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An AI-driven framework for learning analytics and operational optimization in technology and vocational education: Bridging industrial engineering and informatics

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ABSTRACT

This study proposes an artificial intelligence (AI)-driven framework that integrates learning analytics with operational optimization to address the fragmentation between educational data and operational decision-making in technology and vocational education. Although vocational institutions increasingly adopt digital technologies, learning-related data are often analyzed separately from operational processes such as scheduling, task allocation, resource utilization, and process efficiency, despite their interdependence in teaching factory and practical learning environments. Drawing on perspectives from industrial engineering and informatics, the proposed framework integrates machine learning for analyzing learner performance and competency development with optimization techniques for supporting operational decision-making. The framework was designed to be adaptable across different vocational education contexts and was empirically evaluated in a technology-oriented vocational setting to assess its feasibility. The evaluation demonstrates the feasibility of integrating learner-related and operational information within a unified decision-support environment, enabling competency and performance information to inform decisions concerning practical tasks, scheduling, and resource allocation. Rather than positioning AI solely as a predictive or instructional tool, the framework conceptualizes it as a mechanism for connecting pedagogical and operational dimensions of vocational learning. This study contributes an interdisciplinary and system-oriented perspective on AI adoption in vocational education, providing a foundation for more integrated, context-sensitive, and data-informed decision-making in teaching factory and practical learning environments.

INTRODUCTION

Technology and vocational education holds an important position in preparing a workforce that is able to respond to ongoing industrial development and rapid technological change. In contrast to general academic education, vocational education is strongly oriented toward practical activities and production-based learning, with a clear emphasis on the development of competencies that can be directly applied in the workplace (Chong & Ng, 2025). Learning environments such as teaching factories, laboratories, and workshops therefore function not only as instructional spaces, but also as semi-operational settings in which educational activities are closely intertwined with production

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processes. This dual role makes vocational education inherently complex, as institutions are required to achieve learning objectives while simultaneously dealing with operational constraints, including limited resources, scheduling issues, equipment availability, and process efficiency (Varlamis et al., 2025).

Along with these demands, vocational institutions have increasingly adopted digital technologies to support teaching and learning activities. Learning management systems, digital assessment platforms, and various educational applications are now commonly used to document student performance, organize instructional content, and facilitate interaction between instructors and learners (Ghasem, 2024). As a result, a growing amount of educational data is generated on a regular basis. Information related to attendance, assessment results, task completion, and learner interaction patterns has become more readily available, offering new opportunities for data-informed decision-making. However, despite this increasing availability of data, its use in vocational education remains largely fragmented and has not yet been fully utilized to support either learning or operational improvement (Hooper et al., 2025).

A key limitation can be found in the way educational data are commonly analyzed. Most existing practices tend to focus on learning outcomes alone, such as grades, examination scores, or course completion rates. While these indicators are necessary, they capture only a portion of the learning experience in vocational education. Practical learning activities, particularly those carried out in teaching factories and laboratories, also involve operational processes that closely resemble industrial systems. These processes include task sequencing, machine utilization, material handling, and time management. In many cases, data generated from such activities are either not analyzed systematically or are treated separately from learning-related data. Consequently, educators and administrators often lack a comprehensive view of how student learning performance and operational efficiency influence one another (Visakh & Selvan, 2023).

From this perspective, industrial engineering provides a relevant set of concepts and methods. Industrial engineering traditionally focuses on the design, analysis, and improvement of systems that involve people, materials, information, and equipment. Methods related to process optimization, scheduling, resource allocation, and performance measurement have long been applied to improve efficiency and productivity in industrial contexts. Similar challenges also exist in teaching factory environments, although the objectives differ. Rather than prioritizing profit or throughput, vocational institutions must maintain a balance between educational quality and operational feasibility. Despite this potential relevance, industrial engineering approaches are still rarely integrated into educational data analysis in a structured and systematic way (Rakesh et al., 2025).

At the same time, recent advances in artificial intelligence (AI) and machine learning have expanded the possibilities for analyzing complex and heterogeneous data. AI-based approaches are well suited to identifying patterns, making predictions, and supporting decision-making in situations characterized by uncertainty and variability. In the field of education, AI has been applied in various areas, including intelligent tutoring systems, automated assessment, learning analytics, and personalized learning environments. Learning analytics, in particular, has attracted attention as a means of using data to better understand learning processes and outcomes, with the aim of supporting instructional design, targeted interventions, and institutional decision-making (Farkas, 2020).

Nevertheless, the application of AI in vocational education remains uneven. Much of the existing research on AI-based learning analytics focuses on general or higher education settings, often emphasizing online learning environments or theoretical courses. Vocational education, which is strongly grounded in hands-on practice and operational activities, presents characteristics that are not fully captured by these models. In addition, AI applications in vocational contexts frequently concentrate on isolated tools or narrowly defined use cases, such as automated grading or basic performance prediction, without sufficiently considering the broader system in which learning and operational processes are interconnected (Gunarto, 2024).

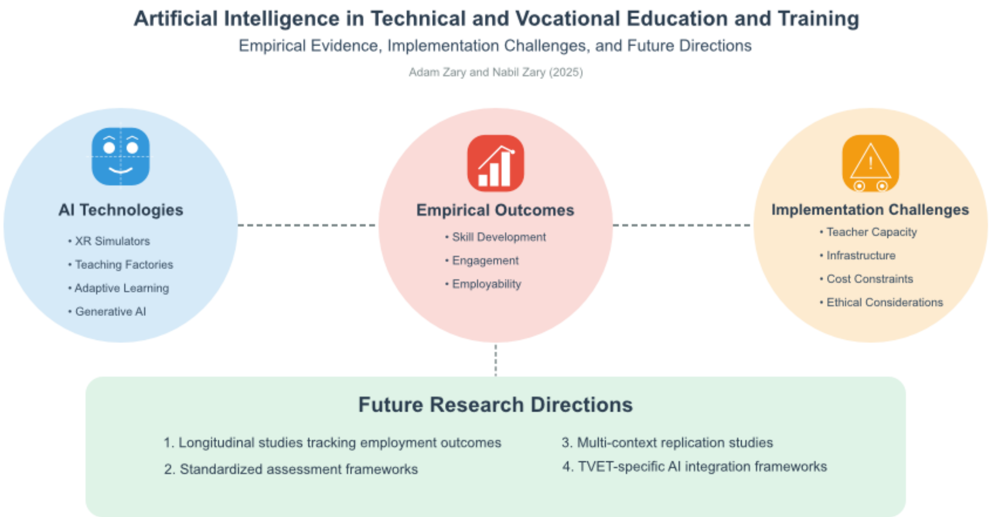

Figure 1. Artificial Intelligence in Technical and Vocational Education and Training: Empirical Evidence, Implementation Challenges, and Future Research Directions

Source: Adapted from Zary and Zary (2025)

As illustrated in Figure 1, previous research on artificial intelligence in TVET has highlighted a broad range of AI technologies and their potential contributions to skill development, learner engagement, and employability. However, their implementation continues to face challenges related to teacher capacity, infrastructure, cost, and ethical considerations. More importantly, the emerging research agenda indicates the need for TVET-specific AI integration frameworks that move beyond isolated technological applications toward more systematic and context-sensitive approaches.

This separation between learning analytics and operational analysis represents a notable gap in the existing literature. In teaching factory and laboratory-based learning environments, student learning outcomes are closely linked to operational conditions. Limited machine availability may reduce practice time, inefficient scheduling can disrupt learning activities, and inadequate resource allocation may increase costs while negatively affecting educational quality (Priyadarshinee et al., 2017). At the same time, learner performance and behavior can also influence operational efficiency, for example when students with lower levels of experience require additional time or supervision to complete tasks. Treating learning and operations as separate domains therefore risks oversimplifying the complex nature of vocational education systems (Uddin et al., 2020).

To address this issue, an integrated approach is required. Such an approach should be able to analyze learning-related data and operational data simultaneously, enabling educators and administrators to better understand their interactions and make more informed decisions. Artificial intelligence offers a promising basis for this integration, as it can accommodate diverse data sources and support both predictive modeling and optimization tasks. By combining AI techniques with principles from industrial engineering and informatics, vocational education can be approached more holistically as an interconnected system in which learning processes, technological resources, operational activities, and industry-oriented practices interact with one another (Saputro et al., 2021; Wahjusaputri et al., 2021).

From this viewpoint, vocational education can be seen not only as a learning environment, but also as an operational system with explicit educational goals. Teaching factories, in particular, can be interpreted as simplified production systems designed to support learning. They involve workflows, constraints, and performance indicators similar to those found in industrial settings, while still incorporating pedagogical considerations. This dual nature suggests that methods commonly used in industrial engineering, such as scheduling algorithms, performance measurement, and process optimization, may be adapted to support educational decision-making when they are combined with learning analytics. However, integrating these domains is not without challenges. Learning data and operational data differ in terms of structure, scale, and interpretation. Learning data often include qualitative and behavioral aspects, such as engagement and competency development, whereas operational data are generally quantitative and process-oriented. Bridging these different data types requires a framework that is capable of accommodating heterogeneity while providing meaningful insights. Without such a framework, AI-based applications risk remaining fragmented and addressing only limited aspects of the overall system (AlMuhayfith & Shaiti, 2020).

Another issue relates to the transferability of research outcomes. Many studies in vocational education rely heavily on context-specific case studies, which can limit the generalizability of their findings. Although case studies offer valuable insights, they often constrain the applicability of proposed solutions to particular institutions or settings. To achieve broader impact, especially in the context of international academic publication, there is a need for conceptual and methodological frameworks that can be adapted to different vocational education contexts. A framework-oriented approach allows researchers to emphasize underlying principles and structures rather than focusing solely on local implementations. In addition, the adoption of AI in vocational education raises practical concerns. Educators and administrators may face limitations related to technical expertise, financial resources, or institutional readiness when attempting to implement complex AI-based systems. For this reason, proposed solutions must be not only theoretically sound but also realistic and aligned with the operational conditions of vocational institutions (Hong et al., 2006). Frameworks that prioritize clarity, modularity, and scalability are more likely to be adopted and sustained in practice.

In response to these challenges, this study proposes an artificial intelligence–driven framework that integrates learning analytics and operational optimization within the context of technology and vocational education. The framework is intended to analyze heterogeneous data generated from learning activities, practical tasks, and operational processes. Machine learning techniques are used to model learner performance, competency development, and process behavior, while optimization methods support decision-making related to task allocation, scheduling, and resource utilization. Through this integration, the framework seeks to provide a more comprehensive understanding of vocational education systems (Lin & Lin, 2008).

The proposed framework is not designed to replace existing educational practices or professional judgment. Instead, it aims to support educators and administrators by offering data-informed insights that complement their experience. Predictive modeling can assist in identifying potential learning difficulties or operational inefficiencies at an early stage, while optimization techniques can be used to explore alternative ways of organizing practical activities in line with educational goals and operational constraints. This study emphasizes the integration of industrial engineering and informatics perspectives. Industrial engineering contributes concepts related to efficiency, optimization, and performance measurement, while informatics provides tools for data management, algorithm development, and computational analysis.

Artificial intelligence serves as the link that enables these perspectives to be combined (Christiansen et al., 2022). By positioning vocational education as an interdisciplinary field that benefits from this integration, the study responds to the need for more system-oriented research in educational technology. To explore the feasibility and potential benefits of the proposed framework, an empirical study is conducted in a technology-oriented vocational education setting. This empirical component is intended not as a final validation, but as an illustration of how the framework can be applied in practice. The analysis examines how learning analytics and operational optimization can be combined to generate insights that are difficult to obtain when these aspects are analyzed separately. The results are then used to discuss the strengths and limitations of the framework, as well as its implications for future research and practical implementation (Zhao et al., 2025).

Overall, this study makes three main contributions. First, it presents a conceptual framework that integrates learning analytics and operational optimization in vocational education, addressing a gap in the existing literature. Second, it demonstrates the potential role of artificial intelligence in supporting both educational and operational decision-making within teaching factory environments. Third, it provides a basis for future research that seeks to examine the intersection of artificial intelligence, industrial engineering, and technology-oriented education in a more systematic way. By adopting an interdisciplinary and framework-based approach, this study moves beyond isolated applications of AI and toward a more integrated understanding of how data can be used to support vocational education systems. In doing so, it responds to the growing need for research that not only introduces new technologies, but also critically examines their role within complex educational and operational contexts. Ultimately, the study aims to contribute to the development of vocational education that is both educationally effective and operationally sustainable in an increasingly data-driven environment (Islam et al., 2025).

RESEARCH METHOD

This study employed a design-oriented research approach supported by empirical analysis to develop, implement, and evaluate an artificial intelligence-based framework integrating learning analytics with operational optimization in technology and vocational education. The study was grounded in the Design Science Research (DSR) paradigm, which emphasizes the development and evaluation of purposeful artifacts to address relevant organizational and technological problems (Hevner et al., 2004). This paradigm was considered appropriate because the study sought not only to analyze an existing phenomenon but also to develop a practical framework addressing the fragmented use of learning-related and operational data in vocational education. Consistent with established DSR principles, the proposed framework was treated as a research artifact whose utility and feasibility were examined through iterative design and empirical evaluation (Hevner et al., 2004; Peffers et al., 2007). The research process was organized into five adapted stages: problem identification and requirement analysis, framework design, model development and integration, implementation and empirical evaluation, and analysis and refinement.

The empirical study was conducted in a technology-oriented vocational education environment involving practical learning activities in teaching factories or laboratories. This setting was selected because vocational learning involves interactions between formal educational processes and authentic or workplace-oriented activities. Previous research has emphasized that learning analytics in vocational education needs to account for learning processes extending across classroom and workplace contexts (Gedrimiene et al., 2020). Data were therefore collected from multiple sources representing both learning and operational dimensions. Learning-related data included assessment scores, task-completion records, attendance data, and competency evaluation results, while operational data included task schedules, machine or equipment usage logs, processing times, and resource-allocation records generated during practical activities. Integrating these data sources was intended to provide a more comprehensive representation of the educational and operational conditions under investigation.

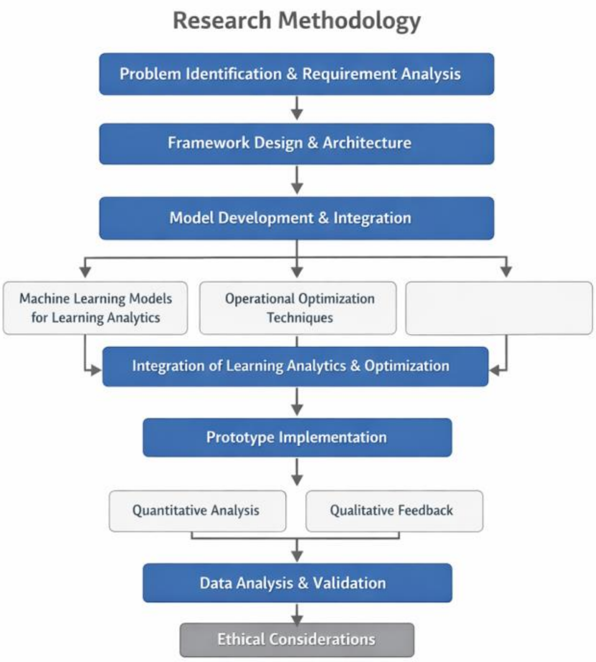

Figure 2. Research Method

The initial stage involved identifying key problems and determining system requirements through document review, discussions with instructors or laboratory managers, and direct observation of practical learning activities. These activities were used to identify inefficiencies, bottlenecks, and limitations in existing learning assessment and operational-management practices. Based on this analysis, functional and non-functional requirements were formulated. Functional requirements included the ability to analyze learner performance, model competency development, and support operational decision-making, whereas non-functional requirements included interpretability, scalability, and adaptability across vocational education contexts. This problem-centered development process is consistent with DSR methodology, in which problem identification and the definition of solution objectives provide the basis for artifact design and subsequent evaluation (Peffers et al., 2007).

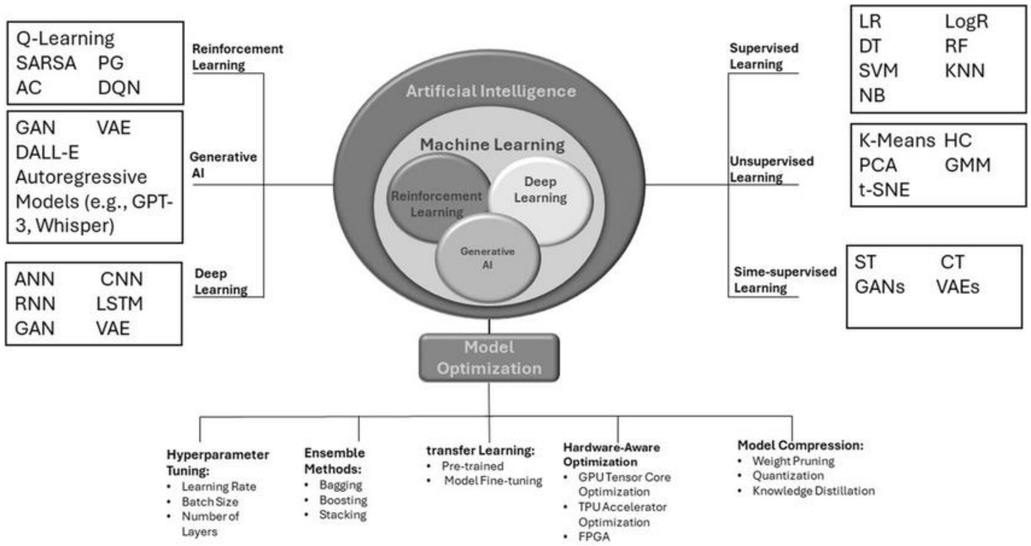

Figure 3. AI and Machine Learning Architecture for Model Optimization

Based on these requirements, the framework was designed as a modular architecture consisting of three main layers: data management, analytics and modeling, and decision support. The data management layer handled data collection, preprocessing, and integration from heterogeneous sources, including data cleaning, normalization, and feature extraction. The analytics and modeling layer integrated machine learning techniques for learning analytics with optimization methods derived from industrial engineering. As illustrated in Figure 3, this layer incorporates relevant artificial intelligence and machine learning approaches to support analytical modeling and model optimization within the proposed framework. The decision support layer subsequently translated the analytical outputs into actionable information that educators and administrators could use to plan and manage practical learning activities.

Supervised machine learning techniques were applied to model learner performance and competency development. Regression models were used to predict continuous outcomes, such as task completion time and competency scores, whereas classification models were used to identify learners at risk of underperforming. Feature selection was conducted to identify relevant learning and behavioral indicators. Model training and validation involved data partitioning and cross-validation to reduce overfitting, while model performance was evaluated using appropriate metrics, including accuracy, precision, recall, and mean absolute error, depending on the analytical task.

Operational optimization methods were incorporated to support scheduling, task allocation, and resource utilization. Scheduling was formulated as a constrained optimization problem considering equipment availability, time constraints, and educational requirements. Linear programming and heuristic-based algorithms were applied to generate feasible and efficient schedules. The optimization objectives considered not only operational efficiency but also educational considerations, including maximizing opportunities for practical learning and balancing learners' workloads. Learning analytics and operational optimization were subsequently integrated by using outputs from the machine learning models, such as predicted learner performance and competency levels, as input parameters for the optimization models. This integration enabled task assignment and scheduling decisions to simultaneously account for learner characteristics, educational objectives, and operational constraints.

The resulting framework was implemented as a prototype to demonstrate its feasibility and the interaction between learning analytics and operational optimization. Empirical evaluation was conducted using historical or real-time data obtained from the vocational education setting. Analytical performance was evaluated by comparing model predictions with observed outcomes, while practical relevance was examined through improvements in scheduling efficiency, resource utilization, and alignment between learning outcomes and operational decisions. Quantitative comparative analysis was conducted between scenarios employing the integrated framework and those without integration, and sensitivity analysis was performed to examine the robustness of the framework under varying conditions. Qualitative feedback from instructors or administrators was also collected to assess the interpretability and practical usefulness of the framework outputs. This combination of quantitative and qualitative evaluation was intended to assess both the technical validity and educational relevance of the proposed framework.

Ethical considerations were maintained throughout the research process. Student data were anonymized to protect privacy and were used exclusively for research purposes. Transparency in model development was emphasized, and fully automated decision-making that could negatively affect learners without appropriate human oversight was avoided. Through these procedures, the study combined design-oriented development with empirical evaluation to provide a structured and replicable approach for examining how artificial intelligence can support learning processes and operational decision-making in technology-oriented vocational education.

RESULT AND DISCUSSION

Learning Analytics Performance and Learner Competency Patterns

The implementation of the proposed AI-driven framework demonstrated how learning-related and operational data could be integrated within a unified analytical environment. The learning analytics component incorporated assessment scores, task-completion records, attendance information, and competency evaluation data to represent learner performance and competency progression. In addition to these conventional learning indicators, the framework incorporated operational variables associated with practical learning activities, including task complexity, equipment availability, and scheduling conditions.

The learning analytics component was structured to support several analytical functions, including learner performance analysis, competency progression analysis, identification of learners requiring additional support, and examination of operational conditions associated with practical learning. Rather than treating these functions independently, the proposed framework connects learner-related indicators with contextual and operational information. The main analytical components, data inputs, and intended outputs are summarized in Table 1.

Table 1. Learning Analytics Components and Their Analytical Functions

Analytical Component	Input Data	Analytical Approach	Intended Output
Learner performance analysis	Assessment scores, task-completion records, attendance data	Descriptive and predictive analysis	Learner performance profiles
Competency analysis	Competency evaluation results and practical-task performance	Regression-based analysis	Estimated competency progression
At-risk learner identification	Learning and behavioral indicators	Classification-based analysis	Identification of learners requiring additional support
Operational-context analysis	Task complexity, equipment availability, and scheduling conditions	Integrated contextual analysis	Identification of operational factors

As shown in Table 1, the proposed framework extends learning analytics beyond conventional academic indicators by incorporating information about the conditions under which practical learning occurs. Task complexity, equipment availability, and scheduling conditions provide contextual information that can be considered alongside assessment scores, attendance, and competency evaluations. This integration is particularly relevant in teaching factory and laboratory environments, where opportunities for competency development are closely associated with access to equipment, task sequencing, and available practice time.

The integration of these data provides a broader basis for interpreting learner performance. Difficulties observed during practical activities may not necessarily originate solely from individual learner characteristics but may also be associated with contextual constraints, such as limited equipment availability, interruptions in practice, or inappropriate task allocation. Accordingly, interpreting learning-related and operational indicators jointly may provide a more comprehensive understanding of the factors associated with competency progression than relying exclusively on conventional academic indicators.

This perspective is consistent with Gedrimiene et al. (2020), who found that learning analytics research has predominantly focused on higher education, while empirical applications in vocational education remain comparatively limited. Their study further emphasized the potential of learning analytics to facilitate knowledge transfer and integration between classroom and workplace learning. The present framework extends this perspective by incorporating operational conditions within practical learning environments, thereby connecting learner-related information not only with learning activities but also with the resources and operational processes through which vocational competencies are developed.

More recent empirical evidence also supports the use of heterogeneous data for competency-oriented analytics in vocational education. Qin et al. (2026) developed an AI-driven learning analytics model that integrated multimodal instructional data, including classroom interactions, technology-use behaviors, resource-development traces, and performance indicators, to classify and predict vocational teachers' digital competence. Their results indicate that multimodal integration can provide a richer data-driven representation of competence than conventional assessment approaches. Although their study focused on teachers' digital competence, the underlying analytical principle is relevant to the present study: competency-related information can be strengthened by integrating multiple sources of evidence rather than relying on isolated indicators. The proposed framework extends this principle to learner competency development by additionally incorporating operational information associated with practical learning conditions.

A similar development has been reported in the context of AI-supported teaching factories. Wahjusaputri et al., (2024) examined the development of an artificial intelligence-based teaching factory in vocational high schools and demonstrated how AI-supported environments could facilitate digital learning and competency development within vocational settings. Their findings highlight the potential of AI to strengthen the integration of technology into practical and industry-oriented learning environments. The present study extends this direction by explicitly incorporating operational conditions, such as task complexity, equipment availability, scheduling, and resource allocation, into the learning analytics framework. Thus, rather than positioning AI primarily as a technology for supporting learning activities, the proposed framework conceptualizes AI as a mechanism for connecting learner-related information with the operational conditions under which practical competency development occurs.

From a pedagogical perspective, this integrated approach may support more context-sensitive interventions. A learner identified as requiring additional support may not necessarily need additional instruction alone; the appropriate response may involve adjusting task complexity, increasing opportunities for practice, modifying task allocation, or improving access to equipment. In this sense, the proposed framework extends the role of learning analytics from identifying who may require support toward providing contextual information that can help educators understand why difficulties occur and determine what type of intervention may be appropriate.

The comparison with previous studies therefore highlights a specific contribution of the proposed framework. Existing studies have demonstrated the value of learning analytics for understanding learning processes, multimodal AI for competency assessment, and AI-supported teaching factories for vocational competency development. The present framework brings these directions together by explicitly incorporating operational conditions into learning analytics and linking the resulting information to decision-support processes. This system-oriented perspective is particularly relevant to vocational education, where competency development is inherently dependent on the interaction among learners, practical tasks, equipment, time, and other institutional resources.

Operational Optimization and Resource Allocation

The operational component of the proposed framework focused on scheduling, task allocation, resource utilization, bottleneck management, and workload distribution within practical learning activities. Optimization was formulated by considering both operational and educational constraints, including equipment availability, predefined time windows, class schedules, learner competency levels, task complexity, and requirements for equitable access to practical learning opportunities. Rather than treating operational efficiency as an independent objective, the framework incorporated pedagogical considerations to ensure that decisions concerning resources and practical activities remained aligned with competency development.

Within the framework, operational optimization was organized around several interrelated decision areas. Scheduling optimization was designed to coordinate practical activities within available time and equipment constraints, while resource allocation addressed the distribution of equipment and facilities according to learner and task requirements. Task allocation incorporated information on learner readiness, competency level, and task complexity to support appropriate practical assignments. Bottleneck management focused on identifying operational constraints that could restrict access to practice or disrupt learning activities, whereas workload distribution sought to balance practical-learning opportunities across learners. These components, together with their operational considerations, optimization objectives, and intended decision-support outputs, are summarized in Table 2.

Table 2. Operational Optimization Components and Their Decision-Support Functions

Optimization Component	Operational Considerations	Optimization Objective	Intended Decision-Support Output
Scheduling optimization	Available time, class schedules, equipment availability	Improve coordination of practical activities	Feasible and learning-oriented schedules
Resource allocation	Equipment capacity, facility availability, learner demand	Improve resource utilization while maintaining equitable access	Allocation of equipment and learning resources
Task allocation	Learner readiness, competency level, task complexity	Align practical tasks with learner capabilities and learning needs	Competency-informed task assignments
Bottleneck management	Equipment constraints, task sequences, processing time	Identify and minimize disruptions in practical activities	Identification of potential bottlenecks and alternative arrangements
Workload distribution	Learner workload, available practice time, task requirements	Balance practical-learning opportunities across learners	More balanced distribution of practical activities

As shown in Table 2, operational optimization within the proposed framework extends beyond conventional objectives such as maximizing equipment utilization or minimizing idle time. Operational decisions are explicitly connected to educational considerations. Scheduling, for example, should account not only for equipment and time availability but also for whether learners receive sufficient opportunities to practice and demonstrate the competencies they are expected to develop. Similarly, task allocation can incorporate learner readiness and task complexity, allowing practical activities to be organized according to both operational feasibility and individual learning needs.

This perspective is consistent with previous research demonstrating that Teaching Factory implementation requires the coordination of educational processes with operational resources. Saputro et al. (2021), for example, evaluated teaching factory implementation in Indonesian vocational education and identified management, workshops, learning patterns, human resources, products and services, and industry relationships as important implementation parameters. Although most dimensions were implemented effectively, several sub-parameters remained uneven, indicating that the availability of a Teaching Factory alone does not guarantee consistent operational performance. The present framework extends this perspective by treating resource coordination, scheduling, and task allocation as interconnected decision-support problems rather than as separate implementation parameters.

Similar evidence was reported by Wahjusaputri and Bunyamin (2022), whose competency-based Teaching Factory model incorporated school management, human resources, workshops and laboratories, learning patterns, and relationships with business and industry. Their findings reinforce the view that competency-oriented vocational learning depends on an ecosystem in which pedagogical activities and institutional resources are jointly organized. The proposed framework advances this perspective by explicitly connecting these operational conditions with learner-related information. In particular, equipment capacity, learner demand, task complexity, and competency level are treated as inputs to decisions concerning scheduling, task allocation, and resource distribution.

The importance of these operational dimensions is also reflected in research examining the critical success factors of teaching factory implementation. Wahjusaputri et al. (2021) identified multiple factors underlying successful competency-based Teaching Factory implementation, reinforcing the notion that effective vocational learning depends on the interaction between educational design and the institutional environment in which practical activities occur. From this perspective, limitations in equipment, facilities, scheduling, or human resources should not be interpreted merely as administrative problems; they may directly influence the opportunities available to learners for developing and demonstrating occupational competencies.

More recent developments further suggest that digital technologies can provide mechanisms for coordinating these complex operational environments. Meditama et al. (2025), for instance, examined the use of internet of things technologies to optimize teaching factory implementation within an Industry 5.0-oriented vocational learning environment. Their work illustrates the growing movement toward technology-supported monitoring and coordination of practical-learning environments. While such approaches primarily emphasize technological infrastructure and connectivity, the present framework adds a decision-support perspective by linking operational information with learner readiness and competency-related information.

Taken together, these studies indicate that teaching factory effectiveness depends not only on the quality of instruction but also on how institutional resources, facilities, practical tasks, and learning opportunities are coordinated. However, previous studies have generally examined these dimensions as implementation factors, management components, or technology-support mechanisms. The proposed framework extends this body of work by conceptualizing scheduling, resource allocation, task assignment, bottleneck management, and workload distribution as interrelated optimization problems that are simultaneously informed by operational constraints and pedagogical requirements.

This distinction is important because optimization in vocational education cannot be treated in the same manner as conventional production optimization. Whereas industrial systems typically prioritize throughput, productivity, resource utilization, and cost efficiency, vocational education requires these objectives to be balanced against competency development, sufficient opportunities for practice, and equitable access to learning resources. An operationally efficient schedule that restricts some learners' access to essential practical experiences may therefore be educationally ineffective.

Accordingly, the contribution of the proposed framework lies in broadening the meaning of operational efficiency in vocational education. A schedule should not be regarded as effective merely because equipment utilization is maximized or idle time is minimized. Instead, an effective operational arrangement should allocate available resources in ways that provide learners with appropriate and sufficient opportunities to engage in practical tasks aligned with their competency development. Operational optimization is therefore positioned as a decision-support mechanism for balancing resource efficiency, operational feasibility, equitable access, and pedagogical objectives, rather than pursuing efficiency as an independent outcome.

Integrated Learning Analytics and Operational Optimization

The central contribution of the proposed framework lies in the integration of learning analytics with operational optimization. Learning analytics provides information about learner performance and competency development, whereas operational optimization supports decisions related to scheduling, task allocation, and resource utilization. When considered independently, each component represents only one dimension of the teaching factory system. The proposed framework connects these dimensions by enabling learner-related information to inform operational decision-making.

Within the integrated framework, information on learner readiness and competency levels can be incorporated into task-allocation and scheduling decisions. Learners identified as requiring additional support may, for example, be assigned tasks of appropriate complexity or provided with additional opportunities for practice, whereas learners demonstrating higher levels of readiness may progress toward more demanding tasks. This mechanism establishes a feedback relationship between educational analytics and operational decision-making rather than treating them as independent processes. The conceptual distinction between conventional and integrated decision-making approaches is summarized in Table 3.

Table 3. Comparison of Conventional and Integrated Decision-Making Approaches

Dimension	Conventional/Non-integrated Approach	Proposed Integrated Framework
Learner performance	Primarily academic indicators	Academic + operational indicators
Identification of difficulties	Learner-centered causes	Learner + contextual/operational causes
Scheduling	Primarily resource-driven	Learner- and resource-informed
Task allocation	Relatively uniform	Based on readiness and competency
Resource management	Operational efficiency	Operational + pedagogical objectives
Decision-making	Predominantly reactive	Predictive and proactive

As shown in Table 3, the integrated framework broadens the basis for decision-making by connecting learner-related information with the operational conditions under which practical learning occurs. This integration directly addresses the fragmentation of educational and operational data identified as a central problem in vocational education. When these dimensions are considered separately, the interpretation of learner difficulties may overlook contextual constraints. For example, declining performance identified through learning analytics may suggest a need for additional instructional support; however, the underlying difficulty may also be associated with inadequate equipment access, insufficient practice time, or inappropriate task allocation. By considering both dimensions simultaneously, the framework provides a more comprehensive basis for distinguishing between learner-related and system-related constraints.

This system-oriented perspective responds to a limitation previously identified in vocational learning analytics. Gedrimiene et al. (2020) found that learning analytics research has been dominated by higher education contexts, with comparatively few empirical applications in vocational education and training. Importantly, they emphasized the potential of learning analytics to facilitate knowledge transfer and integration between classroom and workplace learning. The present framework develops this direction further by extending the analytical scope beyond learning processes themselves. In teaching factory environments, information concerning learner performance is connected with equipment availability, task allocation, scheduling, and other operational conditions that shape opportunities for competency development.

A related perspective can be found in workplace learning analytics. Ruiz-Calleja et al. (2021) demonstrated that learning analytics in professional and workplace settings presents characteristics and challenges that differ from those of conventional formal education. Their review particularly emphasized the importance of evaluating workplace learning analytics in realistic contexts. This observation is particularly relevant to vocational education because teaching factories occupy an intermediate position between formal learning environments and authentic operational settings. The proposed framework responds to this characteristic by treating learning and operational information as interconnected elements of the same socio-technical system rather than analyzing them through separate analytical processes.

The importance of connecting learning processes with authentic operational environments is also supported by developments in AI-based teaching factories. Wahjusaputri et al. (2024) examined an artificial intelligence-based teaching factory model in vocational high schools and demonstrated the potential of AI-supported environments for developing students' digital skills and aligning vocational learning with technological and workplace demands. While their study primarily emphasizes AI integration within teaching factory learning, the present framework adds an operational decision-support dimension. Learner-related information is not only used to understand or support learning but can also inform how practical tasks, equipment, time, and other resources are organized.

This distinction also reflects a broader development in educational analytics. Prinsloo (2019) noted that educational data and analytics increasingly inform not only teaching and learning but also institutional strategy, operations, and resource allocation. From this perspective, the value of learning analytics extends beyond describing learner behavior toward informing decisions within the broader educational system. The proposed framework operationalizes this principle within vocational education by explicitly connecting learner-level analytics with operational decisions. Consequently, learner readiness and competency information can become inputs for decisions concerning task allocation and scheduling, while operational constraints can simultaneously provide contextual information for interpreting learner performance.

Taken together, previous research has established several complementary directions: learning analytics can support the interpretation of learning processes in vocational education; workplace learning analytics highlights the importance of authentic learning contexts; AI-based teaching factories demonstrate the potential of intelligent technologies in vocational learning environments; and educational analytics more broadly can inform institutional and operational decision-making. However, these strands have largely developed as separate areas of inquiry. The contribution of the proposed framework lies in bringing these perspectives together by explicitly connecting learner analytics, competency information, operational constraints, and resource-related decisions within a unified decision-support architecture.

The proposed framework therefore extends the role of AI beyond prediction alone toward integrated decision support. Rather than merely identifying patterns in learning data, AI can connect information about learner performance and competency development with decisions concerning who may require support, what type of task may be appropriate, when practical activities should be scheduled, and how available resources can be allocated. This system-oriented perspective is particularly relevant to teaching factory environments, where educational and production-like processes coexist. The novelty of the proposed approach therefore does not lie merely in applying AI to vocational education, but in using AI as an analytical bridge between pedagogical and operational dimensions that have traditionally been treated separately.

Implications, Limitations, and Future Directions

The proposed framework has implications at both pedagogical and institutional levels. From a pedagogical perspective, integrating learning analytics with operational information provides educators with a broader basis for interpreting learner performance and competency development. Learner difficulties can be considered not only in relation to individual academic performance but also in relation to the conditions under which practical learning occurs. Information concerning learner readiness, task complexity, practice opportunities, and equipment availability may therefore support more context-sensitive decisions regarding task assignment, practice duration, and instructional support. This perspective is particularly relevant to competency-based vocational education, where competency development is closely connected to authentic learning experiences and workplace-oriented activities.

This implication is consistent with Gedrimiene et al. (2020), who emphasized that learning analytics in vocational education should support the integration of learning across classroom and workplace contexts rather than remain limited to conventional course-level indicators. Their review also demonstrated that vocational education remains comparatively underrepresented in learning analytics research. The present framework extends this perspective by incorporating operational information from practical learning environments into the analytical process. Consequently, contextual conditions such as equipment availability, scheduling, and opportunities for practice become part of the information available for interpreting competency development rather than being treated as external administrative factors.

At the institutional level, the framework positions operational planning as an integral component of the learning environment rather than merely an administrative function. Decisions concerning equipment scheduling, resource allocation, workload distribution, and the organization of practical activities can shape learners' opportunities to develop and demonstrate competencies. By connecting these operational decisions with learner-related information, the framework provides a basis for aligning resource management with educational objectives. Such integration may be particularly valuable for vocational institutions and teaching factories operating under constraints related to equipment capacity, laboratory availability, instructional time, and competing demands for practical resources.

This broader decision-support orientation is also consistent with the development of learning analytics as a mechanism for supporting educational interventions rather than merely describing learner behavior. However, the transition from analytical information to institutional decision-making requires careful attention to how AI-generated recommendations are interpreted and acted upon by educators. Alfredo et al. (2024), based on a systematic review of 108 studies on human-centred learning analytics and AI in education, identified limited end-user involvement in system design and emphasized the importance of balancing human control and automation, stakeholder participation, safety, reliability, and trustworthiness. These considerations reinforce the position adopted in the present study that AI-supported optimization should complement rather than replace professional educational judgment.

Nevertheless, several limitations should be considered when interpreting the proposed framework. First, the empirical component was conducted within a single vocational education setting, which limits the extent to which its applicability can be generalized across institutions with different curricular structures, technological infrastructures, teaching factory configurations, and resource capacities. Second, the prototype was primarily intended to demonstrate the feasibility of integrating learning analytics and operational optimization rather than to establish large-scale institutional effectiveness. Consequently, the present study does not provide sufficient evidence to conclude that the proposed framework would generate equivalent outcomes across different vocational education contexts. Future validation is therefore necessary before broader institutional implementation can be recommended.

Third, the effectiveness of the framework depends substantially on the availability, quality, interoperability, and responsible governance of learning and operational data. This issue is particularly important because learning analytics involves potentially sensitive learner information. Pardo and Siemens (2014) emphasized that privacy and ethical issues in learning analytics are closely related to trust, accountability, and transparency, and argued that these considerations should be incorporated into the design of learning analytics environments rather than addressed only after implementation. Similarly, Kitto and Knight (2019) highlighted the practical ethical tensions associated with building learning analytics systems for institutional adoption, including the risks associated with both overly cautious underuse and inadequately governed implementation. These concerns are particularly relevant to the proposed framework because combining educational and operational data potentially expands both the scope and sensitivity of the information used for decision-making.

A further limitation concerns the role of AI-generated recommendations in educational decisions. Predictive and optimization models can provide useful analytical information, but their outputs should not be interpreted as substitutes for professional judgment. Decisions concerning learner progression, task assignment, or instructional intervention involve pedagogical and contextual considerations that may not be fully represented in quantitative data. This concern is supported by Alfredo et al. (2024), who found that although human control has received increasing attention in human-centred learning analytics and AI research, stakeholder involvement in actual system design remains limited. Their findings underline the need to maintain meaningful human oversight and to involve educators and learners in determining the appropriate balance between automated recommendations and human decision-making.

These limitations provide several directions for future research. Further studies should validate the framework across multiple vocational institutions and teaching factory environments to examine its adaptability under different curricular, technological, and operational conditions. Larger and longitudinal datasets would also enable researchers to investigate whether relationships among learner performance, competency progression, and operational conditions remain stable over time. This direction responds to the broader gap identified by Gedrimiene et al. (2020), who reported that empirical applications of learning analytics in vocational education remain relatively limited and called for further development of learning analytics capable of connecting classroom and workplace learning.

Future empirical studies should additionally quantify the performance of both the analytical and optimization components using clearly defined indicators, including predictive accuracy, competency-prediction error, equipment utilization, scheduling efficiency, learner access to practical activities, and workload distribution. Such evidence would enable systematic comparison between integrated and conventional decision-making approaches. Future development may also explore dynamic optimization techniques, including reinforcement learning and adaptive scheduling, particularly in environments where learner readiness and resource availability change continuously.

Equally important, future studies should examine how instructors, laboratory managers, students, and institutional decision-makers interact with AI-generated recommendations in authentic vocational learning environments. Research should investigate whether users understand, trust, accept, modify, or reject such recommendations and how these interactions influence actual educational decisions. This human-centred direction is strongly supported by Alfredo et al. (2024), who identified stakeholder participation, human control, safety, reliability, and trustworthiness as important priorities for future learning analytics and AI systems. Ethical governance should likewise remain central to future implementation, particularly with respect to data privacy, transparency, accountability, and the responsible use of learner information, as emphasized in established learning analytics research.

Overall, the contribution of the proposed framework lies in conceptualizing vocational learning as an interconnected educational and operational system. Previous research has established the potential of learning analytics to connect classroom and workplace learning and has increasingly emphasized the importance of human-centred, trustworthy, and ethically governed AI-supported educational systems. Building on these directions, the present framework extends the analytical scope by explicitly connecting learner performance and competency progression with practical-task requirements, equipment availability, scheduling conditions, and resource utilization. The value of AI in this context therefore lies not primarily in replacing professional judgment or automating isolated educational activities, but in providing an analytical bridge between pedagogical needs and operational conditions. This integration provides a foundation for a more system-oriented approach to AI-supported vocational education in which learner needs, competency development, institutional resources, and operational feasibility can be considered simultaneously.

CONCLUSION

This study developed an AI-driven framework that integrates learning analytics with operational optimization to address the fragmented use of educational and operational data in technology and vocational education. The framework brings together learner performance, competency progression, practical-task requirements, equipment availability, scheduling conditions, and resource allocation within a unified decision-support environment. Rather than treating learning analytics and operational management as separate processes, the proposed approach demonstrates how learner-related information can be interpreted alongside the operational conditions in which practical learning takes place. The main contribution of this study lies in positioning AI not merely as a predictive or instructional technology, but as an analytical bridge between pedagogical and operational dimensions of vocational learning. Through this integration, information on learner readiness and competency development can inform decisions concerning task allocation, scheduling, and resource utilization, while operational constraints can simultaneously provide contextual information for interpreting learner performance. This approach is particularly relevant to teaching factory and laboratory environments, where competency development depends on the interaction among learners, practical tasks, equipment, time, and institutional resources.

From a practical perspective, the framework provides a basis for more context-sensitive and data-informed decision-making. For educators, it may support the identification of learner needs while considering the conditions under which practical learning occurs. For institutional managers, it provides a mechanism for aligning operational decisions, including equipment scheduling, resource allocation, and workload distribution, with educational objectives and equitable opportunities for competency development. Importantly, AI-generated recommendations are intended to complement rather than replace professional educational judgment, maintaining human oversight as an essential component of decision-making. Nevertheless, the framework should be interpreted as an initial demonstration of feasibility rather than evidence of large-scale institutional effectiveness. Its empirical evaluation was conducted within a single vocational education setting, and its applicability may vary according to institutional infrastructure, data availability, curriculum, teaching factory characteristics, and technological readiness. Future research should therefore validate the framework across multiple vocational institutions using larger and longitudinal datasets, quantify the performance of its analytical and optimization components, and investigate adaptive optimization approaches and user interaction with AI-generated recommendations.

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