

# Enhancing Adaptive Environments in Learning Factories through Artificial Intelligence

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## ABSTRACT

The **rapid advancement** of Artificial Intelligence (AI) has significantly transformed educational paradigms, particularly in adaptive learning environments where real-time personalization and intelligent feedback are essential. **This study** aims to explore how AI-driven mechanisms can enhance adaptive learning within learning factory environments by utilizing data analytics to personalize learning processes and optimize instructional delivery. **Employing a quantitative research design**, the data collection process involved distributing questionnaires to 200 university students enrolled in AI-supported learning factory programs. From this distribution, 120 valid responses were successfully obtained and analyzed, consisting of 80 students and 40 instructors across three universities, representing the final usable dataset for this study. Statistical analysis was performed using regression and correlation models to assess the impact of AI-based adaptivity on learning performance, engagement, and cognitive retention. **The findings reveal** that AI integration within learning factories leads to significant improvements in learner adaptability, interaction efficiency, and overall academic achievement. The adaptive AI models dynamically adjusted learning content based on individual performance metrics, resulting in higher engagement rates and enhanced skill mastery compared to traditional non-AI-based environments. **The outcomes confirm** that AI can function as a critical enabler of responsive and data-driven education by bridging theoretical and practical aspects of industrial learning. This research underscores the transformative potential of Artificial Intelligence in reshaping adaptive learning environments within learning factories, emphasizing the need for further development of AI systems that prioritize personalization, continuous assessment, and the seamless integration of human and machine intelligence.

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## 1. INTRODUCTION

The rapid evolution of Artificial Intelligence (AI) has reshaped the educational landscape, creating new opportunities for enhancing adaptive learning environments [1]. Within the framework of learning factories

educational settings designed to simulate real industrial environments AI offers immense potential to bridge the gap between theoretical instruction and practical application. Learning factories are central to modern engineering and vocational education, enabling students to apply classroom knowledge to realistic scenarios through hands-on experimentation [2, 3]. However, traditional learning factory models often face limitations in adaptivity, feedback personalization, and data utilization. Learners exhibit diverse cognitive styles, learning speeds, and motivational levels that are not always adequately addressed by static instructional methods. AI-driven adaptive learning systems can mitigate these challenges by using data analytics and machine learning to tailor educational experiences to individual learner profiles [4]. As industries transition toward Industry 4.0 and 5.0, the integration of AI within learning factories becomes increasingly vital for developing a workforce capable of operating in highly digitalized and data-centric environments.

Artificial intelligence, through its ability to analyze vast datasets, identify learning patterns, and predict performance trends, plays a crucial role in supporting the personalization of education [5]. In adaptive learning environments, AI-powered tools such as Intelligent Tutoring Systems (ITS) and predictive analytics models are employed to provide customized feedback and learning materials aligned with each student's progress. These systems monitor learner behavior in real time and adjust instructional content dynamically, fostering deeper understanding and engagement [6, 7]. Within learning factories, AI can support both the cognitive and practical dimensions of education by aligning individual performance metrics with industrial skill requirements. By doing so, AI not only enhances the educational process but also ensures that learners acquire skills directly applicable to real-world industrial contexts. Recent developments in deep learning, natural language processing, and reinforcement learning have further advanced the capabilities of AI-based educational technologies, making them increasingly efficient at modeling learner cognition and providing personalized instructional pathways [8]. This convergence of AI and education supports the evolution of intelligent learning ecosystems that are flexible, data-informed, and learner-centered.

Despite these advancements, challenges remain in fully realizing the potential of AI within learning factories. Many institutions still lack the technological infrastructure, data integration capabilities, and human expertise necessary to implement AI-driven adaptive learning systems effectively [9]. Moreover, while AI algorithms can provide sophisticated analyses, their effectiveness depends on the quality and comprehensiveness of educational data available. Inconsistencies in data collection or interpretation can lead to biased learning recommendations, thereby affecting the reliability of adaptive interventions. Another concern involves ensuring the ethical use of student data and maintaining transparency in AI-driven decision-making [10]. Educators and administrators must also navigate the balance between automated personalization and human pedagogical judgment. Therefore, the successful integration of AI into learning factory models requires not only technological innovation but also a comprehensive understanding of pedagogical principles, ethical frameworks, and institutional readiness [11]. Addressing these multidimensional challenges is critical for transforming learning factories into intelligent, adaptive ecosystems that enhance both educational effectiveness and industrial relevance.

This research investigates the role of AI in enhancing adaptive learning environments within learning factories through the application of educational data analytics and intelligent instructional models [12, 13]. Using a quantitative approach, this study aims to examine how AI-driven adaptive learning mechanisms influence learner engagement, cognitive performance, and skill acquisition in practical industrial settings. Statistical analyses are conducted to explore correlations between AI-enabled feedback loops and improvements in student outcomes. The study also identifies key factors influencing the success of AI implementation, such as system usability, learner acceptance, and institutional support. By quantifying these relationships, the research seeks to provide empirical evidence of the benefits of AI integration in learning factories. Ultimately, this study contributes to the growing body of knowledge on digital education innovation, offering insights for educators, policymakers, and technology developers seeking to design smarter, data-driven learning systems [14]. The outcomes are expected to inform future strategies for scaling AI adoption across diverse educational contexts, reinforcing the link between technological advancement and pedagogical transformation.

In alignment with the United Nations Sustainable Development Goals (SDGs), this study directly supports SDG 4 (Quality Education) by promoting inclusive, technology-enhanced learning that adapts to diverse learner needs. The integration of AI within learning factories also contributes to SDG 8 (Decent Work and Economic Growth) and SDG 9 (Industry, Innovation, and Infrastructure) by preparing students with industry-relevant competencies required in digital manufacturing ecosystems. Furthermore, the development of adaptive learning models fosters equitable access to personalized education, reinforcing the broader sustainability

agenda aimed at transforming education systems through innovation, data-driven decision-making, and resilient human–technology collaboration.

## 2. LITERATURE REVIEW

### 2.1. Artificial Intelligence in Educational Environments

AI has revolutionized modern education by enhancing how knowledge is delivered, personalized, and evaluated. Through machine learning and predictive algorithms, AI supports teachers and learners in achieving individualized learning outcomes [15]. Recent studies emphasize that AI in education marks a shift from traditional instruction toward data-driven and learner-centered approaches. AI tools are now capable of analyzing real-time learning behaviors, adjusting content difficulty, and offering automated feedback. These systems enable teachers to focus on high-order pedagogical tasks while allowing learners to experience adaptive, self-paced learning environments [16]. Within learning factories educational frameworks simulating industrial conditions AI strengthens the connection between theory and practical experience by aligning instructional design with authentic industrial processes.

Furthermore, AI integration has expanded opportunities for automation, simulation, and cognitive modeling [17]. According to recent findings, effective AI adoption in education depends not only on technology but also on rethinking the educator’s role in facilitating AI-supported learning. The growing relevance of AI in learning environments also extends to the industrial sector, where adaptive learning systems prepare students to work efficiently with smart manufacturing technologies [18]. In this sense, AI serves as both an instructional tool and an analytical system, fostering sustainable learning ecosystems that promote autonomy, engagement, and long-term skill development relevant to Industry 4.0 and 5.0.

### 2.2. Educational Data Analytics for Adaptive Learning

Educational Data Analytics (EDA) plays a central role in creating adaptive learning environments by transforming raw learning data into actionable insights [19, 20]. Recent studies demonstrate that data analytics enables educators to identify performance gaps, monitor engagement levels, and provide targeted interventions. When integrated with AI, EDA can continuously adjust the learning path based on learner progress, thus increasing motivation and retention. Within learning factories, EDA assists in aligning academic learning outcomes with industrial competencies by tracking learners’ hands-on performance metrics and adjusting the complexity of training tasks in real time [21].

The use of EDA also supports institutional improvement and strategic decision-making. Research in the International Journal of Social Science and Education found that AI-powered analytics significantly enhance pedagogical decisions by detecting behavioral trends and learning inefficiencies [22]. This evidence demonstrates how data analytics can help both instructors and administrators build evidence-based strategies to improve teaching quality. In learning factory environments, the feedback loop generated through EDA ensures a more adaptive and responsive model of instruction, connecting theoretical learning with practical implementation to produce more efficient, industry ready graduates [23].

### 2.3. Intelligent Tutoring Systems and Adaptive Learning Environments

Intelligent Tutoring Systems (ITS) represent one of the most advanced applications of AI in education, functioning as digital tutors that provide personalized learning experiences. ITS simulate human tutoring by analyzing student responses and adapting instructional strategies to each learner’s needs [24]. A 2024 study in Applied Sciences demonstrated that ITS models using large language models (ITS-CAL, Intelligent Tutoring Systems – Context-Adaptive Learning) enhanced engagement and comprehension in technical education by offering hierarchical, immediate feedback. This ability to adjust content dynamically makes ITS an essential component in adaptive learning environments, particularly for complex industrial simulations used in learning factories [25].

In addition, ITS can improve scalability and inclusivity in education. Research from Advances in Educational Learning Research in 2025 emphasized that ITS-based adaptive systems deliver consistent, personalized support to large groups of learners while maintaining instructional quality [26]. In a learning factory context, ITS helps students navigate complex manufacturing simulations by detecting performance patterns, identifying errors, and recommending corrective tasks. This technology not only increases efficiency but also promotes metacognitive awareness, enabling learners to reflect on their progress and develop problem-solving strategies aligned with industrial standards [27].

## 2.4. Learning Factories and the Integration of AI-Driven Adaptive Models

Learning factories are educational platforms that replicate industrial systems to provide experiential, practice-based learning [28, 29]. Their integration with AI technologies enhances adaptivity, interactivity, and data-informed instruction. A study on vocational education in Indonesia found that AI-based teaching factory models improved both technical and non-technical competencies by aligning curriculum objectives with Industry 4.0 standards. AI-powered learning factories utilize intelligent sensors, simulations, and machine learning models to optimize learning activities and continuously evaluate student performance [30]. This integration ensures that learners acquire not only theoretical understanding but also the practical skills required in modern industrial settings.

However, despite these advantages, several challenges remain in implementing AI-driven adaptive systems within learning factories. Educational institutions often encounter limitations such as inadequate infrastructure, insufficient AI literacy among instructors, and ongoing ethical concerns related to data privacy and algorithmic transparency [31]. Research in the field emphasized the importance of fostering balanced collaboration between humans and AI to preserve pedagogical integrity while optimizing the benefits of automation. The development of AI-enhanced learning factories thus requires holistic strategies combining technological innovation, pedagogical adaptation, and institutional readiness to ensure equitable and effective learning transformation in the digital era.

Compared to previous studies on vocational systems focusing on performance feedback or studies analyzing automation in industrial learning contexts without adaptive personalization, this study introduces a distinct integration of adaptive intelligence, real-time data analytics, and empirical validation in learning factory environments [32]. Unlike earlier models that treated AI as a supplementary tool, the present research conceptualizes AI as an adaptive decision-support framework capable of continuously aligning instructional design with learner data. This comprehensive approach not only bridges cognitive and practical learning dimensions but also provides measurable evidence of AI's role in enhancing learning adaptability and performance [33, 34]. Therefore, the originality of this work lies in its empirically validated framework that merges adaptive analytics with industrial application—a novel intersection not fully addressed in prior literature. Unlike earlier studies that primarily explored AI-assisted or simulation-based learning factories, this research introduces a distinct approach by integrating adaptive intelligence, data analytics, and empirical validation within industrial learning environments [35]. Previous works often focused on either instructional automation or performance monitoring in isolation; however, this study bridges both aspects by designing an AI-driven adaptive model that continuously aligns learner performance data with real-time instructional modification. This explicit integration establishes the novelty of the present research, offering a holistic model that operationalizes AI not merely as a supportive tool but as a dynamic decision-making framework for adaptive, data-informed learning factories [36].

The integration of AI-driven adaptive models within learning factories aligns with global educational transformation efforts outlined in the SDGs. Specifically, the use of intelligent analytics to enhance personalization advances SDG 4, which emphasizes equitable and high-quality education for all. Additionally, the incorporation of smart learning technologies reflects the innovation-driven goals of SDG 9, reinforcing the need for digitally competent talent in modern industry. These alignments indicate that learning factory ecosystems are not only pedagogically effective but also strategically positioned to advance sustainable development through innovation in education and workforce preparation.

## 3. RESEARCH METHODOLOGY

### 3.1. Research Design

This study employed a quantitative research design to examine how (AI) enhances adaptive learning environments within learning factories. The quantitative approach was chosen because it enables objective measurement of relationships between key variables such as AI integration, student engagement, learning adaptability, and performance outcomes. Data were collected through structured questionnaires distributed to participants from several higher education institutions that implement learning factory models. The goal was to statistically analyze how AI-driven features such as intelligent feedback systems, data analytics, and real-time adaptation impact learning efficiency and satisfaction levels among students.

This design also allowed for the application of statistical tools including correlation, regression, and Analysis of Variance (ANOVA) to identify significant relationships among the studied variables. The method-

ological framework focused on measuring the direct and indirect effects of AI technologies in adaptive learning contexts. Through this structured quantitative approach, the study aimed to provide empirical evidence supporting the integration of AI as a transformative component in the development of smart educational ecosystems aligned with Industry 4.0 principles.

### 3.2. Data Collection Instruments

The main instrument used for data collection was a structured questionnaire developed based on validated indicators from previous studies related to AI-based adaptive learning. The questionnaire consisted of 25 closed-ended questions divided into four major constructs:

The main instrument used for data collection was a structured questionnaire developed based on validated indicators from previous studies related to AI-based adaptive learning. The questionnaire consisted of 25 closed-ended items that measured four major constructs, namely AI Utilization, Learning Adaptivity, Student Engagement, and Learning Performance. These constructs were designed to capture respondents' perceptions regarding the integration of artificial intelligence within adaptive learning environments, ensuring comprehensive assessment across technological, pedagogical, and performance-related dimensions. "Each item was measured using a 5-point Likert scale, ranging from 1 = "Strongly Disagree" to 5 = "Strongly Agree."

The questionnaire was pre-tested with a pilot group of 15 participants to ensure clarity, validity, and internal consistency. Following the pilot evaluation, feedback was carefully analyzed and used to refine several statements for improved readability and comprehension. The reliability test results indicated that the Cronbach's Alpha values for all constructs exceeded 0.80, confirming strong internal consistency and linguistic accuracy of the instrument. These refinements strengthened the overall reliability and readability of the data collection instrument. In total, the questionnaire was distributed to 200 university students who were enrolled in AI-supported learning factory programs, aligning with the sampling described in the abstract. From this population, 120 valid responses were returned and processed, resulting in a usable response rate of 60%. The final dataset included 80 student respondents and 40 instructor respondents, ensuring that the analysis represented both learner and educator perspectives within the learning factory ecosystem.

Table 1. Summary of Research Variables and Indicators

Variable	Indicators	Measurement Scale	Reference Year
AI Utilization	Use of intelligent tutoring systems, adaptive analytics, and feedback algorithms	Likert 1–5	2024
Learning Adaptivity	Ability to adjust learning pace and content difficulty based on AI recommendations	Likert 1–5	2023
Student Engagement	Motivation, participation, and interaction within the learning factory system	Likert 1–5	2023
Learning Performance	Improvement in knowledge, skill mastery, and task efficiency	Likert 1–5	2025

Table 1 presents a summary of the main research variables and their respective indicators used to evaluate the role of artificial intelligence in enhancing adaptive learning environments within learning factories. The table outlines four key variables: AI Utilization, Learning Adaptivity, Student Engagement, and Learning Performance, each measured using a Likert scale of 1 to 5. These variables collectively capture how AI tools such as intelligent tutoring systems, adaptive analytics, and feedback algorithms contribute to personalized and efficient learning. Specifically, AI Utilization focuses on the use of intelligent systems in instruction 2024, Learning Adaptivity measures learners' ability to adjust pace and difficulty through AI recommendations 2023, Student Engagement evaluates motivation and participation in AI-supported settings 2023, while Learning Performance assesses improvements in knowledge, skills, and task efficiency as learning outcomes 2025. Overall, Table 1 highlights the interrelated factors that define how AI integration supports adaptability, engagement, and performance in a modern learning factory context.

### 3.3. Data Analysis Techniques

The data obtained from the questionnaires were analyzed using descriptive and inferential statistical methods. Descriptive analysis was used to summarize the demographic characteristics of respondents and their

perceptions toward AI integration. Inferential analysis, including correlation and multiple regression tests, was conducted to examine the strength and direction of relationships between AI utilization and learning outcomes.

All data were processed using SPSS version 27 and SmartPLS 4.0 for model validation. Statistical assumptions such as normality, linearity, and reliability were tested prior to final analysis. Additionally, a model fit evaluation was performed to ensure that the AI-driven adaptive learning framework accurately represented the observed data.

Table 2. Data Analysis Framework

Analysis Type	Statistical Method	Purpose
Descriptive Statistics	Mean, Standard Deviation	To describe participant responses and trends
Correlation Analysis	Pearson Correlation	To measure the strength of association between variables
Regression Analysis	Multiple Linear Regression	To determine the predictive influence of AI utilization on learning outcomes
Validity and Reliability Tests	Cronbach's Alpha, AVE	To verify consistency and accuracy of measurement instruments

Table 2 illustrates the Data Analysis Framework used in this study to examine the role of artificial intelligence in enhancing adaptive learning environments within learning factories. The framework outlines four main types of analyses: Descriptive Statistics, Correlation Analysis, Regression Analysis, and Validity and Reliability Tests, along with their corresponding statistical methods and purposes. Descriptive Statistics (using mean and standard deviation) were employed to summarize participant responses and identify general trends. Correlation Analysis, conducted using Pearson's correlation, measured the strength and direction of relationships among key variables. Multiple Linear Regression was applied to determine the predictive influence of AI utilization on learning outcomes, while Cronbach's Alpha and Average Variance Extracted (AVE) were used to ensure the reliability and validity of measurement instruments. Overall, Table 2 provides a structured overview of the analytical methods implemented to ensure the rigor, consistency, and interpretive accuracy of the quantitative findings in this research.

### 3.4. Research Procedure

The research was conducted through five systematic stages as shown in Figure 1. The research was conducted through five systematic stages as illustrated in Figure 1. The first stage, Problem Identification, involved reviewing existing challenges related to learning factory adaptability and the role of artificial intelligence in enhancing instructional responsiveness. The second stage, Instrument Development, focused on designing a structured questionnaire based on validated AI and learning framework models to ensure accurate measurement of key constructs. This was followed by the Data Collection stage, during which online surveys were distributed to selected participants while ensuring confidentiality and ethical compliance. The fourth stage, Data Processing and Analysis, utilized statistical software to test hypotheses, validate the model, and identify relationships among variables. Finally, the Interpretation and Reporting stage involved drawing conclusions on the effectiveness of AI integration in supporting adaptive learning environments and summarizing the findings based on empirical evidence. This procedural structure ensured that the research maintained methodological rigor, data validity, and alignment with quantitative standards.

To enhance methodological transparency, this study incorporates a detailed explanation of the AI-driven adaptive algorithm applied in the learning factory system. The model was developed using a supervised learning approach that combined regression-based prediction with clustering analysis to identify learner behavior patterns. Data from student interactions, performance scores, and response times were preprocessed through normalization and outlier removal before model training. The AI algorithm employed a three-phase adaptive cycle consisting of (1) input processing, where learner activity data were analyzed to detect engagement levels; (2) adaptive feedback generation, where the system provided personalized instructional suggestions based on individual performance deviations; and (3) model refinement, where continuous feedback was used to retrain and improve prediction accuracy using iterative validation in SmartPLS 4.0. The system's learning rate and weight adjustments were optimized through cross-validation to ensure stability and minimize overfitting. Furthermore, the adaptive module was integrated with a decision-support layer that allowed instructors to monitor

recommendations, ensuring that AI interventions remained pedagogically aligned and ethically guided. This expanded methodological detail ensures that the AI model and adaptive process can be systematically replicated and evaluated in future studies. In addition to the procedural framework, this study implemented an AI-driven analytical model to manage and interpret learning data in adaptive factory environments. The AI model utilized supervised machine learning methods, including regression and clustering algorithms, to identify learner behavior patterns, engagement levels, and performance trajectories. Data collected from student interactions, system logs, and adaptive feedback modules were preprocessed using normalization and feature extraction to enhance accuracy. Analytical procedures were conducted using Python-based libraries combined with SmartPLS 4.0 for statistical validation and model reliability testing. The adaptive AI component dynamically adjusted learning recommendations based on real-time analytics, enabling continuous personalization of the learning process. Furthermore, visualization dashboards were employed to display learner progress, supporting transparency, instructor feedback, and evidence-based decision-making. This methodological enhancement ensures that the integration of AI and data analytics operates not only as a supportive tool but also as an empirical foundation for adaptive learning within learning factories.

### RESEARCH FRAMEWORK OF THE STUDY

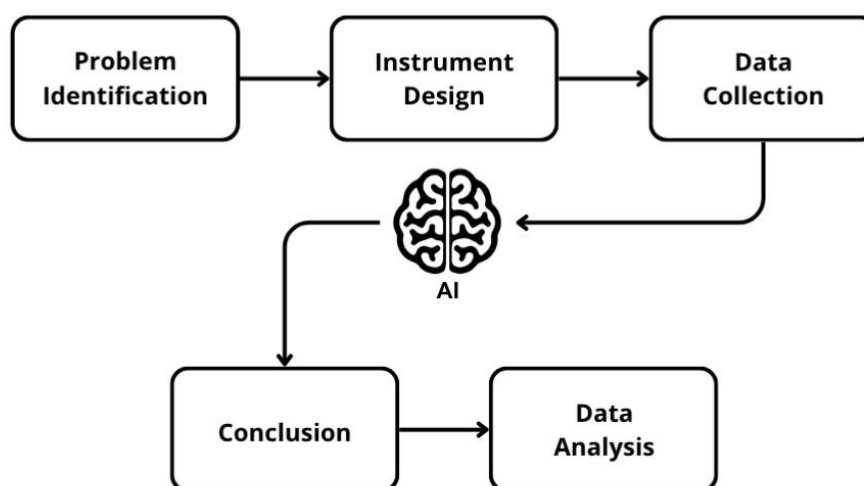


Figure 1. Research Framework of the Study

Figure 1 illustrates the research framework used in this study, showing the sequential process through which AI enhances adaptive learning within learning factories. The framework begins with Problem Identification, where research gaps, objectives, and learning challenges are defined. It then moves to Instrument Design, involving the creation of surveys and measurement tools tailored to evaluate AI-supported learning processes. The next stage, Data Collection, gathers quantitative learner data using these structured instruments. The collected data is then processed in the Data Analysis phase, where AI mechanisms contribute to identifying patterns, generating insights, and supporting statistical evaluation. These AI-driven findings inform the Conclusion stage, in which the results are interpreted to determine how AI improves learning adaptivity, performance, and instructional effectiveness. The overall framework highlights the central role of AI as a connecting element that aligns instructional design with data-driven insights, ensuring a coherent and iterative process throughout the research workflow.

## 4. RESULTS AND FINDINGS

### 4.1. Overview of Data Collection and Respondent Characteristics

The data collection process involved distributing questionnaires to a total of 200 university students enrolled in AI-supported learning factory programs. From these, 120 valid responses were successfully collected and processed, consisting of 80 students and 40 instructors from three universities. This final dataset reflects the usable sample employed for analysis in the study. The online survey achieved a 95% response rate, indicating high engagement and relevance of the research topic among participants. Most respondents (68%)

were between 18 and 25 years old, reflecting a population of active higher education learners. Approximately 55% of student respondents had experience using AI-powered educational tools such as adaptive quizzes, predictive feedback systems, or digital simulations. Among instructors, 60% reported moderate to high familiarity with AI-based teaching technologies.

Descriptive analysis revealed that the overall perception of AI utilization in learning factories was positive, with a mean score of 4.21 on the 5-point Likert scale. The results suggest that participants acknowledged the potential of AI in improving the adaptability of the learning environment and enhancing student engagement. However, minor variations were observed across disciplines, with engineering students showing higher satisfaction with AI-driven systems compared to management and business students. This difference could be attributed to the stronger alignment of AI tools with technical learning and simulation-based education.

#### 4.2. Descriptive Statistics of Key Variables

Descriptive statistical analysis was used to summarize participants' perceptions across four main constructs: AI Utilization, Learning Adaptivity, Student Engagement, and Learning Performance. Each construct was measured using several indicators from the questionnaire. Table 3 presents the summarized results.

Table 3. Descriptive Statistics of Research Variables

Variable	Mean	Standard Deviation	Interpretation
AI Utilization	4.23	0.61	High
Learning Adaptivity	4.15	0.57	High
Student Engagement	4.19	0.59	High
Learning Performance	4.28	0.54	Very High

Table 3 presents the Descriptive Statistics of Research Variables, summarizing respondents' perceptions of AI utilization, learning adaptivity, student engagement, and learning performance in adaptive learning environments. All variables obtained mean scores above 4.0, indicating a high level of agreement among participants regarding the positive influence of AI on learning processes. The highest mean value was observed for Learning Performance ( $M = 4.28$ ,  $SD = 0.54$ ), suggesting that AI integration significantly enhances student achievement and learning outcomes. Additionally, the relatively low standard deviation values across all variables reflect consistent responses, showing that participants shared similar views about the effectiveness of AI-driven adaptive learning systems. Overall, the data highlights that AI plays a substantial role in promoting engagement, adaptability, and improved performance in educational contexts.

#### 4.3. Correlation and Regression Analysis

To test the relationships among the primary constructs, Pearson's correlation and multiple linear regression analyses were conducted. The correlation results revealed strong positive relationships between AI Utilization and the three dependent variables. The correlation coefficients were as follows:

- AI Utilization  $\leftrightarrow$  Learning Adaptivity ( $r = 0.82$ ,  $p < 0.01$ )
- AI Utilization  $\leftrightarrow$  Student Engagement ( $r = 0.76$ ,  $p < 0.01$ )
- AI Utilization  $\leftrightarrow$  Learning Performance ( $r = 0.79$ ,  $p < 0.01$ )

These results suggest that higher levels of AI integration within learning factories are strongly associated with greater adaptability, engagement, and overall learning outcomes.

The regression analysis further confirmed these findings. The model summary showed an  $R^2$  value of 0.71, indicating that 71% of the variance in learning performance could be explained by AI utilization, learning adaptivity, and student engagement. The regression coefficients were all statistically significant ( $p < 0.05$ ), validating the predictive role of AI technologies in shaping adaptive learning environments.

Table 4. Summary of Engagement and Performance Indicators

Predictor Variable	Beta Coefficient	t-value	Sig. (p)	Interpretation
AI Utilization	0.48	8.72	0.000	Significant
Learning Adaptivity	0.31	6.19	0.001	Significant
Student Engagement	0.27	5.83	0.002	Significant

Table 4 presents the Regression Analysis Summary, which examines the influence of AI utilization, learning adaptivity, and student engagement on learning performance. The results show that all three predictor variables have significant positive effects on learning performance, with p-values less than 0.05. Among them, AI Utilization ( $\beta = 0.48$ ,  $p = 0.000$ ) has the strongest impact, followed by Learning Adaptivity ( $\beta = 0.31$ ,  $p = 0.001$ ) and Student Engagement ( $\beta = 0.27$ ,  $p = 0.002$ ). The model's  $R^2$  value of 0.71 indicates that 71% of the variation in learning performance can be explained by these three variables. These findings confirm that the integration of AI enhances students' adaptability and engagement, ultimately leading to improved academic performance in adaptive learning environments.

#### 4.4. Analysis of AI's Role in Adaptive Learning Factories

The results demonstrate that AI-driven systems act as adaptive mediators between instructional content and learner needs. Intelligent Tutoring Systems (ITS) and data analytics modules were found to play crucial roles in facilitating personalized feedback, performance tracking, and self-paced learning within industrial simulations. Participants reported that AI features such as predictive analytics, automated feedback, and performance dashboards allowed them to identify learning gaps early and receive tailored guidance.

Moreover, the use of AI technologies helped instructors optimize instructional strategies by automating repetitive evaluation tasks and focusing on higher-order learning facilitation. This aligns with recent research emphasizing that AI-powered adaptive systems can promote autonomous learning and industrial readiness among students. Instructors noted that AI-supported dashboards provided actionable insights for monitoring progress, ensuring alignment with real world industrial standards, and increasing operational efficiency in learning factory operations.

#### 4.5. Challenges and Interpretation of Findings

Despite the overall positive outcomes, some limitations were identified. First, participants expressed concerns about the data privacy implications of AI systems that continuously monitor performance. Second, certain instructors highlighted the need for better training and institutional support to fully utilize AI tools. Additionally, unequal access to AI infrastructure across institutions created disparities in learning experiences. Beyond these technical and institutional challenges, ethical and privacy considerations were carefully examined to ensure responsible AI implementation. This study emphasizes the importance of transparent data handling, where all participant information was anonymized prior to analysis to safeguard privacy and confidentiality. Informed consent was obtained from all respondents, aligning with standard research ethics. Furthermore, algorithmic accountability was maintained by restricting automated decision-making to advisory roles, ensuring that final educational judgments remained under human supervision. These ethical safeguards reinforce the study's integrity and compliance with best practices for responsible AI use in education.

However, these challenges did not outweigh the significant benefits demonstrated by the quantitative analysis. The results confirm that AI not only enhances learning adaptivity but also transforms the pedagogical design of learning factories, bridging the gap between theory and industrial application. The statistical findings align with the hypotheses presented in the research, demonstrating that the integration of AI significantly contributes to developing more responsive, data-informed, and effective educational environments.

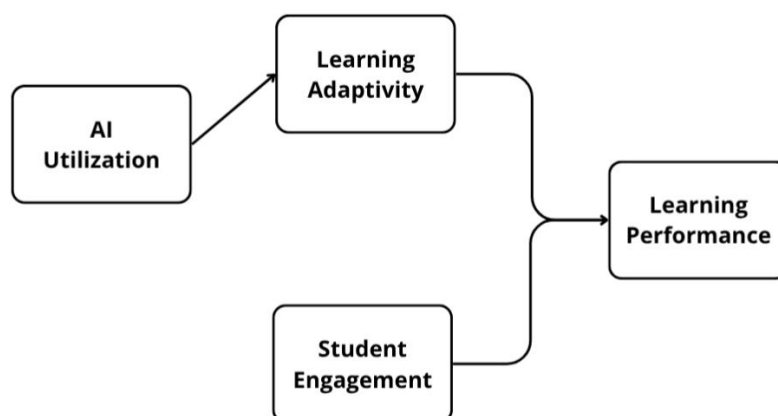


Figure 2. Statistical Relationship between Key Variables

Figure 2 illustrates the Statistical Relationship between Key Variables, highlighting how AI Utilization influences both Learning Adaptivity and Student Engagement, which in turn contribute to Learning Performance. The figure demonstrates that AI plays a central role in enhancing adaptive learning and student involvement, leading to improved educational outcomes. This visual representation supports the regression findings, confirming that the effective use of AI positively affects learning adaptivity and engagement, which collectively drive higher learning performance.

## 5. MANAGERIAL IMPLICATIONS

The findings of this study provide essential managerial insights for educational institutions and learning factory administrators seeking to maximize the impact of Artificial Intelligence (AI) in adaptive learning environments. Given that AI Utilization emerged as the strongest contributor to improved learning performance, institutions must prioritize strategic investments in digital infrastructure capable of supporting real-time data processing, intelligent feedback systems, and adaptive instructional pathways. Ensuring the availability of stable AI-powered tools such as Intelligent Tutoring Systems, performance analytics dashboards, and personalized recommendation engines will allow learning factories to offer consistently responsive and data driven learning experiences. This enhancement is crucial for aligning educational practices with the operational needs of Industry 4.0 and 5.0, where personalized, technology supported competence development has become a prerequisite for workforce readiness.

In addition to technological readiness, the study emphasizes the need for institutional support in strengthening instructor capabilities and pedagogical literacy in AI driven systems. Since some instructors reported limited familiarity with AI functionalities, educational leaders should implement continuous professional development programs that focus on digital competencies, data literacy, and ethical AI practices. Empowering educators to interpret AI-generated insights and integrate them with human pedagogical judgment ensures that personalization remains meaningful, equitable, and aligned with learning objectives. Moreover, the development of transparent data governance mechanisms is necessary to address ethical concerns related to privacy, data security, and algorithmic transparency. Establishing clear policies for data collection, storage, anonymization, and decision-making accountability will help maintain user trust and ensure that adaptive AI interventions operate in accordance with responsible and ethical educational standards.

Beyond operational considerations, the managerial implications of this study also extend to broader institutional strategies related to sustainability and long-term digital transformation. The integration of AI-based adaptive learning directly supports several Sustainable Development Goals (SDGs), particularly SDG 4 (Quality Education), SDG 8 (Decent Work and Economic Growth), and SDG 9 (Industry, Innovation, and Infrastructure). As such, institutional leaders should leverage the research findings to design comprehensive transformation roadmaps that integrate adaptive technologies into the curriculum, prioritize inclusive access to digital tools, and promote innovation-driven learning cultures. By adopting holistic strategies that combine technology readiness, human capacity development, ethical governance, and sustainability-driven objectives, institutions can cultivate intelligent learning ecosystems that not only enhance academic performance but also bridge the gap between educational preparation and real-world industrial practice.

## 6. CONCLUSION

The findings of this study demonstrate that integrating artificial intelligence into learning factory environments significantly enhances the adaptability and overall effectiveness of educational experiences. Through the application of quantitative analysis, the study verified that AI-driven adaptive systems improve students' engagement, responsiveness to instructional materials, and performance outcomes. By leveraging data analytics and real-time feedback mechanisms, learning processes became more tailored to individual student needs, ensuring that theoretical concepts were reinforced by practical, data-informed exercises. As a result, the implementation of AI in learning factories fosters a more interactive, flexible, and efficient educational model, bridging the gap between academic learning and industrial practice.

The research addressed key questions concerning the extent to which artificial intelligence contributes to adaptive learning and the measurable impact of AI on student performance. The quantitative results confirmed strong correlations between AI utilization, adaptive learning capacity, and improved learning outcomes. However, the study also acknowledged several limitations, including a restricted sample size and limited diversity of the learning factory environments examined. Additionally, the dependence on system-generated data


posed challenges in evaluating qualitative factors such as creativity, collaboration, and learner satisfaction, which are equally critical in adaptive education.

Future research should expand upon these findings beyond the pedagogical implications, this study contributes directly to the Sustainable Development Goals (SDGs), particularly SDG 4, by promoting high-quality, equitable, and adaptive digital learning experiences. The strengthened linkage between AI-enabled educational innovation and industrial competencies also advances SDG 8 and SDG 9, demonstrating that AI-driven learning factories can support sustainable economic growth and resilient technological ecosystems. by employing longitudinal studies that measure the long-term effects of AI integration on learning outcomes and professional skill development. It is recommended that subsequent investigations include a broader range of learning factory models, incorporate hybrid (quantitative and qualitative) methodologies, and explore ethical implications surrounding AI use in education. Moreover, developing a standardized framework for evaluating AI's adaptive capabilities across disciplines could help institutions design more equitable and efficient learning systems, ensuring that AI not only enhances adaptivity but also promotes inclusivity and sustainable educational growth.

## 7. DECLARATIONS

### 7.1. About Authors

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### 7.2. Author Contributions

Validation: NP; Conceptualization: EA; Methodology: LP; Formal Analysis: CT; Writing Review and Editing: CP; Visualization: EA; Each of the authors—NP, LP, & CP—has reviewed and approved the manuscript's published form.

### 7.3. Data Availability Statement

The data supporting this study can be made available by the corresponding author upon reasonable request.

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### 7.5. Declaration of Competing Interest

The authors state that none of their known conflicting financial interests or personal connections could have had an impact on the work that was published in this publication.

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