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Designing an Educational Information System to Enhance Learning Factory Management in Higher Education

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ABSTRACT

The increasing adoption of Learning Factory concepts in higher education has highlighted the need for effective educational information systems that can support operational efficiency, resource utilization, and knowledge integration. However, many Learning Factories still face challenges in coordinating instructional activities, managing training equipment scheduling, and ensuring alignment between educational objectives and industrial practices. **This study aims** to design an educational information system that optimizes Learning Factory operations through the integration of workflow management, resource allocation, and instructional monitoring components. **The research employs** a qualitative design involving observations of operational processes, semi-structured interviews with instructors and laboratory managers, and document analysis to identify functional requirements and system specifications. **The findings reveal** that existing management practices are largely manual, leading to inefficiencies such as scheduling conflicts, inconsistent training documentation, and limited real-time feedback mechanisms. The proposed system design features centralized resource scheduling, digital competency tracking, and process visualization dashboards, which collectively support more structured learning activities and improved synchronization between theoretical instruction and practical engagement. **The study concludes** that developing an educational information system tailored to the Learning Factory environment enhances operational coordination, improves transparency in instructional management, and strengthens the linkage between educational outcomes and industrial competencies, thereby contributing to more effective and industry-aligned learning experiences.

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1. INTRODUCTION

The rapid transformation of industrial sectors in the era of Industry 4.0 has prompted educational institutions to adopt more practice-oriented learning environments to prepare students with competencies that reflect real-world industrial settings [1]. One such approach is the implementation of Learning Factories, which simulate actual manufacturing workflows, production processes, and industrial decision-making within an academic context. Learning Factories aim not only to enhance technical skills but also to promote critical thinking and collaboration, aligning with the global push for improved educational quality and skill readiness as encouraged by the Sustainable Development Goals (SDG 4). However, managing Learning Factory environments presents challenges due to the need for synchronized interactions among multiple instructional components, including equipment scheduling, resource allocation, competency evaluation, and documentation of learning outcomes [2]. Unlike conventional classrooms, Learning Factories require dynamic coordination of physical resources, instructional tasks, and assessment mechanisms, making their operation more complex and dependent on well-structured management processes [3]. Without systematic coordination, institutions often encounter inefficiencies such as scheduling conflicts, underutilization of equipment, gaps in competency monitoring, and misalignment between learning objectives and industrial standards. These challenges highlight the importance of developing an educational information system specifically designed to support operational processes in Learning Factory environments [4], which in turn reinforces global efforts to strengthen innovation ecosystems and resilient infrastructure in line with SDG 9.

Figure 1. SDGs

As illustrated in Figure 1, the Sustainable Development Goals (SDGs) highlight the global emphasis on quality education, innovation, and resilient infrastructure principles that closely align with the operational ideals of Learning Factories. Despite this alignment, many institutions still rely on manual or fragmented systems for managing key operational processes, which limits their ability to fully support these sustainability-oriented goals [5]. Scheduling is frequently handled through spreadsheets or informal communication channels, increasing the risk of laboratory scheduling conflicts and inefficient time allocation. Documentation of student training progress is often recorded manually, resulting in inconsistencies in assessment formats and challenges in comparing performance across sessions [6]. Moreover, the absence of integrated systems reduces the traceability of learning outcomes, making it difficult for educators to evaluate competency development effectively. Industrial partners who collaborate with educational institutions also require transparent evidence of student capability, and the lack of systematic monitoring can undermine long-term partnership credibility [7]. Addressing these operational gaps is therefore essential not only for improving institutional efficiency but also for advancing decent work readiness and strengthening workforce development pathways in alignment with SDG 8. While previous studies emphasize digital transformation in Learning Factories, they generally focus on simulations or instructional technologies rather than on the core operational management system itself. This study addresses that gap by proposing an educational information management system tailored to the workflow demands of Learning Factories [8].

The design of an educational information system tailored to Learning Factory operations requires a comprehensive understanding of the interaction between technical resources, instructional design, and competency-based learning outcomes. In this research, the design process is grounded in qualitative inquiry to capture the lived experiences and operational needs of those directly involved in Learning Factory environments, including instructors, laboratory managers, and students [9]. Through observations, semi-structured interviews, and document analysis, the study uncovers key functional requirements and pain points that need to be addressed in order to enhance operational efficiency. A conceptual system architecture is then developed to integrate scheduling management, digital learning documentation, resource tracking, and performance feedback mechanisms. This architecture aims to ensure systematic coordination between theoretical and practical learning, providing a clearer pathway for competency evaluation and supporting continuous improvement in instructional delivery [10]. By strengthening data-driven decision-making, optimizing resource usage, and enhancing workflow transparency, the proposed design contributes to broader sustainability goals related to quality education, innovation, and efficient use of institutional resources areas emphasized within SDG 4, SDG 9, and SDG 12. The significance of this research lies not only in proposing a solution but also in demonstrating how an information system can align educational processes with industrial expectations, thereby reinforcing the relevance and applicability of Learning Factory pedagogy [11].

This research contributes both academically and practically to the field of educational technology and industrial-based learning models. Academically, it provides a conceptual and empirical foundation for the development of management-oriented information systems in practice-based educational settings. It adds to the literature by shifting attention from learning content delivery to the operational coordination that enables effective experiential learning [12]. Practically, the proposed system design can serve as a blueprint for institutions seeking to strengthen their Learning Factory management strategies. By ensuring better resource usage, structured competency tracking, and improved coordination between stakeholders, the system supports enhanced learning outcomes and greater alignment with workforce demands. These improvements further contribute to advancing workforce readiness and promoting sustainable economic productivity, reinforcing SDG 8 [13]. The research also offers implications for policymakers and administrators regarding the need to invest in integrated digital infrastructure to support vocational and engineering education, consistent with global calls to expand inclusive and high-quality learning opportunities (SDG 4) and strengthen technological innovation capacity (SDG 9). Ultimately, the development of such systems is expected to contribute to producing graduates who are not only technically competent but also operationally literate and industry-ready, supporting wider national efforts toward workforce modernization and industrial competitiveness [14].

In addition to these growing expectations, the rapid expansion of Industry 4.0 technologies across global manufacturing ecosystems has further intensified the need for Learning Factory environments that accurately reflect contemporary industrial practices [15]. Over the past several years, Learning Factories have undergone a significant shift from traditional workshop-style laboratory spaces toward digitally augmented, cyber-physical learning environments equipped with automation tools, real-time monitoring systems, and data-driven production analytics. This transition demonstrates a clear movement toward educational models that not only simulate industrial workflows but also incorporate intelligent technologies that mirror the complexities of modern production systems [16]. As a result, institutions are now required to adopt more structured and technology-supported approaches to manage these increasingly dynamic learning settings, a progression that also advances global initiatives encouraging innovation, infrastructure resilience, and high-quality technical training as promoted by SDG 4 and SDG 9.

Despite these advancements, many Learning Factory initiatives continue to rely on fragmented administrative routines and unstandardized instructional management processes. Laboratory schedules are often organized through spreadsheets, messaging applications, or instructor-specific routines, creating inconsistencies in machine usage planning and instructional delivery [17]. Similarly, the absence of unified documentation systems frequently leads to incomplete or non-uniform records of competency development, limiting educators' ability to track individual progress or evaluate learning outcomes systematically. These gaps pose a significant challenge, particularly as Learning Factories expand in scale and attempt to accommodate larger student cohorts, more complex production scenarios, and higher expectations for industry alignment [18]. Addressing these challenges is essential not only for improving educational quality but also for supporting sustainable operational practices within learning environments, in line with the resource efficiency principles highlighted in SDG 12.

Furthermore, the increasing integration of cyber-physical systems and real-time data within Learning Factories underscores the importance of information systems capable of supporting seamless coordination between pedagogical, operational, and technological components [19]. Existing digital tools used in academic contexts such as Learning Management Systems, virtual laboratories, and simulation platforms primarily address content delivery rather than the operational demands of managing shared physical resources and competency-based learning workflows. This discrepancy highlights a critical gap in both practice and scholarly discourse, the lack of Educational Information Systems specifically designed to address the unique orchestration challenges of Learning Factory environments [20]. The development of such systems not only enhances institutional efficiency but also supports innovation-driven learning ecosystems that resonate with the broader goals of SDG 9.

A dedicated information system that unifies scheduling, instructional documentation, resource tracking, and competency evaluation would therefore play a pivotal role in enhancing the reliability and efficiency of Learning Factory operations [21]. Beyond improving administrative coordination, such a system can strengthen the continuity between theoretical instruction and practical engagement, ensuring that students experience structured, repeatable, and industry-aligned learning processes. Moreover, by capturing data related to machine utilization, learning activities, and performance indicators, the system can generate valuable insights that enable instructors and managers to continuously refine pedagogical strategies, optimize workflows, and support evidence-based decision-making [22]. These capabilities directly contribute to strengthening workforce competencies and promoting sustainable industrial development in alignment with SDG 8 and SDG 9.

Given these considerations, the development of an Educational Information System tailored specifically to Learning Factory settings is not merely a technological enhancement but a strategic necessity for institutions that aim to deliver high-quality experiential learning [23]. Such a system enables Learning Factories to function as cohesive, data-informed environments where educational objectives, operational processes, and industrial standards are systematically aligned. This expanded perspective reinforces the relevance and urgency of the present study, which seeks to design a system capable of addressing operational inefficiencies while strengthening the pedagogical foundations of Learning Factory-based education, in harmony with the global sustainability agenda outlined in SDG 4, SDG 8, and SDG 9 [24].

2. LITERATURE REVIEW

2.1. Learning Factory in Modern Education

Learning Factories have evolved into an educational approach that integrates real or simulated industrial environments into academic instruction [25]. This concept places students in operational contexts that resemble manufacturing systems, enabling the development of technical, managerial, analytical, and collaborative competencies. Learning institutions have increasingly adopted Learning Factories to align curricula with the growing demand for digital and data-driven industrial skills [26]. A Learning Factory typically includes production machinery, workflow systems, resource scheduling tools, sensor-based data monitoring, and process simulation activities.

The purpose of a Learning Factory extends beyond providing hands-on training, it also cultivates problem-solving mindsets grounded in real-world production dynamics. Students take active roles in monitoring processes, evaluating workflow performance, and making data-supported decisions [27]. With the advancement of Industry 4.0 technologies, Learning Factories now integrate IoT networks, automation, and AI-based analytics, making digital and data literacy essential competencies for learners. Thus, Learning Factories serve as environments where theoretical knowledge and industrial application intersect effectively.

In recent years, the Learning Factory model has also been recognized as a strategic mechanism for bridging interdisciplinary competencies, combining engineering, management, data analytics, and digital literacy within a unified learning environment. Contemporary implementations emphasize not only the replication of physical production systems but also the integration of cyber-physical components, automation interfaces, and collaborative problem-solving platforms that enable students to work with real operational data [28]. As a result, Learning Factories increasingly serve as innovation ecosystems where learners engage with real-time decision-making scenarios, interpret complex workflow interactions, and optimize system performance through iterative experimentation. This expanded pedagogical function positions Learning Factories as critical infrastructures for preparing graduates to operate within digitally connected, human–machine collaborative environments consistent with Industry 4.0 and 5.0 frameworks.

2.2. Educational Information Systems for Learning Factory Management

Educational Information Systems (EIS) play a crucial role in supporting the management and operational efficiency of Learning Factories [29]. These systems enable structured coordination of resources such as equipment, materials, schedules, learning activities, and student performance records. Studies indicate that EIS implementation reduces operational inefficiencies, increases transparency in resource allocation, and enhances the clarity of learning workflows within Learning Factory settings [30]. Unlike ERP-based systems that emphasize enterprise-wide transaction management or digital-twin platforms that replicate physical production environments virtually, the proposed EIS focuses on real-time operational coordination, instructional monitoring, and competency-based evaluation within educational contexts. This distinction establishes its novelty as a management-oriented framework specifically tailored to Learning Factory operations rather than industrial automation systems [31].

A primary function of EIS in Learning Factory environments is the provision of real-time, centralized access to critical operational and instructional information [32]. Students can readily view machine availability schedules, equipment condition updates, digital work instructions, and standardized production procedures, allowing them to prepare more effectively and coordinate their activities within authentic industrial workflows [33]. Instructors, meanwhile, benefit from the ability to continuously monitor learning progress, assess student performance against predefined competency indicators, and evaluate the effectiveness of operational tasks carried out within the facility. Furthermore, the EIS facilitates data-based assessment by capturing, organizing, and analyzing performance and production data, thereby enabling systematic evaluation, timely feedback, and ongoing improvement of both learning outcomes and operational efficiency within the Learning Factory [34].

Beyond enabling operational efficiency, EIS solutions provide a digital foundation that supports structured competency development, transparent learning pathways, and standardized documentation of instructional processes. Several studies highlight the need for integrated platforms capable of managing heterogeneous data sources such as machine operation logs, student performance metrics, and maintenance records and translating them into actionable insights for instructors and managers [35]. In the context of Learning Factories, these systems must address the dual challenge of supporting pedagogical goals while simultaneously aligning with industrial workflow logic. This requirement differentiates Learning Factory-oriented EIS from conventional academic technologies and underscores why the design must consider both instructional and operational dimensions. As hybrid learning modes become more prevalent, the demand for EIS that can coordinate remote preparation, on-site execution, and post-activity analytics is expected to increase substantially.

2.3. Integration of Industrial Workflow and Pedagogical Design

Successful Learning Factory development requires a well-orchestrated integration between industrial workflow structures and pedagogical strategies to ensure that learning mirrors real-world manufacturing environments [36]. The instructional design must be carefully aligned with actual production sequences, process flow logic, quality control protocols, and safety standards that govern industrial operations, ensuring that learners develop both technical accuracy and procedural discipline [37]. Recent educational developments further emphasize that Learning Factory pedagogy should prioritize experiential learning, reflective practice, and iterative problem-solving, enabling students to engage in authentic tasks, evaluate the outcomes of their decisions, and refine strategies through continuous cycles of experimentation. This combination of operational realism and pedagogical rigor strengthens learners' practical competencies and supports the development of industry-ready skills [38].

A well-designed learning process generally includes theoretical introduction, contextual understanding of industrial operations, hands-on implementation, performance evaluation based on production output, and reflective review. By incorporating these elements, the Learning Factory becomes not only a space for technical practice but also an environment that strengthens professional competence [39]. Unlike digital twin–based EIS models that primarily emphasize real-time process simulation, or AR-integrated scheduling systems that focus on user interaction and visualization, the proposed EIS in this study distinctly targets operational coordination and workflow management within institutional learning environments [40]. This system design introduces a practical framework that connects administrative scheduling, instructional monitoring, and resource allocation domains often overlooked in previous frameworks. Consequently, the novelty of this work lies in integrating management-oriented functionality into Learning Factory operations, making it adaptable across diverse educational contexts rather than limited to specific technology infrastructures [41].

Recent literature also emphasizes that successful Learning Factory design requires a multi-layered pedagogical approach that integrates cognitive, procedural, and metacognitive training elements. Students must not only acquire operational skills but also engage in reflective practices that evaluate their decision consequences, production outcomes, and team interactions [42]. This synthesis of industrial workflow with pedagogical intent allows Learning Factories to cultivate higher-order thinking skills such as troubleshooting, system optimization, and critical evaluation of process efficiency. Moreover, instructors play a pivotal role in facilitating learning experiences that balance autonomy with structured guidance, ensuring that students develop both technical proficiency and systemic awareness. Effective Learning Factory pedagogy thus requires close alignment between instructional sequencing, production task design, and the digital tools used to monitor and assess learner performance.

2.4. Digital Platforms and E-Learning Support for Learning Factories

The use of digital learning platforms has become an essential component in supporting Learning Factory operations, particularly with the growing prevalence of hybrid and technology-enhanced learning environments [43]. These platforms serve as a critical preparatory layer by offering structured access to foundational training materials, interactive production simulations, introductory machine operation modules, and data analytics exercises that learners can engage with prior to entering the physical production environment [44]. By enabling students to acquire baseline competencies, familiarize themselves with industrial workflows, and practice decision-making in a risk-free virtual setting, digital learning platforms significantly enhance readiness, reduce operational errors, and create a more seamless transition into hands-on Learning Factory activities [45].

Digital platforms enhance flexibility by allowing students to access instructional content anytime, collaborate through virtual discussion spaces, and submit work outputs electronically [46]. Additionally, integrated data dashboards can facilitate real-time analysis of production patterns, performance bottlenecks, and resource utilization trends. As a result, learners move beyond mechanical task execution and develop analytical capabilities for system optimization and innovation. Therefore, digital integration extends Learning Factory education toward developing critical thinking and intelligent decision-making skills.

As digital platforms evolve, their role in Learning Factory environments extends beyond preparatory instruction to include integrated analytics, collaborative dashboards, and digital logbooks that track student progress over time. These platforms increasingly incorporate adaptive learning algorithms, enabling personalized pathways that adjust task difficulty, provide targeted feedback, or recommend content based on performance patterns. This personalization enhances student readiness before engaging with physical machinery, reducing errors and improving safety outcomes [47]. Additionally, the convergence of cloud-based tools, industrial IoT data, and mobile-access interfaces has enabled more flexible and scalable Learning Factory configurations, making it possible for institutions with limited physical infrastructure to simulate advanced industrial processes through blended or hybrid formats.

2.5. Challenges in Learning Factory Digitalization

Despite substantial progress in integrating digital tools into Learning Factory environments, several challenges continue to hinder the development of fully optimized and scalable systems. One of the most prominent challenges is the fragmentation of data systems across instructional, operational, and maintenance domains [48]. In many institutions, machine logs, competency assessments, and instructional materials reside on separate platforms, limiting interoperability and complicating the process of constructing comprehensive performance insights. This fragmentation restricts the ability of instructors to make timely, data-informed decisions and undermines the potential for continuous improvement in instructional design.

Infrastructure limitations also pose a significant barrier, particularly for institutions in regions with uneven digital readiness. Stable connectivity, reliable hardware, and consistent access to updated industrial technologies are essential for sustaining Learning Factory operations, yet they are often difficult to maintain in resource-limited settings [49]. Additionally, the lack of standardized protocols for documenting learning activities and recording operational data contributes to inconsistencies in system implementation. These issues are compounded by the need for instructors to acquire new competencies related to digital system management, workflow monitoring, and data interpretation skills that may fall outside their traditional expertise.

Another challenge lies in aligning Learning Factory activities with rapidly evolving industrial standards. As industries adopt automation, autonomous systems, and advanced analytics, Learning Factories must continuously update their operational models, equipment capabilities, and instructional strategies [50]. Without dedicated information systems capable of supporting such dynamic adaptations, the gap between educational environments and real-world industrial contexts widens. These challenges collectively highlight the urgent need for integrated Educational Information Systems that can streamline coordination, enhance traceability, and support sustainable digital transformation within Learning Factory settings.

2.6. Comparison with Existing Information System Models

A review of existing information system models reveals that most platforms used in educational or industrial settings are not fully suited for the hybrid nature of Learning Factory operations. Traditional Learning Management Systems (LMS), for example, excel in delivering digital content, managing assignments, and facilitating communication but lack the ability to coordinate physical resources, production workflows, or real-time learning activities [51]. Conversely, Enterprise Resource Planning (ERP) and Manufacturing Execution Systems (MES) are designed to manage industrial operations but are often too complex, rigid, or incompatible with the pedagogical flexibility required in educational settings.

Digital Twin platforms offer sophisticated simulations of industrial processes but typically focus on modeling system behaviors rather than managing instructional sequences, student interactions, or competency evaluation [52]. Similarly, scheduling automation tools can optimize resource allocation yet remain disconnected from broader learning objectives and performance monitoring frameworks. These limitations illustrate why Learning Factory environments require a specialized EIS that integrates the strengths of multiple system categories while addressing their shortcomings.

The proposed Educational Information System in this study differentiates itself by prioritizing operational coordination in conjunction with pedagogical alignment. Unlike ERP or MES systems which emphasize production throughput and compliance the proposed EIS supports iterative learning cycles, real-time instructional oversight, and competency-based assessment [53]. It is designed to offer instructors and laboratory managers a holistic view of both operational conditions and student learning trajectories, enabling more meaningful, data-informed educational interventions. This hybrid functionality positions the EIS as a novel contribution in the field of educational technology, filling an important gap that neither conventional academic systems nor industrial management tools have adequately addressed.

3. RESEARCH METHODOLOGY

3.1. Research Approach

This research employs a qualitative descriptive approach to explore the operational needs and functional requirements of an Educational Information System within a Learning Factory environment [54]. The qualitative approach is selected because the primary goal of this study is to understand experiences, workflow challenges, and management patterns that occur in real practice. The process focuses on capturing perspectives from instructors, laboratory managers, and students regarding scheduling, resource usage, competency tracking, and instructional integration [55]. Qualitative inquiry allows for deeper interpretation of organizational behavior and system interactions that cannot be measured solely through numerical indicators. The findings obtained from field interactions are then translated into system requirements and conceptual system architecture.

In expanding the qualitative descriptive approach, this study also employed a systematic coding structure to transform raw data into meaningful analytical themes. The coding process consisted of two stages, open coding in which recurring keywords and behavioral patterns were identified, and axial coding which organized these patterns into broader thematic categories relevant to Learning Factory operations. This systematic process ensured that conclusions drawn from the data were grounded in observable evidence rather than subjective interpretation.

To further enhance the transparency of the research process, an audit trail was maintained throughout data collection and analysis. This included detailed logs of interview notes, observation checklists, analytic memos, and reflective discussions between members of the research team. The audit trail provided a chronological record of methodological decisions, enabling greater accountability and replicability for future research.

3.2. Research Site and Participants

The research is conducted within a Learning Factory facility in a higher education environment that operates production-based learning activities. This setting provides an authentic context where academic concepts are directly applied to simulated industrial processes. Participants in this study consist of instructors involved in hands-on teaching, students who actively engage in laboratory sessions, and laboratory managers responsible for overseeing daily operations and ensuring workflow continuity. The selection of participants follows a purposeful sampling approach, which intentionally targets individuals who have direct experience with Learning Factory activities. This method ensures that the data collected is not only relevant but also deeply reflective of real operational dynamics, thereby capturing insights that are accurate, context-driven, and aligned with the practical nature of the Learning Factory environment.

Table 1. Participant Classification

Participant Role	Number of Participants	Involvement in Learning Factory Operations
Instructors	4	Responsible for teaching, supervision, and learning evaluation
Laboratory Managers	2	Managing equipment, schedules, and operational documentation
Students	12	Engaged in production workflows and competency-based training

Table 1 Participant Classification presents the composition of participants involved in the study conducted within a Learning Factory environment. The table 1 shows three key participant groups, instructors (4 participants), laboratory managers (2 participants), and students (12 participants). Each group plays a distinct role in Learning Factory operations where instructors are responsible for teaching, supervision, and learning evaluation, laboratory managers handle equipment management, scheduling, and operational documentation, while students participate in production workflows and competency-based training. This classification, as shown in Table 1, ensures that the research captures diverse perspectives and experiences relevant to the Learning Factory's operational and instructional processes.

The selected Learning Factory site represents a mid-sized educational facility equipped with conventional machining tools, semi-automated production stations, and modular learning areas used for competency-based training. This environment allowed the researchers to observe a realistic mixture of manual, hybrid, and technology-assisted workflows. The facility also operates under a structured semester-based schedule, providing opportunities to analyze peak activity periods and resource utilization patterns.

The diversity of participants was intentionally chosen to reflect the interdependent roles within Learning Factory operations. Instructors contributed insights related to instructional planning and supervision, laboratory managers provided perspectives on logistics and maintenance challenges, while students offered first-hand accounts of procedural clarity, equipment accessibility, and learning experiences. This holistic selection ensured that data represented the full spectrum of interactions within the Learning Factory ecosystem.

3.3. Data Collection Techniques

The research employs three primary data collection methods, namely semi-structured interviews, direct observation, and document review. Semi-structured interviews are conducted to obtain detailed insights into user needs, perceived challenges, and inefficiencies within existing operational workflows, giving participants space to express both explicit requirements and implicit expectations. Direct observations are carried out during laboratory activities to understand real scheduling patterns, machine usage behavior, coordination practices between students and instructors, and situational factors that influence workflow continuity. In addition, document review is conducted to examine existing recording formats, training modules, workflow procedures, competency checklists, and equipment allocation logs, enabling a comprehensive understanding of the current documentation system and operational standards. Collectively, these three methods provide a robust and triangulated foundation for informing system design and ensuring alignment with actual Learning Factory conditions.

Table 2. Data Collection Matrix

Method	Data Source	Purpose of Data
Semi-Structured Interview	Instructors, Managers, Students	Understanding workflow needs and operational issues
Observation	Learning Factory Activities	Capturing real-time resource use and task execution
Document Review	Operational Records & Modules	Identifying gaps in documentation and coordination

Table 2 provides an overview of the three main methods used in the study to gather data, namely semi-structured interviews, observation, and document review. Each method is aligned with specific data sources and purposes. Semi-structured interviews were conducted with instructors, managers, and students to understand workflow needs and operational challenges. Observations were carried out during Learning Factory activities to capture real-time resource utilization and task execution. Meanwhile, document reviews focused on operational records and training modules to identify gaps in documentation and coordination. As shown in Table 2, this triangulated data collection approach ensures a comprehensive understanding of Learning Factory operations from multiple perspectives.

To strengthen the reliability of the data collection process, multiple iterations of interviews and observations were conducted at different times of the semester. This allowed the research team to capture variations in workflow patterns during early, mid, and peak operational phases. For instance, early-semester sessions typically involved orientation and skill familiarization, whereas later sessions focused on higher-complexity production tasks, offering richer insight into coordination issues that emerged under greater workload.

Digital tools such as audio recorders, observation grids, and document coding sheets were employed to support consistent data capture across sessions. These tools ensured that subtle interactions such as brief verbal instructions, machine downtimes, or student hesitation during procedural tasks were accurately documented and incorporated into the analysis.

3.4. Data Analysis Procedure

Data analysis is conducted using thematic analysis, which consists of three key stages involving data reduction, data classification, and interpretation. During the reduction stage, interview transcripts, field notes, and documents are reviewed to extract meaningful statements. The classification stage involves grouping recurring findings into themes, such as scheduling challenges, resource traceability gaps, instructional misalignment, and evaluation inconsistencies. In the interpretation stage, themes are translated into system requirements, which form the basis for the Educational Information System design. The result of this process is the formulation of the system architecture that integrates scheduling automation, digital documentation, performance tracking, and centralized workflow control.

In conducting thematic analysis, the research team held collaborative review sessions in which each researcher independently examined the coded data before comparing interpretations. This cross-validation process helped reduce individual bias and ensured that emergent themes were consistently identified. Discrepancies in interpretation were resolved through discussion, with reference to the original data sources when necessary.

Additionally, data saturation was monitored throughout the analysis. Saturation was considered achieved when further interviews and observations no longer yielded new categories or insights. Reaching saturation enhanced the credibility of the findings by confirming that the themes reflected stable patterns in Learning Factory operations rather than isolated experiences.

To provide deeper technical clarity, this study includes a detailed explanation of the internal data flow and module interactions within the Educational Information System (EIS). The system operates using a sequential processing workflow that begins when users such as instructors, students, or laboratory managers initiate a request. The request first passes through the Scheduling and Resource Planning module, where the system validates machine availability, instructor allocation, and potential scheduling conflicts. Once validated, the structured request is forwarded to the Equipment and Inventory Monitoring module, which retrieves real-time machine conditions, maintenance records, and inventory availability.

After confirming resource readiness, the Digital Instruction and SOP Access module automatically selects relevant instructional content based on the user's role, the scheduled task, and competency requirements. Students then receive real-time operational guidance that aligns with system data. When learners perform assigned activities, the system captures task duration, performance quality, and competency indicators. These outputs are transmitted to the Competency-Based Performance Evaluation module, which processes and updates the learner's performance profile, synchronizing it with the centralized dashboard accessible to instructors and laboratory managers.

This end-to-end sequence creates a closed-loop data flow that ensures transparency, consistency, and instructional alignment across all operational components of the Learning Factory. Furthermore, a conceptual sequence model has been incorporated to illustrate how user-triggered interactions propagate through the system, how data is exchanged between modules, and how final evaluations are stored for continuous instructional improvement. This sequence model enhances reproducibility and reinforces the technical structure of the proposed EIS.

3.5. Research Design Framework

The research design framework is developed to illustrate how each methodological component contributes to the overall flow of this study. It outlines the structured progression from identifying operational challenges within the Learning Factory to formulating user requirements and translating them into system features. This framework also reflects the iterative nature of the research, where findings from each stage inform subsequent phases to ensure coherence and alignment with study objectives. By visualizing these interconnected steps, the framework provides a clearer understanding of how empirical analysis, system conceptualization, and validation activities are systematically integrated throughout the research process.

The overall research flow illustrating the methodological steps is shown below:

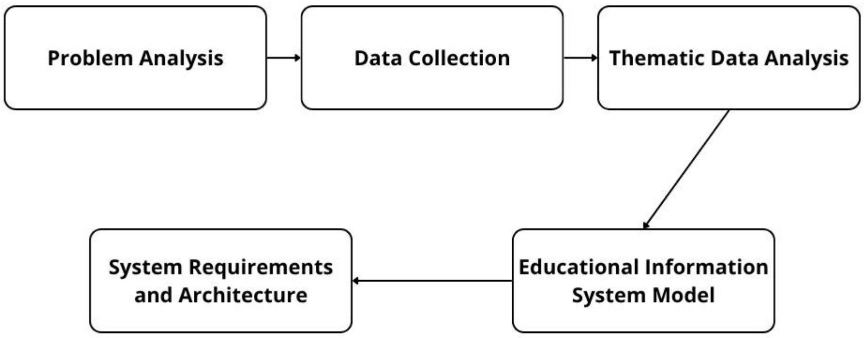

Figure 2. Research Design Framework

Figure 2 illustrates the overall methodological flow of the study, outlining the sequential steps followed to develop the Educational Information System model. The process begins with Problem Analysis, which identifies operational challenges in the Learning Factory environment. This is followed by Data Collection through interviews, observations, and documentation to gather relevant qualitative data. The next step, Thematic Data Analysis, organizes and interprets the collected data into meaningful themes. These insights are then used to define the System Requirements and Architecture, which ultimately lead to the creation of the Educational Information System Model. As shown in Figure 2, this framework ensures a systematic and logical progression from problem identification to model development.

The framework also served as a guide for maintaining coherence across research activities. Each stage was documented to ensure that emerging findings directly informed subsequent methodological steps. For example, insights derived from early observation sessions influenced the refinement of interview questions, while preliminary themes from interviews shaped the analysis of operational documents.

This iterative process enabled the researchers to adapt to conditions within the Learning Factory environment while maintaining methodological rigor. The use of a structured yet flexible design allowed the study to capture the complexity of real-world operational systems and translate those insights into actionable system requirements for the proposed Educational Information System.

4. RESULTS AND FINDINGS

4.1. Learning Factory Operational Challenges Identified

The results of interviews, observations, and document reviews indicate that the existing Learning Factory environment faces several operational challenges that affect both instructional flow and resource efficiency. Participants reported frequent scheduling conflicts, limited visibility of machine availability, and inconsistent documentation of student performance. Laboratory managers explained that resource allocation was conducted manually, leading to delays and redundant administrative work. Students noted that they often lacked clear procedural guidance before operating machinery, causing variations in task execution. These findings confirm that the absence of a centralized information system contributes to workflow inefficiencies and uneven learning experiences. Therefore, the need for an Educational Information System is strongly justified based on operational realities observed in the Learning Factory.

In addition to the challenges already identified, several instructors noted that miscommunication frequently occurred during peak laboratory periods, especially when multiple student groups accessed shared equipment simultaneously. These communication gaps often resulted in duplicated efforts, delayed task initiation, and inconsistent adherence to safety procedures. Participants emphasized that without a unified digital interface capturing real-time operational status, both instructors and students relied heavily on verbal updates that were often incomplete or outdated. This situation not only created uncertainty in task sequencing but also contributed to inconsistent learning experiences among different student cohorts.

Moreover, observations revealed that documentation gaps extended beyond performance records and affected the traceability of process deviations. For instance, when students encountered machine issues or workflow errors, these incidents were rarely logged systematically, making it difficult for instructors to review procedural weaknesses or provide targeted remedial training. The absence of structured digital logging mechanisms also hindered laboratory managers from accurately anticipating maintenance needs or equipment downtime patterns. These additional findings reinforce the importance of implementing a digitally integrated system capable of enhancing visibility, communication, and documentation across all Learning Factory operations.

4.2. User Requirements for Educational Information System

Thematic analysis revealed four primary categories of system requirements for the Educational Information System, which include Scheduling Management, Resource Availability Monitoring, and Digital Work Instruction Access. Instructors specifically emphasized the importance of a scheduling module that integrates class timetables with machine usage allocation. Students, on the other hand, requested access to real-time operating procedures and task instructions that can be reviewed both before and during laboratory work. Furthermore, all participant groups agreed on the need for automatic logging of equipment conditions and usage records. Overall, a digital system for evaluating student competency and tracking learning progress was deemed essential to support a consistent and measurable learning model, and these requirements formed the foundation for designing the system architecture.

Further insights from participants suggest that the system should also incorporate personalized user dashboards that adapt to the needs of different roles within the Learning Factory. For example, instructors expressed interest in dashboards that highlight student progress trends, competency attainment patterns, and common bottlenecks encountered during laboratory sessions. Students, on the other hand, preferred interfaces that clearly display upcoming tasks, required materials, safety prerequisites, and automated reminders linked to scheduled activities. These role-specific features would help ensure that information is presented in a way that aligns with each user's responsibilities and enhances clarity in task execution.

Participants additionally emphasized the importance of seamless integration between the Educational Information System and existing institutional platforms, such as learning management systems or digital attendance tools. Doing so would reduce the administrative burden associated with switching between multiple systems and support a more unified digital ecosystem. Lab managers also recommended embedding alert mechanisms for equipment thresholds, low inventory levels, and overdue maintenance routines to enhance operational reliability. Collectively, these additional requirements underscore the need for a holistic system capable of supporting diverse user workflows while maintaining operational coherence.

4.3. Proposed System Architecture and Functional Features

Based on the identified needs, a conceptual system architecture was designed to integrate administrative, operational, and instructional components within the Learning Factory. This architecture aims to create a cohesive digital environment that supports efficient management of resources, enhances instructional delivery, and ensures smooth workflow coordination. To address the complexities of Learning Factory operations such as machine scheduling, material tracking, performance monitoring, and adherence to standardized procedures the proposed system is structured into several interconnected functional modules. Each module is designed to handle a specific aspect of the operational ecosystem while collectively forming a comprehensive information management framework. By organizing the system into clear functional components, the architecture ensures scalability, ease of use, and the ability to support evolving educational and industrial demands. The proposed system consists of four core functional modules outlined in Table 3:

Table 3. Proposed System Functional Modules and Their Descriptions

Module Name	Function Description
Scheduling and Resource Planning	Allocates machine usage, student rotation, and instructor supervision schedules.
Equipment and Inventory Monitoring	Displays machine condition, maintenance needs, and material availability.
Digital Instruction and Standard Operating Procedures Access	Provides step by step learning tasks, safety protocols, and workflow documentation.
Competency Based Performance Evaluation	Records task outcomes and generates feedback for student learning progress.

Table 3 outlines the four main modules that form the core of the proposed Educational Information System for Learning Factory operations. The Scheduling and Resource Planning module manages machine usage, student rotation, and instructor supervision schedules to ensure efficient time and resource utilization. The Equipment and Inventory Monitoring module tracks machine conditions, maintenance needs, and material availability in real time. The Digital Instruction and Standard Operating Procedures Access module provides structured learning materials, safety guidelines, and workflow documentation to support consistent instructional delivery. Lastly, the Competency-Based Performance Evaluation module records student task outcomes and provides feedback to monitor learning progress. As presented in Table 3, these modules collectively enhance coordination, transparency, and the alignment between educational activities and industrial workflows.

Beyond the four core modules described, the proposed architecture would benefit from incorporating a centralized data integration layer designed to synchronize information dynamically across all system components. This layer would act as an intelligent middleware, ensuring that scheduling updates, performance evaluations, and equipment status changes are reflected instantly across the relevant user interfaces. Such synchronization is crucial for minimizing operational delays caused by outdated information and for enabling instructors to intervene promptly when workflow disruptions occur. Furthermore, integrating analytics capabilities into the architecture would allow stakeholders to derive insights from accumulated performance data, such as identifying frequently encountered errors or optimizing machine allocation patterns.

To enhance system scalability, the architecture could also adopt a modular microservices approach, allowing institutions to implement specific features based on their digital maturity and operational priorities. For example, institutions with advanced Learning Factory environments might integrate real-time sensor data from manufacturing equipment, while those in early stages could begin with digital work instruction modules. This modular flexibility ensures that the system remains adaptable across various educational contexts and can evolve as institutions expand their technological infrastructure.

4.4. Implications for Learning Factory Instructional Model

The integration of the Educational Information System transforms the instructional model from manual coordination into a data-supported learning process. With automated scheduling and accessible digital instructions, students prepare more efficiently, reduce operational errors, and strengthen their learning autonomy. Instructors gain clearer visibility into student progress and task performance, enabling more targeted feedback and competency-based assessment. Laboratory managers benefit from streamlined resource control and reduced administrative workload, allowing them to focus on preventive maintenance and workflow improvement.

These findings demonstrate that the system not only enhances operational efficiency but also significantly reinforces the pedagogical value of Learning Factory environments by enabling more structured, data-informed, and context-aware learning experiences. The integration of the Educational Information System supports smoother coordination between digital and physical learning activities, promotes timely instructional interventions, and ensures that learners engage with processes that closely mirror real industrial practices. The results clearly align with the research objective stated in the abstract, confirming that the design and implementation of an Educational Information System constitute a feasible and highly effective strategy for optimizing Learning Factory operations while simultaneously strengthening the achievement of industrially relevant learning outcomes.

The integration of the Educational Information System also reshapes the instructional model by promoting greater learner autonomy and self-regulated learning. With reliable access to organized workflows, digital instructions, and competency status, students can better prepare for upcoming activities and engage in reflective practices that enhance their understanding of production concepts. This shift places learners in a more active role, enabling them to identify personal skill gaps and monitor their own progress throughout the training cycle. Instructors, in turn, can transition from primarily supervising tasks to delivering targeted guidance informed by real-time performance data.

Additionally, the system's ability to standardize documentation and competency assessment contributes to more equitable learning experiences across student groups. By reducing reliance on subjective and manually recorded evaluations, the EIS supports consistent monitoring mechanisms that help ensure fairness in grading and competency recognition. This structured approach enhances the credibility of the Learning Factory model and aligns it more closely with industrial certification standards. As a result, the instructional model not only becomes more efficient but also more aligned with workforce development requirements, ultimately improving graduate preparedness for industry environments.

5. MANAGERIAL IMPLICATIONS

The results of this study highlight the critical role of institutional management in ensuring the successful integration of an Educational Information System within Learning Factory environments. Administrators and laboratory managers must view the EIS not merely as a technological upgrade but as a strategic component of operational and instructional governance. By adopting a unified digital platform that consolidates scheduling, resource allocation, progress monitoring, and documentation processes, management can significantly reduce inefficiencies caused by manual coordination and fragmented communication channels. This centralization enables smoother workflow execution, minimizes downtime, and enhances instructional consistency across multiple student cohorts.

From an organizational development perspective, the implementation of the EIS provides management with richer data for decision-making and long-term planning. Real-time insights into equipment usage trends, student competency progression, task completion rates, and maintenance patterns allow institutions to optimize budgeting, schedule infrastructure updates, and allocate instructional staff more effectively. Managers can also utilize system-generated analytics to identify operational bottlenecks, forecast peak laboratory demands, and develop policies that ensure balanced resource utilization. This data-driven approach strengthens institutional agility, enabling administrators to anticipate challenges and respond proactively rather than reactively.

Moreover, the findings underscore the importance of managerial support in fostering a digital-ready learning culture. The successful deployment of the EIS requires not only technological investment but also strategic capacity-building initiatives such as staff training, workflow redesign, digital literacy development, and policy reforms that align with system functionalities. Managers must ensure that instructors and students are adequately prepared to use the system, as user engagement directly influences system effectiveness. Additionally, the standardization of learning documentation and competency assessments enabled by the EIS enhances institutional credibility and strengthens partnerships with industry stakeholders, positioning the institution as a leader in digitally enabled, industry-aligned education. By championing these changes, management can drive sustainable improvements that elevate both operational performance and educational outcomes.

6. CONCLUSION

The findings of this research show that the proposed educational information system significantly improves operational efficiency by integrating real-time data processing, workflow tracking, and instructional guidance. The system strengthens production activities, enhances communication between instructors and learners, and optimizes resource utilization through data-driven coordination. This research confirms that a Learning Factory benefits from digital coordination mechanisms that reinforce experiential learning, foster problem-solving competencies, and provide actionable insights for operational decision-making.

This study demonstrates that an educational information system optimizes Learning Factory operations by improving workflow transparency, enhancing learning engagement, and reducing errors. However, this research has limitations, particularly in terms of system scalability and generalizability. Furthermore, the scalability of the proposed EIS enables its adaptation across different institutional contexts. The modular architecture allows implementation in vocational schools, universities, or industrial training centers by modifying functional modules such as scheduling, competency tracking, and monitoring according to each institution's digital readiness and operational complexity. This flexibility ensures that the proposed EIS can be scaled effectively without redesigning the entire system. Additionally, some system components may require further customization to address different institutional needs and varying levels of digital readiness among users.

For future research, it is recommended to expand system testing across multiple Learning Factory models and diverse educational or vocational institutions to validate adaptability and performance consistency. Integration with more advanced technologies, such as automation analytics, AR-guided training, or intelligent scheduling algorithms, could further enhance the system's capability. Further studies may also explore the development of a standardized framework to guide implementation in various educational and industrial learning settings, ensuring sustained practicality and wide-scale usability.

7. DECLARATIONS

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Validation: AK; Conceptualization: SM; Methodology: YS; Formal Analysis: AA; Writing Review and Editing: IY; Visualization: AA; Each of the authors YS, SM, & IY has reviewed and approved the manuscript's published form.

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The corresponding author can provide access to the data used in this study upon reasonable request.

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The authors declare that they have no known financial or personal relationships that could have influenced the work reported in this publication.

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