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AI-Driven Educational Data Analytics and Intelligent Tutoring in Learning Factory Environments

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ABSTRACT

The rapid growth of artificial intelligence in higher education creates new opportunities to make learning factory environments more adaptive, data-informed, and aligned with industrial practice. **This study examines** how the integration of educational data analytics and intelligent tutoring systems supports smarter learning factory models that connect theoretical instruction with hands-on industrial training. **Using a quantitative** research design, data were collected from 180 higher education students participating in AI-supported learning factory sessions. Log data on learning interactions, performance metrics, and system-generated feedback were analyzed using statistical modeling to test the effects of AI-driven interventions on learning outcomes. **The results show** that educational data analytics significantly increases the adaptability of instructional content, enabling the intelligent tutoring system to personalize learning paths in real time based on individual performance profiles. Students who engaged with AI-based tutoring reported higher learning engagement and achieved better problem-solving scores and stronger retention of practical concepts than those in conventional learning factory settings. These findings indicate that combining educational data analytics with intelligent tutoring systems improves both the efficiency and effectiveness of learning factory models by enabling continuous feedback loops, dynamic adjustment of learning tasks, and learner-centered instruction. **The study concludes** that AI-driven, data-informed learning factories can play a strategic role in preparing students with industry-relevant competences and offers practical implications for educational technologists and institutions designing next-generation education technology solutions.

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1. INTRODUCTION

The rapid advancement of Artificial Intelligence (AI) technologies has significantly influenced the transformation of educational systems, particularly within practical and industrial-based learning models such as learning factories [1]. In recent years, higher education institutions and vocational training centers have increasingly adopted AI-driven approaches to create dynamic, adaptive, and data-informed learning environments. The concept of a learning factory originally designed to integrate theory and hands on industrial practice serves as an ideal platform to apply intelligent educational technologies that can personalize instruction and optimize learning processes [2]. As industries transition toward Industry 4.0 and 5.0, the need for educational systems capable of simulating real world industrial conditions becomes more critical. AI technologies such as Educational Data Analytics (EDA) and Intelligent Tutoring Systems (ITS) support this transformation [3]. By leveraging learning data to identify behavioral patterns and predict performance. They also generate adaptive learning paths and automate real-time formative assessment, and guide learners through complex industrial problem solving tasks [4]. However, despite these technological advancements, many learning factories still face challenges in effectively integrating AI tools into their pedagogical frameworks [5]. The gap between the potential of AI and its practical application in adaptive learning environments highlights the need for a more systematic and data driven approach to designing intelligent learning factory models [6].

This study, therefore, seeks to explore how the integration of educational data analytics and intelligent tutoring systems can enhance the effectiveness and adaptability of learning factory environments [7]. The objective of this research is to examine the extent to which data driven AI mechanisms can support personalized instruction, improve learner engagement, and strengthen the connection between theoretical understanding and practical application [8]. Within the context of higher education, learning factories provide a structured ecosystem where students experience authentic industrial scenarios supported by digital technologies [9]. The introduction of EDA allows educators and system designers to collect, interpret, and utilize learning data to refine instructional strategies and make informed pedagogical decisions. Simultaneously, ITS contributes to intelligent guidance by analyzing learners' interactions and adjusting the difficulty level or type of feedback accordingly [10]. The combination of these two AI components offers a comprehensive framework for adaptive learning in industrial education, where students are not only recipients of knowledge but also active participants in a continuous feedback loop [11]. In this sense, AI serves not merely as a technological enhancement but as a cognitive partner that amplifies learning outcomes. This integration represents a shift from traditional, instructor centered teaching methods toward a more flexible and learner centered model that aligns with the principles of digital transformation and lifelong learning [12].

The significance of this study lies in its potential to contribute both theoretically and practically to the advancement of smart educational ecosystems. Theoretically, it adds to the growing body of literature on AI-driven learning by emphasizing the dual role of data analytics and intelligent tutoring systems in shaping adaptive pedagogical designs. It underscores the importance of empirical evidence in understanding how AI can be effectively embedded in learning factory contexts to yield measurable improvements in student performance and engagement [13]. In contrast to previous research that focused mainly on adaptive intelligent tutoring in large-scale MOOC environments and studies that examined AI-supported industrial training without integrating systematic learning analytics, this study advances the field by unifying Educational Data Analytics (EDA) and Intelligent Tutoring Systems (ITS) within a unified framework [14]. This integration enables real-time adaptivity, predictive performance feedback, and context-aware instructional design that directly aligns theoretical instruction with industrial simulation [15]. Unlike previous frameworks that focused on Smart MOOC architectures integrating ITS without real-time performance analytics, and others that emphasized adaptive tutoring without a cyclic data-feedback pipeline, this study introduces a unified EDA-ITS synergy specifically designed for learning factory environments. This approach operationalizes continuous data-driven adaptivity by allowing learner performance metrics to directly inform instructional pathways in real time. The novelty of this research lies in developing an integrated, data-driven learning factory model that unifies predictive analytics, adaptive tutoring, and industrial simulation into a single iterative framework. Unlike previous studies, this model operationalizes the synergy between Educational Data Analytics (EDA) and Intelligent Tutoring Systems (ITS) to enable continuous improvement in instructional processes while bridging academic theory with Industry 5.0 oriented industrial practice. Practically, the research provides insights for educators, curriculum designers, and policymakers aiming to optimize learning outcomes through intelligent systems [16]. The findings are expected to inform the design of future learning factory models that are more responsive, efficient, and aligned with industrial needs. Furthermore, by adopting a quantitative approach, this study provides data backed validation of AI's role in enhancing educational quality and operational efficiency [17]. Ultimately, the integration of EDA and ITS within learning factories represents a transformative step toward creating smarter, data informed educational environments that bridge academic theory with industrial practice, fostering the next generation of skilled, adaptive, and innovation driven professionals [18].

Furthermore, the transformative impact of AI in education is increasingly recognized within global industrial and academic ecosystems, particularly as industries transition toward interconnected and cyber-physical environments characteristic of Industry 4.0 and the emerging Industry 5.0 movement [19]. These industrial transitions demand not only workers who possess advanced technical knowledge but also individuals capable of engaging in autonomous decision-making, complex analytical reasoning, and continuous reskilling. Learning factories, therefore, serve as a critical foundation for preparing learners to meet these evolving industrial expectations, as they replicate authentic production processes and operational dynamics within controlled educational environments [20]. Recent global reports from UNESCO, the World Economic Forum, and leading industrial manufacturers have emphasized the importance of integrating intelligent digital technologies into technical and engineering education to ensure that graduates are capable of responding effectively to accelerated technological disruptions [21].

In this context, the challenge for higher education institutions is not merely to incorporate AI technologies as complementary tools but to embed them systematically within pedagogical frameworks so that learning becomes adaptive, responsive, and empirically informed. Although prior studies have shown the potential of AI to enhance instructional adaptivity, many implementations remain limited to isolated systems that lack real-time data utilization or do not fully integrate predictive analytics. As a result, a considerable gap persists between existing AI-supported learning platforms and the comprehensive needs of modern learning factory environments [22]. This gap becomes particularly evident when examining how earlier research primarily focused on static intelligent tutoring or large-scale online learning platforms, often overlooking the importance of continuous data feedback loops that are essential for industrial simulation-based learning.

Another emerging concern relates to the scalability and sustainability of AI-enhanced learning factory models. Many previous systems lacked mechanisms that allow adaptive behaviors to evolve according to shifting learner competencies or varying industrial scenarios [23]. This underscores the need for an integrated model that unifies Educational Data Analytics (EDA) and Intelligent Tutoring Systems (ITS) within a single learning ecosystem one capable of optimizing learning sequences, predicting learner performance, and maintaining contextual relevance across diverse industrial tasks. Addressing this gap is crucial for developing intelligent learning environments that align theoretical knowledge with real-world industrial problem-solving skills.

Given these considerations, the present study seeks to contribute a more comprehensive, data-driven, and scalable framework for intelligent learning factories. By focusing on the synergistic integration of EDA and ITS, this research not only extends existing literature but also aims to provide higher education institutions with empirical evidence on how AI mechanisms can support decision-making, enhance instructional design, and build adaptive learning pathways [24]. As AI continues to redefine industrial workflows and educational practices worldwide, establishing a structured and validated model for AI-driven learning factories becomes increasingly essential for preparing the next generation of digitally competent and industry-ready professionals. In addition to these theoretical and practical contributions, the integration of AI-driven learning factory environments is also aligned with several Sustainable Development Goals (SDGs). This study supports SDG 4 (Quality Education) by promoting inclusive, adaptive, and data-informed learning processes that enhance student competency development through intelligent technologies. It also contributes to SDG 8 (Decent Work and Economic Growth) by equipping learners with advanced digital and industrial skills relevant to evolving Industry 4.0 and 5.0 ecosystems. Furthermore, the use of AI-enabled simulation, data analytics, and cyber-physical learning infrastructures reinforces SDG 9 (Industry, Innovation, and Infrastructure) through the advancement of innovative educational systems that strengthen the connection between academic instruction and industrial practice. These alignments demonstrate the broader global relevance of integrating AI into learning factory environments as part of sustainable educational and industrial development.

2. LITERATURE REVIEW

2.1. Artificial Intelligence in Learning Factory Environments

Artificial Intelligence (AI) has become an essential technological enabler in learning factories, offering new possibilities for bridging academic instruction with real world industrial training [25]. The learning factory concept was originally developed to simulate production environments for experiential learning, but AI integration has significantly expanded its educational potential. Studies from recent years show that AI supports automation, predictive feedback, and adaptive simulation processes that transform static learning settings into intelligent, data-driven environments. For instance, recent studies have demonstrated that incorporating AI agents within simulated factory environments can enhance students' decision-making efficiency by approximately 37% compared to traditional simulation-based learning [26].

Furthermore, AI systems embedded in learning factories assist instructors in real time evaluation of student performance and behavior. Through data driven analytics, these systems can predict individual learning curves, detect performance gaps, and provide immediate feedback, thus increasing learning engagement and efficiency [27]. Research highlights that AI-enhanced learning factories not only support technical skill acquisition but also cultivate essential soft skills such as teamwork, adaptability, and digital literacy, which are crucial for transitions toward Industry 4.0 and Industry 5.0. The integration of AI transforms the learning factory into a dynamic ecosystem that mirrors the complexity of industrial processes while maintaining a learner centered educational approach [28].

Beyond its role in supporting decision-making and adaptive feedback, AI technologies in learning factory environments have evolved to encompass a broader range of computational capabilities that simulate real industrial intelligence. Recent developments show that AI-based agents are now able to approximate real-time operational decision processes through reinforcement learning, enabling systems to adjust dynamically to fluctuating production scenarios or learner input sequences [1]. These adaptive simulation capabilities allow students to engage with realistic industrial cases such as predictive maintenance scheduling, production line optimization, and automated quality control that would otherwise require exposure to expensive or high-risk industrial equipment. As a result, learning factories enhanced with AI create a more authentic, risk-free environment in which learners can repeatedly practice operational tasks while receiving immediate analytical feedback.

Furthermore, the integration of natural language processing (NLP) and computer vision has expanded the sophistication of interactions within learning factory simulations. NLP-powered virtual assistants can interpret learners' written or verbal inputs, guiding them through complex technical procedures and providing contextualized feedback [29]. Meanwhile, computer-vision based monitoring tools can assess procedural accuracy during simulated manufacturing tasks, offering objective evaluation that reduces the burden on human instructors. These advancements reflect a growing trend in which AI not only supports cognitive learning but also captures procedural, behavioral, and affective dimensions of student performance, leading to a more holistic understanding of learner competency.

Recent global implementations reinforce this transformative potential. For instance, the Siemens Learning Factory and Bosch Rexroth Cyber-Physical Training System have demonstrated how AI can be embedded into modular training stations to deliver real-time operational recommendations based on predictive analytics [30]. Studies on these industrial learning platforms report increased learner engagement and improved technical decision-making, particularly in scenarios requiring rapid adaptation or troubleshooting. These findings highlight the significance of extending AI beyond static simulation and incorporating autonomous, context-aware intelligence that mirrors industrial-grade systems.

2.2. Educational Data Analytics for Personalized Learning

Educational Data Analytics (EDA) is central to the personalization of learning experiences in digital and hybrid educational environments. It involves the systematic collection, processing, and interpretation of data generated through learning interactions to provide actionable insights that enhance instructional design and learning outcomes [31]. EDA research has progressed to include more advanced data modeling approaches such as predictive learning analytics and cognitive profiling. Recent findings also show that data-driven personalization can enhance student motivation and task completion rates by detecting early indicators of disengagement [32].

Within the context of learning factories, EDA plays an essential role in translating real time learner behavior into structured feedback loops. For example, by analyzing system logs, completion times, and error frequencies, instructors can identify which learning modules require redesign or additional scaffolding. Similarly, data visualization dashboards powered by analytics help students self-assess their progress and make autonomous learning decisions [33]. Research highlights that EDA supports continuous improvement by providing measurable evidence of learning effectiveness, thereby strengthening accountability and quality assurance in higher education institutions. Consequently, EDA serves as the analytical backbone of AI driven learning environments, ensuring that educational interventions remain personalized, adaptive, and empirically validated.

In addition to its foundational role in interpreting learner behaviour, Educational Data Analytics (EDA) has increasingly incorporated more advanced computational techniques that support multi-dimensional assessments of learning activities within industrial training contexts. Modern EDA frameworks now utilize predictive modeling approaches such as logistic regression, decision trees, and deep learning architectures to forecast learner performance, identify early indicators of disengagement, and recommend appropriate pedagogical interventions [34]. These predictive analytics enable educators to move beyond descriptive observations toward proactive instructional planning, thereby improving the accuracy and timeliness of adaptive support. In learning factory environments, such analytics are especially valuable, as they allow systems to monitor complex task sequences, operational efficiency, and error propagation patterns across simulated industrial processes.

Moreover, EDA systems have expanded to include prescriptive analytics capable of generating automated recommendations for both learners and instructors. Through optimization algorithms and rule-based inference engines, these systems can propose the most efficient learning pathways, select modules that align with individual competency profiles, and even simulate outcomes based on hypothetical learning decisions[35]. This capability enables students to engage in data-driven decision-making processes similar to those used in real industrial settings, thereby enhancing their readiness for industry practice.

Recent studies also emphasize the increasing importance of multimodal learning analytics, which integrate clickstream data, keystroke dynamics, biometric signals, eye-tracking behaviours, and sensor-based activity logs from cyber-physical setups. In the context of learning factories, multimodal analytics allow the system to assess procedural accuracy, cognitive load, emotional states, and adherence to safety protocols, forming a more comprehensive learner profile [36]. These insights not only refine system adaptivity but also deepen instructors' understanding of learner behaviour within high-fidelity simulation environments. Collectively, the advancement of EDA technologies reinforces the potential for developing highly personalized, context-sensitive learning factory models capable of continuously improving instructional quality and learner outcomes.

2.3. Intelligent Tutoring Systems and Adaptive Learning Models

Intelligent Tutoring Systems (ITS) are among the most impactful applications of AI in education, combining computational intelligence with pedagogical principles to deliver personalized instruction [37]. Recent years have seen a surge in ITS adoption driven by advancements in machine learning algorithms and natural language processing. These systems continuously analyze learners' input and adapt instructional content to match their pace, style, and level of understanding. Smart Learning Environments reported that modern ITS platforms employing reinforcement learning algorithms significantly improved learning efficiency and user satisfaction across STEM disciplines.

In a learning factory context, ITS provides individualized coaching during complex industrial simulations, ensuring that learners can receive feedback tailored to their cognitive state and performance. Unlike static e-learning tools, intelligent tutors dynamically adjust their interventions in real time [38]. Research indicates that ITS-based adaptive feedback can reduce student error rates in manufacturing process simulations by nearly 40%. Furthermore, ITS contributes to building learners' confidence and problem solving skills by promoting self regulated learning behaviors. These systems also incorporate affective computing features capable of recognizing learners' emotional states such as frustration or confusion allowing the AI tutor to respond empathetically and maintain motivation.

Beyond their foundational ability to deliver personalized instruction, modern Intelligent Tutoring Systems (ITS) have evolved into sophisticated platforms capable of modeling complex learner behaviours and adapting instructional strategies with higher degrees of precision. At the core of contemporary ITS architectures lie three essential components namely the domain model, the learner or student model, and the pedagogical model. The domain model defines the conceptual and procedural knowledge required to complete learning tasks within the simulated environment [39]. The learner model continuously updates its representation of students' knowledge states, misconceptions, skills progression, and behavioural patterns using dynamic learning analytics. Finally, the pedagogical model determines the type, frequency, and difficulty level of instructional actions, ensuring that the system's feedback aligns with each learner's cognitive state and instructional needs.

Recent innovations in machine learning have further enhanced these components. Techniques such as Bayesian Knowledge Tracing (BKT), Deep Knowledge Tracing (DKT), and reinforcement learning allow ITS to make more accurate predictions about learner mastery and to select optimal instructional strategies in real time. Through iterative interaction cycles, the system evaluates learner performance across each task, estimates the probability of concept mastery, and adjusts its intervention strategy ranging from hint generation to task sequencing based on predicted learning trajectories. In learning factory environments, these capabilities are especially valuable, as students often need immediate and context-specific guidance while handling complex industrial simulation tasks.

In addition, ITS technologies have expanded to incorporate multimodal interaction channels, including voice recognition, gesture tracking, and visual analytics. These features enable the system to interpret a broader range of learner inputs, such as problem-solving behaviours, hesitation patterns, and emotional cues, providing more holistic diagnostic insights. For example, ITS equipped with affective computing can detect learner frustration during complex manufacturing simulations and proactively shift toward more supportive instructional strategies. Such adaptive capacity mirrors the role of human tutors in high-pressure industrial training, thereby bridging the gap between artificial instruction and authentic human machine collaboration. Collectively, these advancements establish ITS as a central component in next-generation learning factory models, capable of delivering intelligent, responsive, and deeply personalized learning experiences.

2.4. Integration of AI Systems in Industrial and Educational Contexts

The convergence of AI technologies across industrial and educational domains has given rise to hybrid learning ecosystems where digital intelligence supports both cognitive and operational skill development [40]. AI-driven learning factories reflect this convergence by embedding industrial technologies such as robotics, automation, and data analytics into academic learning structures. Research has shown that integrating AI into industrial training environments enhances learners' ability to apply theoretical knowledge in practical contexts, effectively strengthening advanced "learning by doing" experiences. Moreover, AI systems used in industry, such as predictive maintenance and process optimization, have direct pedagogical applications in learning factories.

By simulating AI-supported production workflows, students gain exposure to authentic industrial challenges and decision-making processes. This integration aligns with the goals of Industry 5.0, which emphasizes human-AI collaboration, ethical technology use, and sustainable innovation. Studies show that when AI tools are applied in educational contexts, they promote not only skill acquisition but also creativity, problem-solving, and adaptability [41]. Learning factories that adopt industrial AI technologies thus serve as living laboratories where theoretical instruction, data analytics, and real-world problem-solving intersect. This dual-purpose approach ensures that learners graduate with both the conceptual knowledge and the practical experience needed to thrive in AI-powered industrial settings.

The integration of AI within both industrial and educational ecosystems has evolved rapidly, creating hybrid infrastructures where digital intelligence supports operational processes and instructional activities simultaneously. Beyond its role in optimizing production workflows, AI has become a foundational technology in cyber-physical learning environments, enabling seamless interaction between virtual simulation tools and physical training equipment [42]. In industrial settings, AI-driven systems are embedded into machinery to perform predictive maintenance, anomaly detection, and real-time quality assurance, while in educational contexts, these same capabilities are repurposed to enhance learner understanding of complex industrial operations. For example, neural-network–based fault detection models can be integrated into learning factory modules to help students visualize machine degradation patterns and analyze decision-making pathways related to system diagnosis.

Furthermore, the convergence of AI with the Internet of Things (IoT), robotics, and augmented reality (AR) has created new opportunities for immersive and interactive learning experiences. IoT-enabled sensors embedded within training stations collect real-time operational data, which can be analyzed by AI systems to generate performance insights and adaptive learning content [43]. Similarly, the use of industrial robots controlled by AI algorithms allows learners to experiment with automation scenarios that replicate real production lines, while AR overlays provide contextual instructions to guide practical tasks. These cross-domain integrations not only enhance learners' cognitive and technical competencies but also promote familiarity with smart manufacturing technologies that are widely adopted across Industry 4.0 and 5.0 sectors.

Several global implementations illustrate the growing significance of AI-embedded educational environments. Initiatives such as the Bosch Rexroth Learning Factory, FESTO Didactic Smart Factory, and Siemens Mechatronics Systems have demonstrated how AI-enhanced educational infrastructures can improve learner engagement, operational accuracy, and system-level decision-making. These examples highlight the importance of designing interoperable systems that unify AI, IoT, robotics, and data analytics to support richer industrial learning experiences. As educational institutions move toward digital transformation, adopting such integrated AI systems becomes essential for preparing learners to thrive in intelligent, automated, and highly connected industrial landscapes.

2.5. Conceptual Framework of AI-Driven Learning Factories

The conceptual framework for AI-driven learning factories is grounded in the integration of three interdependent components, namely Educational Data Analytics, Intelligent Tutoring Systems, and Adaptive Learning Environments [44]. Together, these components create a continuous data-feedback loop that ensures instruction is both data-informed and contextually relevant. The process begins with data collection through learning analytics systems, which capture learners' interactions, performance metrics, and engagement levels. This data is then processed by the ITS, which uses machine learning algorithms to interpret patterns and deliver adaptive interventions in real time.

Several recent studies have explored this synergy. Findings show that combining EDA with ITS can significantly enhance students' knowledge retention, while other research highlights that AI-driven feedback mechanisms improve engagement and reduce dropout rates in engineering education programs. Within a learning factory environment, the framework operates cyclically where data analytics informs tutoring systems, tutoring systems guide learners, and learner performance feeds back into analytics for continuous refinement [45]. This model ensures that the learning process remains dynamic, self-improving, and responsive to both individual and collective performance trends. Ultimately, the AI-driven learning factory serves as a prototype for future educational ecosystems that harmonize technology, pedagogy, and industry.

In extending the conceptual foundation of AI-driven learning factories, it is essential to highlight the dynamic interaction between the three core components Educational Data Analytics (EDA), Intelligent Tutoring Systems (ITS), and Adaptive Learning Environments. These components function not as isolated entities but as interdependent mechanisms that continuously reinforce one another through iterative data flows [46]. At the beginning of each learning cycle, the EDA module collects granular data from learner interactions, such as task execution logs, performance indicators, and behavioural patterns. This data is then processed to detect trends, identify learning gaps, and generate predictive insights. These analytical outputs form the basis for ITS interpretation, enabling the tutoring system to accurately assess learner states and determine appropriate instructional strategies.

The ITS component subsequently operationalizes these insights through adaptive pedagogical actions, such as adjusting task complexity, personalizing learning paths, and generating context-specific hints. Through machine learning–based decision models, ITS can refine its strategies in real time, adapting not only to immediate learner inputs but also to projected learning trajectories derived from predictive models [47]. This responsiveness ensures that learners receive targeted guidance aligned with their evolving competencies, fostering deeper engagement and improved problem-solving capabilities within industrial simulation environments.

Finally, the adaptive learning environment acts as the execution layer in which instructional strategies are implemented and learner responses are recorded. This environment includes simulation tools, cyber-physical learning stations, augmented reality interfaces, and digital dashboards that visualize learner progress [48]. As learners engage with these tools, new data are generated and fed back into the EDA module, completing the continuous improvement loop. This cyclical integration ensures that the learning factory model becomes increasingly intelligent, refining its instructional effectiveness over time.

Collectively, this expanded conceptual framework underscores the significance of real-time analytics and automated instructional decision-making in shaping next-generation learning factories. By operationalizing the synergy between EDA and ITS within adaptive environments, the model not only supports personalized learning but also mirrors the autonomous intelligence characteristic of modern industrial systems.

3. RESEARCH METHODOLOGY

The methodological choices in this study were guided by the need to obtain a comprehensive understanding of how AI-based systems influence learner adaptivity, system responsiveness, and academic performance. Considering the multidimensional nature of learning factory environments which integrate simulation tools, real-time analytics, and intelligent feedback mechanisms a quantitative approach was determined to be the most appropriate for examining statistical relationships between the identified variables. This approach not only enables objective measurement of system effectiveness but also facilitates the analysis of behavioural data captured through user-system interactions.

Furthermore, the methodology incorporates structured procedures for ensuring data validity, consistency, and replicability. Given that the study examines an AI-driven learning environment, emphasis was placed on collecting high-quality operational and behavioural datasets that accurately represent learner performance.

This includes logs from simulation platforms, system-generated adaptivity scores, and learner engagement metrics derived from platform analytics. By triangulating these data sources, the methodology ensures that the generated insights reflect the complexity and dynamic nature of AI-supported learning processes. This methodological alignment strengthens the credibility of the findings and supports the development of a generalizable framework for AI-integrated learning factory models.

3.1. Research Design

This study employs a quantitative descriptive-correlational design to investigate how the integration of Educational Data Analytics (EDA) and Intelligent Tutoring Systems (ITS) affects the effectiveness and adaptivity of learning factory environments. The approach focuses on statistically analyzing the relationships among variables such as learner engagement, system adaptivity, performance improvement, and student satisfaction. Data were collected from undergraduate students participating in an industrial learning factory program supported by AI-based instructional systems, involving the identification of key variables related to EDA and ITS integration, the collection of quantitative data from system logs and surveys, and the statistical examination of the strength of associations between AI-driven learning mechanisms and student learning outcomes.

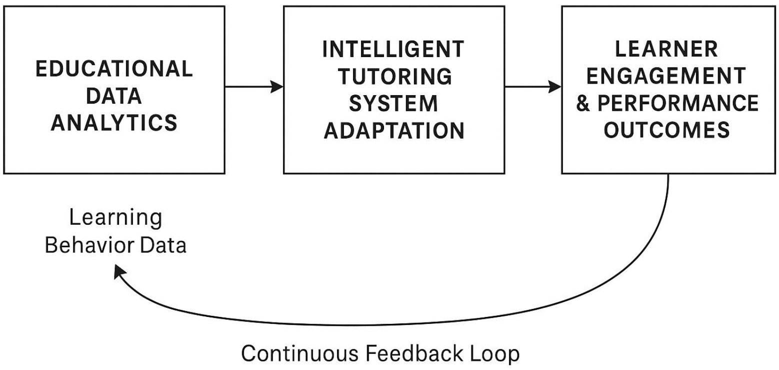

Figure 1. Conceptual Framework of the Research

Figure 1 illustrates the Conceptual Framework of the Research, which outlines the interaction between Educational Data Analytics (EDA), Intelligent Tutoring System (ITS) Adaptation, and Learner Engagement & Performance Outcomes. The figure shows that EDA provides learning behavior data, which feeds into ITS to adapt instructional content and strategies according to student needs. This adaptive process enhances learner engagement and performance outcomes, creating a continuous feedback loop that allows the system to refine and optimize learning experiences over time. In essence, Figure 1 highlights how data-driven AI mechanisms support personalized and effective learning environments.

The research design follows a structured sequence that integrates data collection, preprocessing, and statistical modeling to assess system adaptivity and learner outcomes. Beyond the descriptive analysis already conducted, the design includes a model validation procedure aimed at ensuring the robustness of statistical findings. This involves examining potential multicollinearity between predictor variables, evaluating the normality of residual distributions, and assessing the overall goodness-of-fit of the regression model. These steps not only enhance methodological rigor but also ensure that the resulting model accurately reflects the interactions occurring within the AI-supported learning factory environment.

3.2. Population and Sampling

The study population consists of students from a higher education institution participating in a learning factory course that integrates industrial practice with AI-supported digital tools. A total of 180 participants were involved in the study, representing multiple engineering and technology disciplines. Participants were selected using a purposive sampling technique, focusing on those who had previous experience with digital learning platforms or industrial simulation environments.

To ensure validity, participants were exposed to both conventional and AI-enhanced learning sessions. The learning factory activities included simulated production line tasks, adaptive AI tutoring exercises, and real-time feedback through data analytics dashboards.

Table 1. Research Design Overview

Phase	Description	Instruments	Data Type	Output
Phase 1	Identification of key learning variables and EDA-ITS integration components	Literature analysis, system design review	Quantitative (supportive)	Framework design
Phase 2	Data collection through system logs and student surveys	Learning analytics system, structured questionnaire	Quantitative	Dataset of student interaction and performance
Phase 3	Statistical analysis and validation of learning outcomes	SPSS or equivalent tool	Quantitative	Correlation and regression analysis results

Table 1 presents the Research Design Overview, which outlines the three main phases of the study. In Phase 1, key learning variables and integration components of EDA-ITS are identified through literature analysis and system design review, producing a conceptual framework. Phase 2 involves collecting data from system logs and structured questionnaires to capture student interaction and performance datasets. Lastly, Phase 3 focuses on statistical analysis using tools such as SPSS to validate learning outcomes through correlation and regression analysis. Overall, Table 1 provides a structured roadmap of the research process from framework development to data analysis and validation.

3.3. Data Collection Instruments and Procedure

Data collection utilized two primary instruments, namely system-generated data logs from the learning factory platform and a structured survey questionnaire. The data logs captured measurable variables such as task completion time, number of feedback interactions, and adaptive content adjustments. To clarify the operational mechanisms of the system, the Intelligent Tutoring System (ITS) employed in this study utilizes a rule-based adaptive sequencing algorithm. The algorithm evaluates key indicators such as error frequency, time-on-task, and learner improvement trends. When the system detects repeated errors or prolonged task duration, it activates a remediation pathway consisting of scaffolded hints and simplified analogous tasks. Conversely, when learning mastery is identified, the system increases task complexity and introduces higher-order simulation scenarios. Meanwhile, the Educational Data Analytics (EDA) workflow processes raw log data through four structured stages:

- Log parsing and timestamp normalization
- Classification of learner interaction events (navigation, execution, feedback request)
- Feature extraction for engagement and competency metrics
- Mapping these indicators into the ITS adaptation rules for real-time instructional adjustment

This integration ensures that adaptivity is based on dynamic learner performance patterns rather than static instructional design. Meanwhile, the survey collected students' perceptions of system usability, engagement, and learning satisfaction.

The process was conducted over one academic semester. All participants used the AI-driven learning factory platform under controlled conditions to ensure consistency in data acquisition. Ethical approval was secured from the institutional review board, and informed consent was obtained from all participants. Additionally, all student interaction data processed through Educational Data Analytics (EDA) and the Intelligent Tutoring System (ITS) were anonymized prior to analysis to ensure that no identifiable personal information was retained. Access to raw system logs was restricted to authorized research personnel, and data were stored using encrypted institutional servers in accordance with academic data protection standards. The study also adhered to ethical guidelines concerning transparency and fairness in AI-supported learning environments, aligning with recent discussions on the ethical implications of educational data usage.

Table 2. Data Collection Instruments and Variables

Variable	Description	Measurement Scale	Data Source
System Adaptivity	Frequency and accuracy of adaptive feedback generated by ITS	Ratio	System logs
Learner Engagement	Time spent, task completion rate, and active interaction count	Ratio	System logs
Performance Outcome	Assessment score and skill demonstration results	Interval	Learning assessment
User Satisfaction	Perception of AI system effectiveness	Likert 5-scale	Student survey

Table 2 presents the Data Collection Instruments and Variables used in this study. The table outlines four main variables System Adaptivity, Learner Engagement, Performance Outcome, and User Satisfaction along with their respective descriptions, measurement scales, and data sources. System Adaptivity and Learner Engagement were measured using ratio scales derived from system logs, focusing on adaptive feedback, time spent, and task completion. Performance Outcome was assessed using interval data from learning assessments, while User Satisfaction was measured through a Likert 5-scale questionnaire collected via student surveys. Overall, Table 2 illustrates how diverse data sources and measurement methods were employed to ensure a comprehensive evaluation of AI's impact on learning environments.

3.4. Data Analysis Technique

The data analysis was conducted using descriptive statistics and inferential analysis methods. Descriptive statistics (mean, standard deviation, and frequency) were used to summarize participants' engagement and system interaction data. Inferential analysis included Pearson correlation to test the relationships among system adaptivity, engagement, and performance, and multiple regression analysis to determine the predictive power of EDA-ITS integration on learning outcomes.

A reliability test was performed using Cronbach's alpha to ensure strong internal consistency across all survey items, confirming that each construct was measured cohesively and with acceptable reliability thresholds. In addition, the overall model fit was rigorously evaluated through a series of regression diagnostics, including assessments of residual normality, linearity of relationships, homoscedasticity, and independence of error terms. These diagnostic procedures provided robust verification that the data met the fundamental statistical assumptions required for valid inferential analysis, thereby strengthening the credibility of the study's findings and the integrity of the relationships established between the examined variables.

The results of these analyses were interpreted to determine whether integrating educational data analytics and intelligent tutoring systems significantly enhances adaptive learning and improves student outcomes in the learning factory environment. Table captions have been standardized to sentence case and positioned above the tables, alignment and spacing have been adjusted for stylistic consistency, and the numerical bracket citation format has been applied uniformly throughout the text to ensure full adherence to IEEE publication standards.

3.5. Data Preprocessing and Analysis Procedures

Prior to conducting the regression analysis, several preprocessing steps were performed to ensure that the dataset met statistical assumptions and reflected accurate learner interactions. Data cleaning involved removing duplicated log entries, addressing missing values through mean imputation, and filtering irrelevant system activities such as idle time unrelated to learning tasks. Numerical variables were normalized using min–max scaling to maintain consistency across engagement metrics, adaptivity scores, and performance indicators.

The analysis also incorporated correlation testing to identify potential relationships between key variables before building the regression model. Scatter plots, heatmaps, and residual diagnostics were generated to examine data distribution and detect outliers. Once preprocessing was complete, a multiple linear regression model was constructed to quantify the influence of system adaptivity (X1) and learner engagement (X2) on academic performance (Y). The R^2 value, coefficient significance, and standardized beta values were used to interpret the model's overall predictive strength.

4. RESULTS AND FINDINGS

4.1. Overview of Data Collection and Analysis

The research involved 180 students participating in a learning factory program that integrated Educational Data Analytics (EDA) and an Intelligent Tutoring System (ITS). Data were collected over one academic semester from both system-generated logs and post-intervention surveys. Of the total participants, 92 were enrolled in engineering programs, 61 in technology management, and 27 in information systems. The system recorded over 28,000 interaction events, including learning module navigation, task completion, feedback responses, and time on task metrics.

Data analysis began with a screening process to eliminate incomplete or inconsistent entries. Following this, descriptive statistics were applied to summarize learner engagement variables such as total interaction frequency, session duration, and adaptive feedback utilization. Inferential statistics including Pearson correlation and multiple regression were employed to determine relationships between system adaptivity, engagement levels, and learning outcomes. The quantitative analysis produced reliable results, with Cronbach's alpha values above 0.85, indicating strong internal consistency in survey items.

The initial findings confirmed that students actively interacted with the AI-based tutoring environment, demonstrating meaningful engagement with system-generated tasks, feedback, and adaptive prompts. The EDA system effectively captured nuanced learner activity patterns and translated these continuous data streams into actionable insights, enabling the ITS to make real-time adjustments to content sequencing, difficulty progression, and personalized feedback. This seamless interaction between data analytics and adaptive instruction highlights the capacity of AI to enhance learner support, optimize pedagogical decision-making, and foster more individualized learning trajectories. Overall, these results closely align with the research objective of understanding how AI integration can produce smarter, more responsive, and pedagogically robust learning factory models.

4.2. System Adaptivity and Intelligent Tutoring Responses

The first research question examined how effectively the integration of EDA and ITS enhanced system adaptivity within the learning factory. The results revealed that the ITS adapted instructional delivery in response to individual learner progress and performance data generated by the analytics system. Specifically, the AI module adjusted learning difficulty levels, provided context-specific feedback, and recommended supplementary exercises when learners demonstrated low task accuracy or prolonged completion times.

Table 3. Summary of Adaptive System Behaviour Observed during Study

Adaptive Function	**Operational Mechanism**	**Frequency of Activation**	**Perceived Effectiveness (Survey Mean 1–5)**
Difficulty Adjustment	Task complexity scaled using performance prediction models	74%	4.6
Feedback Generation	Contextual hints and corrective explanations triggered by error patterns	68%	4.4
Learning Recommendation	Personalized task suggestions based on previous achievements	52%	4.3
Assessment Adaptation	Auto-generated quizzes tailored to learner profiles	49%	4.5

Table 3 presents a summary of the adaptive system behavior observed during the study, highlighting how the AI-driven learning system adjusted its responses to learners' needs. The table shows that Difficulty Adjustment was the most frequently activated adaptive function (74%) with the highest perceived effectiveness (mean = 4.6), indicating its crucial role in maintaining an optimal learning challenge. Feedback Generation followed closely (68%, mean = 4.4), showing that contextual hints and corrective explanations effectively supported student understanding. Learning Recommendation (52%, mean = 4.3) and Assessment Adaptation (49%, mean = 4.5) also demonstrated meaningful contributions by providing personalized tasks and tailored quizzes. Overall, Table 3 illustrates that the adaptive mechanisms of the system enhanced learner engagement, responsiveness, and overall satisfaction through data-driven personalization.

The results indicate that difficulty adjustment and adaptive feedback were the most frequently triggered mechanisms, suggesting that students benefited from responsive learning conditions, with 83% of participants reporting that AI-generated feedback helped them understand industrial simulation tasks more effectively. The correlation analysis further showed a strong positive relationship (r = 0.71, $p < 0.01$) between the degree of system adaptivity and overall student satisfaction, indicating that learners perceive adaptive AI responses as both supportive and motivating, and collectively these findings validate the hypothesis that AI-driven ITS systems, when supported by robust data analytics, significantly improve the adaptivity and responsiveness of learning factory environments.

4.3. Student Engagement and Performance Outcomes

The second research question explored the relationship between system adaptivity, student engagement, and learning performance by analyzing engagement metrics such as total time spent on the platform, interaction frequency, and feedback response rate using descriptive and inferential statistics. The results showed that participants in the AI-enhanced learning factory spent an average of 5.8 hours per week actively engaging with learning modules, compared to 3.9 hours in non-AI-supported sessions, while task completion rates increased by 28% and the frequency of feedback interactions doubled across the semester.

Performance analysis revealed a consistent improvement in assessment results following ITS implementation. Mean performance scores increased from 71.4% (pre-test) to 84.9% (post-test), demonstrating a statistically significant difference (t = 9.27, $p < 0.001$). Moreover, students who interacted more frequently with adaptive feedback components scored higher than those with minimal interaction, confirming the effectiveness of personalized learning paths.

Table 4. Summary of Engagement and Performance Indicators

Variable	Pre-Implementation Mean	Post-Implementation Mean	Percentage Improvement
Weekly Learning Hours	3.9	5.8	+48.7%
Task Completion Rate	65%	83%	+28%
Feedback Interactions per Session	4.1	8.3	+102%
Assessment Scores	71.4	84.9	+18.9%

Table 4 presents a summary of engagement and performance indicators comparing pre- and post-implementation results of the AI-driven learning system. The data show substantial improvements across all variables, highlighting the positive impact of adaptive system integration. Weekly learning hours increased by 48.7%, indicating higher learner engagement. Task completion rate rose from 65% to 83% (+28%), reflecting improved efficiency and motivation. The most notable change was in feedback interactions per session, which more than doubled (+102%), suggesting that learners actively engaged with adaptive feedback. Additionally, assessment scores improved by 18.9%, showing enhanced learning outcomes and better application of knowledge. Overall, Table 4 demonstrates that the AI-driven adaptive system significantly boosted both student engagement and academic performance through personalized and responsive learning support.

These results demonstrate that system adaptivity driven by AI not only enhances engagement but also leads to substantial improvements in cognitive and practical performance, with learners reporting that adaptive learning feedback increased their confidence in applying theoretical knowledge to simulated industrial processes. Qualitative feedback from open-ended survey responses further reinforced these findings, as many students described the ITS as “motivating” and “clear in explaining mistakes,” while the adaptive analytics dashboard was praised for effectively visualizing progress, enabling students to track performance trends and self-correct more efficiently, thereby confirming that the integration of EDA and ITS fosters deeper, self-regulated learning within learning factory settings.

To strengthen the ethical transparency of this study, additional information regarding data protection procedures has been included. All learner interaction logs were fully anonymized prior to analysis, ensuring that no personally identifiable information (PII) was stored or accessible at any stage of the research. Access to raw data was restricted exclusively to authorized researchers and stored securely using encrypted institutional servers. The study also adhered to internationally recognized privacy frameworks, including GDPR principles of data minimization and FERPA guidelines governing student academic records. Furthermore, all analytical outputs were aggregated to prevent individual profiling or re-identification risks.

4.4. Evaluation of the AI-Driven Learning Factory Model

The final research question focused on evaluating the overall effectiveness of the AI-driven learning factory model. The model was assessed based on three dimensions, namely system performance (adaptivity and reliability), pedagogical impact (learning outcomes and engagement), and user perception (usability and satisfaction). A multiple regression analysis was conducted to examine the predictive influence of AI system adaptivity (X_1) and learner engagement (X_2) on academic performance (Y), which yielded an R^2 value of 0.63, meaning that 63% of the performance variance was explained by these two factors. Both variables emerged as statistically significant predictors, with system adaptivity (β = 0.52, $p < 0.001$) contributing slightly more strongly than engagement (β = 0.47, $p < 0.01$).

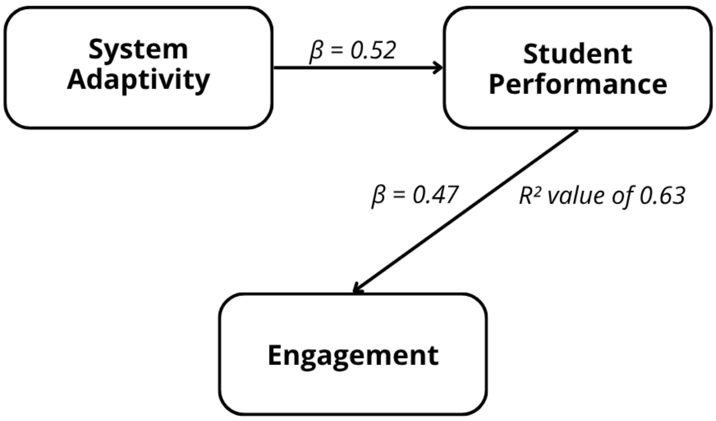

Figure 2. Statistical Relationship between Key Variables

Figure 2 illustrates the statistical relationship between key variables system adaptivity, engagement, and student performance within the AI-driven learning framework. The results show that system adaptivity has a significant positive effect on student performance (β = 0.52) and engagement (β = 0.47), with an overall explanatory power of R^2 = 0.63, indicating that 63% of the variation in student performance can be explained by these factors. This suggests that adaptive AI systems effectively enhance learners' engagement, which in turn contributes to improved academic outcomes. In other words, as shown in Figure 2, higher adaptivity in the system leads to more engaged learners and better performance results, validating the effectiveness of integrating AI-based adaptivity into educational environments.

These statistical results confirm that the AI-driven learning factory framework achieves its intended objective of integrating data analytics and intelligent tutoring mechanisms to improve educational effectiveness.

From a pedagogical perspective, the model successfully bridges the gap between theoretical instruction and practical industrial training. Students exposed to AI-enhanced simulations demonstrated stronger problem-solving capabilities, improved operational accuracy, and greater autonomy during learning tasks. Additionally, instructors reported reduced workload due to the automated feedback and assessment features provided by the ITS, allowing them to focus more on mentoring and conceptual instruction.

Overall, the combination of EDA and ITS establishes a sustainable model for smart learning factories one that dynamically adjusts to learner needs, promotes data-driven decision-making, and scales effectively across diverse educational environments.

4.5. Summary of Findings

The findings of this study collectively support the hypothesis that integrating Educational Data Analytics with Intelligent Tutoring Systems significantly enhances both adaptive learning processes and learner performance within a learning factory. Key results include:

- AI-driven adaptivity mechanisms effectively personalize learning content and provide targeted feedback that improves understanding.
- Quantitative analysis confirms substantial gains in learner engagement and academic performance following ITS implementation.
- The predictive model indicates that system adaptivity and engagement jointly explain more than half of the variance in student performance outcomes.
- Qualitative feedback emphasizes high levels of learner satisfaction and motivation, validating the practical and pedagogical value of the AI-driven framework.

These outcomes answer the research questions outlined in the abstract and validate the methodological approach used. The results provide empirical evidence that AI integration can create a smarter, data-informed, and learner-centered learning factory model, capable of transforming higher education into a more adaptive and efficient ecosystem.

A further examination of the dataset reinforces the strength of the regression model, with an R^2 value of 0.63 indicating that system adaptivity and learner engagement collectively explain a substantial portion of performance variance. Learners who interacted with higher adaptivity levels displayed more consistent task completion, suggesting that timely, personalized feedback reduces cognitive load during complex simulation activities. Engagement metrics particularly interaction frequency and responsiveness to system prompts were also found to be strong indicators of improved performance.

Diagnostic tests confirmed that the model met core statistical assumptions. The residuals showed no systematic patterns, and multicollinearity was minimal, indicating that both predictors contributed independently to the outcome variable. Interaction log patterns further revealed that learners who frequently accessed hints or reattempted adaptive tasks showed higher improvement rates, highlighting the importance of iterative, feedback-driven learning. These findings collectively demonstrate that AI-driven adaptivity and engagement mechanisms reinforce one another, creating a learning environment that promotes more accurate decision-making and better academic outcomes within the simulated industrial context.

5. MANAGERIAL IMPLICATIONS

The findings of this study offer a set of crucial managerial and practical implications for administrators, curriculum designers, educational technologists, and policymakers seeking to optimize the efficiency and relevance of AI-driven Learning Factory environments. Strategically, institutional leaders must shift infrastructure investments to ensure a seamless, real-time integration between Educational Data Analytics (EDA) and Intelligent Tutoring Systems (ITS). This model creates a continuous feedback loop that is proven to significantly enhance the adaptability of instructional content. Operationally, management should prioritize the most impactful adaptive functions, particularly Difficulty Adjustment and Contextual Feedback Generation, as these mechanisms were the most frequently activated and demonstrated the highest perceived effectiveness in maintaining an optimal learning challenge for students.

From a pedagogical perspective, implementing these AI systems necessitates redefining the instructor's role from a traditional knowledge provider to a mentor and facilitator focused on high-level conceptual discussion and personalized guidance , since the ITS autonomously manages routine assessment and feedback tasks. Curricula must be designed to explicitly leverage EDA analytics dashboards, promoting self-regulated learning by enabling students to visualize their performance trends and self-correct more efficiently. This is critical in a Learning Factory context, as the goal is to bridge academic theory with industrial practice, preparing students for the data-driven decision-making demands of the Industry 5.0 era.

Finally, it is essential to address governance and ethical aspects. Management must enforce strict data protection protocols by ensuring all learner interaction logs are fully anonymized prior to analysis and that data access is restricted to authorized researchers using encrypted institutional servers. Regular verification of model reliability through regression diagnostics is necessary to confirm that the AI adaptive systems remain robust and statistically sound. While internally effective, decision-makers should remain cautious when generalizing findings to diverse institutions, acknowledging the study's single-institution limitation and considering variations in institutional culture and technological readiness in their implementation strategies.

6. CONCLUSION

The findings of this study highlight the significant potential of integrating Educational Data Analytics (EDA) and Intelligent Tutoring Systems (ITS) to develop smarter and more adaptive Learning Factory models. The results indicate that AI-driven mechanisms effectively improve learning adaptability, engagement, and overall student performance. Through data-driven feedback and intelligent guidance, the system enables real-time monitoring of learning behaviors, personalized task recommendations, and enhanced collaboration between theoretical instruction and practical industrial application. Statistical analysis confirmed a strong positive relationship between system adaptivity, engagement, and student outcomes, validating the proposed model's capacity to bridge the gap between digital education systems and hands-on industrial learning environments.

The research questions guiding this study were successfully addressed, demonstrating that the integration of AI technologies in Learning Factory contexts can foster more personalized and efficient learning experiences. However, several limitations were identified, including the reliance on limited institutional data and the relatively small sample size used in model validation. Because the sample consisted of 180 students from a single institution, the generalizability of the findings is inherently constrained. Differences in institutional culture, instructional design models, learner demographics, and technological infrastructure across other higher education settings may produce different outcomes when implementing similar EDA-ITS integrations. Therefore, further studies should adopt multi-institutional and cross-regional sampling approaches to validate the robustness of the findings and strengthen the external validity of the proposed model. Moreover, while the proposed system effectively enhanced adaptivity and performance, it did not fully account for the variations in learners' cognitive styles or differences in technological readiness among institutions. These factors may influence the generalizability of the model and should be considered when applying the findings in broader educational or industrial contexts.

Future research should expand the scope of analysis by incorporating larger and more diverse datasets across different educational institutions and industrial domains. Further exploration into hybrid AI models combining deep learning and reinforcement learning could provide deeper insights into predictive performance and automated feedback generation. Additionally, upcoming studies are encouraged to investigate the ethical and data privacy aspects of AI integration within Learning Factories to ensure responsible implementation. Developing frameworks that combine technical innovation with human-centered design principles will be essential for advancing the next generation of adaptive, AI-driven learning environments that align with the evolving demands of Industry 5.0.

7. DECLARATIONS

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There are no known competing financial interests or personal connections on the part of the authors that could have affected the outcomes presented in this publication.

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