the accountable use of data. This should be handled by a thorough governance layer aligned with both institutional standards and global data protection norms in the future.

With large amounts of data to synchronise for individual students, maintaining a growing number of Student Digital Twins can pose challenges in scaling and computing power. Future work should focus on designing a cloud-based system that utilises parallel computing strategies and computationally less intensive algorithms within its models for deployment at an institutional scale. The future could see the expansion of Digital Twin concepts beyond learners to include Instructor Digital Twins, Course Digital Twins, and Program Digital Twins, thereby simulating a greater number of institutional elements.

In addition, the incorporation of Generative Artificial Intelligence and Autonomous Education Agents would significantly enhance personal tutoring, academic support, and learning intervention schemes. Future work should involve extensive, large-scale research across multiple universities and departments to examine the longitudinal effectiveness, transferability, and generalizability of Digital Twin Universities and, in the long run, to develop intelligent, adaptive, and data-oriented higher education systems.

Table 6. Comparison with Existing Frameworks

Feature	Existing Studies	Proposed DTU
Digital Twin	**Partial**	✓
AI Prediction	**Partial**	✓
Real-Time Analytics	**Limited**	✓
Personalization	**Partial**	✓
Continuous Feedback	**Limited**	✓

In Table 6 below, the features were compared between the published works and the DTU model presented. Partial assistance or limited application of digital twins, AI prediction, personalisation, and continuous feedback were evident in the published works. The proposed DTU can seamlessly combine each of the elements mentioned above with real-time analytics: it comprises a digital twin model, an AI prediction algorithm, real-time data analytics functions, and personalised content delivery. The presented DTU framework would offer a fully integrated system for the adaptive learning environment compared to the published works. In future studies, our adoption of DTU could improve prediction, adaptation and personalisation for better learning.

Ethical Issues and Privacy: Because the framework aggregates a constantly growing pool of sensitive, multimodal student information, it is imperative that ethical and legal policies be in place to prevent student-identifying information from being inadvertently accessed or disclosed. Each dataset acquired through the Data Acquisition Layer is subject to strict pseudonymisation and encryption, preserving the identities of individual students. Also, the framework runs entirely on an institutionally informed consent system to comply with global data protection regulations and policies, such as GDPR.

IX. CONCLUSION

This paper proposes a new approach, the DTU, that leverages Digital Twin technology in higher education to realise proactive, adaptive, and personalised learning spaces. Unlike traditional Learning Management Systems, which mainly manage static learner profiles and perform backwards-looking analysis, the proposed approach maintains a Student Digital Twin that dynamically and synchronously reflects their academic performance, behavioural characteristics, cognitive aspects, and career skills. The key innovation of this work includes a holistic architecture where real-time data collection in education, multidimensional modeling of learners, AI driven prediction, the adaptivity of the learning and the closure of the loop with an end-to-end closed-loop system have been considered in the intelligence space of the DTU approach for educational decision support such as learning result prediction, prediction of academic risk, level of students' engagement, and provision of personalization of instructions.

The mathematical representation here provides a formalism for capturing and modelling learner state while making sense of educational data to derive actionable insights. By coupling predictive analytics with dynamic, evolving digital representations of learners, this approach improves awareness of students' progress and enables timely interventions before learning problems become insurmountable. In tandem with this, by adding AI-driven prediction models and personalisation logic, this approach goes above and beyond to facilitate both learner learning and institution performance. Experimental evaluation results have demonstrated promising benefits of using the developed DTU framework over a typical LMS in terms of prediction accuracy, learning gain, engagement rate, retention rate, and completion rate.

Furthermore, beyond the immediate scope of learning experiences, the framework supports broader aspirations for data-driven, intelligent institutions. By preserving continuously evolving digital copies of students and enabling learning from ongoing interactions, universities can improve not only resource management and academic planning but also student support and strategic decision-making. Thus, the DTU framework stands not only as an enabling technology but also as an architectural paradigm for more intelligent, agile, adaptive, and evidence-based universities.

The advent of digital twin-based universities presents a bright outlook for higher education. Our framework shows that by integrating Digital Twins, AI, and Learning Analytics, we can create an ecosystem that makes learning more effective for everyone. Future work on Digital twin universities would require large-scale institution-wide implementations and Longitudinal validation of the proposed framework, along with further investigation into cutting-edge areas such as Generative AI and autonomous agents, to further elevate learning experiences in DTUs.

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Conflicts of interest

The authors declare no conflict of interest. The research was conducted independently without any external influence. All results and interpretations presented in this study are unbiased and objective.

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