International Transactions on Education Technology (ITEE)
Vol. 4, No. 2, May 2026, pp. 116−130
E-ISSN: 2963-1947 | P-ISSN: 2963-6078, DOI:10.33050

Understanding Data Driven Decision Making Practices in Learning Factory Environments

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Article Info

Article history:

Submission February 15, 2026
Revised February 27, 2026
Accepted March 21, 2026
Published May 13, 2026

Keywords:

Data Driven
Learning Factory
Learning Analytics
Organizational Culture
Training Effectiveness

ABSTRACT

The increasing integration of data science and learning analytics in learning factory environments has created new opportunities to enhance training effectiveness and align educational processes with real industrial needs, yet understanding how decision making practices are enacted in these contexts remains limited. **This study aims** to explore how stakeholders interpret and utilize data to support instructional, operational, and strategic decisions that influence skill development and adaptive training in learning factories. **A qualitative research** design was employed through multiple case studies involving semi structured interviews, direct observations, and analysis of institutional documents to capture in depth insights into practices, challenges, and contextual dynamics surrounding data driven decision making. **The findings indicate** that successful implementation is shaped by factors such as organizational culture, data literacy levels, leadership support, and the availability of integrated information systems, while common challenges include fragmented data sources, limited analytical competencies, and resistance to data informed change, participants reported that collaborative reflection and continuous feedback loops significantly improved training relevance and learner engagement. **The study concludes** that strengthening governance structures, investing in capacity building, and promoting a culture that values evidence based decision making can enhance both learning outcomes and operational performance in learning factory settings, providing meaningful implications for educators, industry partners, and policymakers seeking to advance sustainable and technology enhanced workforce development.

DOI: https://doi.org/10.33050/itee.v4i2.1096

1. INTRODUCTION

The rapid digital transformation occurring across industries has fundamentally altered how organizations approach training, knowledge development, and decision making, placing increasing emphasis on the effective use of data to support continuous improvement and innovation [1]. Within this evolving landscape, learning factory environments have emerged as a powerful educational approach that integrates authentic industrial processes with experiential learning to better prepare learners for real world challenges [2]. By simulating or directly connecting with production systems, learning factories allow participants to develop technical competencies, problem solving abilities, and collaborative skills in contexts that closely resemble actual workplaces [3]. At the same time, the integration of digital technologies such as learning management systems, operational monitoring tools, and data analytics platforms has generated significant amounts of information related to training activities, learner performance, and process outcomes. These data resources offer substantial opportunities to enhance educational quality and operational efficiency by informing evidence based decisions [4]. However, despite the increasing availability of data, many learning factory initiatives struggle to fully realize its potential due to fragmented systems, limited analytical capabilities, and organizational complexities that hinder effective data use. As a result, there is a growing need to understand how data driven decision making practices are implemented in learning factory environments and how stakeholders interpret and utilize data to support meaningful improvements [5].

From a conceptual perspective, data driven decision making is closely associated with broader theoretical frameworks such as organizational learning, reflective practice, and knowledge management, which emphasize the importance of using information to guide action and foster continuous development [6]. In learning factory contexts, decision making is inherently multifaceted because it involves diverse stakeholders, including educators, training coordinators, industry partners, technical staff, and learners, each contributing unique perspectives and priorities [7]. While existing research has largely focused on the development of technological solutions such as learning analytics dashboards, predictive algorithms, and intelligent tutoring systems, comparatively less attention has been devoted to understanding how these tools are embedded in everyday practices and how individuals make sense of the information they receive [8]. Decision making within learning factories often requires balancing competing demands, such as achieving educational objectives, maintaining operational efficiency, ensuring safety, and meeting industry expectations [9]. These complexities highlight the importance of examining not only technological capabilities but also the human and organizational dimensions that shape how data is interpreted and used. A deeper exploration of these aspects can provide valuable insights into how data becomes actionable knowledge and how organizations can cultivate cultures that support effective and reflective decision making [10].

The practical importance of examining data driven decision making practices is underscored by the increasing demand for education systems that are agile, responsive, and capable of preparing learners for rapidly changing technological environments [11]. Learning factories play a crucial role in supporting workforce development by offering opportunities for hands on learning, experimentation, and innovation, enabling participants to acquire skills that are directly relevant to industry needs [12]. To maintain their relevance and effectiveness, learning factories must continuously adapt their training programs based on insights derived from performance data, participant feedback, and operational observations [13]. For example, analyzing patterns in learner engagement can help identify areas where instructional strategies need adjustment, while process data can reveal inefficiencies that require attention. Nevertheless, implementing data driven approaches often presents challenges, including resistance to change, lack of coordination among stakeholders, and difficulties in integrating multiple information systems [14]. Additionally, varying levels of data literacy among participants may influence how data is interpreted and whether it is perceived as a valuable resource for improvement. By investigating how organizations navigate these challenges and leverage data to inform decisions, this study seeks to generate practical insights that can support the development of more effective learning factory models and enhance their contribution to skill development and innovation [15].

Beyond practical considerations, this study also addresses the critical role of organizational culture, leadership, and communication in shaping the success of data driven initiatives within learning factory environments [16]. The effectiveness of data use depends not only on technological infrastructure but also on the willingness of individuals to engage with information, share insights, and collaborate in decision making processes [17]. Learning factories, as socio technical systems, are characterized by complex interactions between people, technologies, and processes, making it essential to understand how these elements influence one another [18]. Leadership support can play a pivotal role in promoting a culture that values evidence based decision making, while open communication channels can facilitate the sharing of knowledge and encourage collective reflection. Conversely, organizational silos, lack of trust, and unclear data governance structures may hinder the effective use of information [19]. Exploring these dynamics can provide a more comprehensive understanding of the factors that enable or constrain data driven practices and inform strategies for fostering environments where data is used effectively to support continuous improvement and innovation [20].

This research aims to develop a comprehensive understanding of how data driven decision making practices are enacted within learning factory environments by examining how data is generated, interpreted, and utilized to support both educational and operational goals [21]. Through an in depth qualitative inquiry, the study seeks to capture the experiences and perspectives of stakeholders, identify key processes and challenges, and uncover the mechanisms through which data informs decisions. The research is guided by the objective of contributing to both theoretical and practical knowledge by extending existing understanding of organizational learning and education technology while providing actionable insights for practitioners [22]. The findings are expected to highlight the importance of aligning technological capabilities with human expertise and organizational context, demonstrating how effective data use can enhance training effectiveness, support adaptive learning, and improve overall performance [23]. Furthermore, the study offers implications for educators, administrators, and policymakers seeking to design learning environments that are responsive to evolving industry demands and capable of supporting sustainable workforce development. By shedding light on the complexities of decision making in data rich environments, this research contributes to ongoing efforts to advance learning factories as dynamic and intelligent systems that promote continuous learning, innovation, and long term organizational success [24].

2. LITERATURE REVIEW

2.1. Data Driven Decision Making in Educational and Training Contexts

In recent years, data driven decision making has emerged as a foundational paradigm in education and professional training, reflecting a broader shift toward evidence informed practices across sectors [25]. The growing availability of digital learning platforms, performance tracking systems, and institutional data infrastructures has enabled organizations to collect, analyze, and interpret large volumes of information related to learner engagement, achievement, and operational processes. Contemporary research since 2021 emphasizes that data driven approaches can enhance instructional planning, support continuous monitoring of learning progress, and enable timely interventions that improve outcomes [26]. Scholars argue that the integration of data into decision making processes allows institutions to move beyond intuition based practices toward systematic evaluation and continuous improvement cycles. In training environments that closely mirror industry settings, such as learning factories, data plays a crucial role in identifying skill gaps, assessing competency development, and aligning training programs with evolving workforce requirements [27].

However, recent literature also highlights that the successful implementation of data driven decision making depends on several contextual factors, including organizational readiness, leadership commitment, and stakeholder engagement [28]. Studies indicate that merely providing access to data does not guarantee its effective use. Rather, individuals must possess the necessary analytical skills and interpretive capabilities to translate data into meaningful insights. Furthermore, decision making in complex educational environments often involves balancing multiple objectives, such as improving learning quality, maintaining operational efficiency, and meeting external standards [29]. Researchers have therefore called for more in depth investigations into how decision making practices unfold in real contexts, particularly in environments where educational and industrial priorities intersect. Understanding these dynamics is essential for developing frameworks that support sustainable and context sensitive data use [30].

Another important theme emerging in recent scholarship is the role of collaborative decision making in leveraging data effectively [31]. Evidence suggests that organizations that foster collaborative cultures, where stakeholders engage in dialogue around data, are more likely to develop shared understanding and collective responsibility for improvement. In learning factory settings, where instructors, technical staff, and industry partners must coordinate activities, collaborative interpretation of data can enhance decision quality and support more holistic perspectives [32]. Moreover, research underscores the importance of establishing feedback loops that allow organizations to evaluate the impact of decisions and refine strategies over time. These insights reinforce the need to examine not only the technical aspects of data systems but also the social processes through which data informs action.

2.2. Learning Factory as an Experiential Learning Environment

The learning factory concept has gained increasing recognition as a powerful approach to bridging the gap between academic learning and industrial practice [33]. Designed to replicate or integrate with real production environments, learning factories provide opportunities for learners to engage in hands on activities, experiment with processes, and develop practical competencies that are directly applicable to workplace contexts. Recent studies emphasize that experiential learning within learning factories supports deeper understanding by allowing learners to connect theoretical knowledge with real world applications, thereby enhancing retention and transfer of skills [34]. The integration of digital technologies, automation systems, and simulation tools further enriches the learning experience, enabling participants to explore complex scenarios and develop problem solving capabilities.

Research published after 2021 highlights that learning factories play a critical role in preparing individuals for the demands of digital transformation and Industry 4.0 by fostering interdisciplinary collaboration and systems thinking [35]. These environments encourage learners to engage in iterative cycles of planning, execution, reflection, and improvement, which are essential for developing adaptive expertise. Moreover, learning factories often serve as platforms for collaboration between educational institutions and industry partners, facilitating knowledge exchange and innovation. Such collaborations can enhance curriculum relevance and provide opportunities for learners to work on authentic challenges that reflect current industry needs [36].

Despite their potential benefits, the effectiveness of learning factories depends on how learning activities are designed, implemented, and evaluated. Recent literature points out that many learning factory initiatives face challenges related to resource constraints, coordination among stakeholders, and the integration of diverse technological systems [37]. Additionally, the complexity of learning factory environments requires robust mechanisms for monitoring performance and ensuring that learning objectives are achieved. Data driven approaches can support these processes by providing insights into learner behavior, process efficiency, and training effectiveness. However, understanding how stakeholders interact with data within these environments remains an area that requires further exploration, particularly from a qualitative perspective that captures contextual nuances [38].

2.3. Learning Analytics and Data Science in Skill Development

Learning analytics and data science have become central to efforts aimed at improving educational outcomes and supporting personalized learning experiences [39]. Advances in analytical techniques have enabled researchers and practitioners to examine patterns in learner behavior, predict performance trajectories, and design interventions that address individual needs. Recent studies emphasize that learning analytics can provide valuable insights into engagement levels, learning strategies, and competency development, allowing educators to tailor instruction and provide targeted support. In industry aligned training contexts, data science approaches can also be used to evaluate training effectiveness, optimize processes, and support evidence based decision making [40].

However, contemporary research also underscores the importance of interpreting analytics within context, noting that quantitative data alone may not capture the full complexity of learning processes. Scholars have highlighted the need for complementary qualitative approaches that explore how learners and instructors experience and interpret data driven initiatives [41]. This perspective is particularly relevant in learning factory environments, where learning occurs through hands on activities, social interactions, and iterative experimentation. Understanding how stakeholders perceive and utilize analytics can provide deeper insights into the mechanisms through which data influences learning and decision making [42].

Another emerging theme in recent literature is the ethical and governance considerations associated with the use of learning analytics. Researchers emphasize the importance of ensuring transparency, protecting privacy, and fostering trust among stakeholders when implementing data driven systems [43]. In learning factory contexts, where data may include operational metrics and performance indicators, establishing clear guidelines for data use is essential for maintaining stakeholder confidence and ensuring responsible practices. By examining how data science is integrated into skill development processes, this study contributes to ongoing discussions about the role of analytics in shaping the future of education and training [44].

2.4. Organizational Culture and Human Factors in Data Use

The role of organizational culture and human factors has gained increasing attention in recent research on data driven initiatives, reflecting recognition that technological solutions alone are insufficient to ensure successful implementation [45]. Studies conducted since 2021 emphasize that organizations with cultures that promote collaboration, openness, and continuous learning are more likely to effectively leverage data for improvement. Leadership plays a crucial role in shaping these cultures by setting expectations, providing resources, and encouraging stakeholders to engage with data in meaningful ways. Conversely, environments characterized by resistance to change, limited communication, or lack of trust may struggle to realize the benefits of data driven practices [46].

Human factors such as data literacy, professional experience, and attitudes toward technology also influence how individuals interpret and use data. Research indicates that stakeholders who possess strong analytical skills and confidence in data are more likely to engage in reflective decision making and adopt evidence informed practices [47]. In learning factory environments, where diverse groups collaborate on complex tasks, differences in expertise and perspectives can shape how data is perceived and utilized. Understanding these dynamics is essential for developing strategies that support effective data use and foster shared understanding among stakeholders.

Furthermore, recent literature highlights the importance of professional development and capacity building in enhancing data literacy and supporting organizational change. Training programs that focus on developing analytical skills, promoting collaborative inquiry, and encouraging reflective practice can empower stakeholders to engage more effectively with data [48]. In addition, establishing communities of practice where individuals share experiences and insights can facilitate knowledge exchange and strengthen organizational learning. By examining how cultural and human factors influence decision making practices, this study provides insights into the conditions that enable or hinder the effective integration of data into learning factory operations.

2.5. Challenges and Opportunities in Implementing Data Practices in Learning Factories

While the potential benefits of data driven approaches are widely recognized, recent research identifies several challenges associated with implementing data practices in complex training environments. One of the most frequently cited issues is the fragmentation of data systems, which can hinder the integration and analysis of information across different platforms [49]. Limited interoperability among systems may result in incomplete or inconsistent data, making it difficult for stakeholders to gain comprehensive insights. Additionally, organizations may face constraints related to technical infrastructure, financial resources, and availability of skilled personnel, all of which can affect the effectiveness of data initiatives.

Another significant challenge involves the interpretation and communication of data, as stakeholders may have varying levels of expertise and differing perspectives on what data represents. Misinterpretation of data can lead to ineffective decisions or skepticism toward data driven approaches [50]. Recent studies also highlight concerns related to data governance, including issues of privacy, ownership, and ethical use, which must be carefully addressed to ensure responsible practices. In learning factory environments, where data may encompass both educational and operational dimensions, establishing clear governance frameworks is particularly important.

Despite these challenges, the literature also identifies numerous opportunities for enhancing data practices through technological innovation and organizational strategies. Advances in integrated learning platforms, real time monitoring systems, and visualization tools can improve data accessibility and support more informed decision making [51]. Furthermore, initiatives aimed at developing data literacy, fostering collaborative cultures, and promoting reflective practices can enhance stakeholders' ability to engage with data effectively. By exploring how these challenges and opportunities manifest in real contexts, this study contributes to a deeper understanding of how learning factories can leverage data to support adaptive learning, continuous improvement, and sustainable workforce development.

3. RESEARCH METHODOLOGY

3.1. Research Design

This study consists of two main variables: Interdisciplinary Learning Factory Projects (X) and Student Learning Outcomes (Y). The independent variable represents students' participation in interdisciplinary project-based learning activities, while the dependent variable reflects the competencies developed as a result of these learning experiences. These variables are operationalized through several indicators that represent key aspects of interdisciplinary learning and student competency development.

The interdisciplinary Learning Factory variable includes indicators such as collaboration among students from different disciplines, experiential learning through hands-on project activities, and the integration of knowledge from multiple academic fields. Meanwhile, student learning outcomes are measured through indicators such as critical thinking skills, problem-solving ability, teamwork competence, and the application of theoretical knowledge in practical contexts. In addition, the indicators used in this study were adapted from previous research related to project-based learning, interdisciplinary education, and experiential learning. The adaptation process ensures that the measurement items are relevant to the Learning Factory context while maintaining their theoretical foundation. All variables are measured using a five-point Likert scale, which enables the transformation of respondents' perceptions into quantitative data that can be analyzed statistically.

3.2. Research Setting and Participants

The research is conducted in selected learning factory environments that integrate digital technologies such as learning analytics systems, production simulation platforms, and performance monitoring tools. These environments are chosen because they represent advanced training ecosystems where data plays a critical role in supporting decision-making processes.

Participants are selected using purposive sampling to ensure relevance and depth of insight. The study involves key stakeholders who actively engage with data in their professional roles, including training managers, instructors, data analysts, technical staff, and trainees. The inclusion criteria require participants to have direct experience in interpreting or utilizing data for decision-making purposes, ensuring that the findings reflect practical and authentic experiences rather than theoretical assumptions.

A total of approximately 15–25 participants are included in the study, which is considered adequate for achieving data saturation in qualitative research. This range allows for diverse perspectives while maintaining depth of analysis. The diversity of participants ensures that the study captures multiple viewpoints across organizational levels, contributing to a holistic understanding of data-driven practices.

3.3. Data Collection Methods

This study employs multiple qualitative data collection methods to obtain comprehensive insights into Data-Driven Decision-Making (DDDM) practices within learning factory environments. The use of multiple methods strengthens the credibility of the findings through methodological triangulation, allowing the researcher to compare and validate information from different sources. The primary data collection methods used in this study include semi-structured interviews, non-participant observations, and document analysis. Semi-structured interviews are conducted with training managers, instructors, technical staff, data analysts, and trainees who have direct experience in utilizing data within learning factory activities. This method allows participants to explain their experiences, perceptions, and challenges related to the implementation of DDDM practices. All interviews are audio-recorded with participant consent and transcribed for further analysis.

In addition to interviews, non-participant observations are conducted to examine real-time interactions and decision-making activities within learning factory environments. Observations focus on training sessions, operational meetings, and the use of analytics dashboards or monitoring systems. Furthermore, document analysis is employed to examine institutional materials such as training reports, performance records, analytics dashboards, and policy documents. These documents provide contextual information regarding formal organizational practices and data governance procedures. The combination of interviews, observations, and document analysis enables the researcher to obtain a broader understanding of DDDM implementation. The data collection techniques used in this study are summarized in Table 1.

Table 1. Data Collection Techniques

Method	Source of Data	Purpose	Expected Output
Semi-structured Interviews	Managers, instructors, trainees	Explore perceptions and experiences of DDDM	Transcribed narratives
Observations	Training sessions, meetings	Capture real decision processes	Field notes
Document Analysis	Reports, dashboards, policies	Understand formal practices	Understand formal practices

As presented in Table 1, each data collection method contributes different yet complementary forms of evidence that strengthen the comprehensiveness and credibility of the study. Interviews provide in-depth insights into stakeholder perceptions and experiences, observations capture authentic interactions and operational behaviors, while document analysis supports the validation of institutional practices and formal procedures. The integration of these methods enhances methodological triangulation and allows the study to generate a more accurate and contextually rich understanding of how data-driven decision-making practices are implemented and sustained within learning factory environments.

3.4. Data Analysis Procedures

The data analysis procedure in this study is conducted systematically through a thematic analysis approach that is both iterative and inductive, aimed at transforming complex qualitative data into meaningful findings regarding Data-Driven Decision Making (DDDM) practices within learning factory environments.

The initial phase begins with data familiarization, where the researcher organizes the entire data corpus, including semi-structured interview transcripts, field notes from training session observations, and institutional policy documents, to gain a deep understanding of how instructors and managers utilize data. Subsequently, the researcher performs open coding by breaking down raw data into smaller units of meaning that cover technical aspects such as platform fragmentation, human factors like data literacy, and operational aspects such as curriculum adjustment. These initial codes are then developed through axial coding to group similar phenomena into broader categories, such as analytical competency barriers or collaborative interpretation practices, in order to understand the relationship between data availability and the supporting organizational culture.

Once the categories are established, thematic mapping is performed to synthesize the relationships between phenomena, encompassing the dynamics of the DDDM cycle, the influence of organizational culture, and socio-technical integration within the learning factory ecosystem. This analysis also involves cross-case comparison to identify unique patterns, such as differences in decision-making response speeds between units with integrated systems versus those with fragmented data systems. Throughout the process, the researcher utilizes reflexive memo writing to document every analytical decision, minimizing subjective bias and ensuring that findings remain rooted in authentic data. The procedure concludes with a validation stage through data source triangulation, where interview findings are confirmed with performance data in evaluation reports and field observations to produce a comprehensive, credible, and accurate narrative regarding DDDM practices.

3.5. Research Procedure

This study follows a systematic research procedure to ensure consistency, transparency, and methodological rigor throughout the investigation process. The procedure begins with the identification of research problems and the formulation of research objectives related to Data-Driven Decision-Making (DDDM) practices within learning factory environments. After determining the research focus, appropriate learning factory settings are selected based on their use of digital technologies and analytics systems. Subsequently, research instruments such as interview guidelines and observation protocols are prepared to support the data collection process. Data are then collected through semi-structured interviews, non-participant observations, and document analysis involving stakeholders who actively utilize data within learning factory activities. Following the data collection stage, the researcher conducts coding and thematic analysis to identify patterns, themes, and relationships among the findings. To ensure the credibility and validity of the results, triangulation and member checking are also performed during the analysis process. The overall research procedure applied in this study is illustrated in Figure 1.

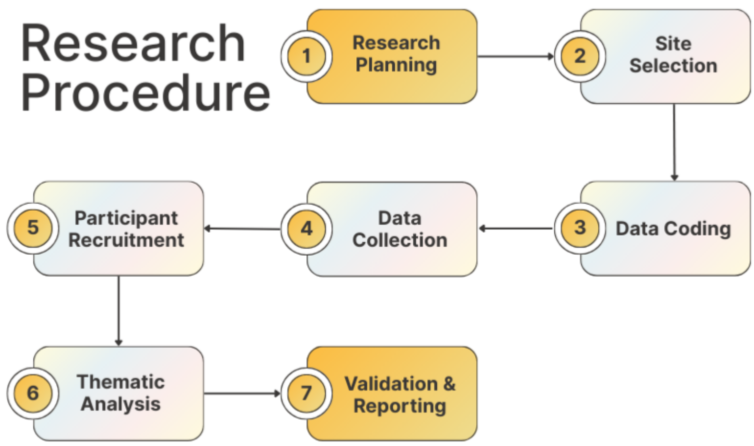

Figure 1. Research Procedure

As illustrated in Figure 1, the research procedure follows several systematic stages, including problem identification, research planning, site selection, data collection, data analysis, validation, and reporting of findings. The figure shows how qualitative data are collected through interviews, observations, and document analysis within learning factory environments, followed by coding and thematic analysis to identify key patterns related to Data-Driven Decision-Making (DDDM) practices. Furthermore, validation processes such as triangulation and member checking are applied to ensure the credibility and reliability of the findings throughout the research process.

3.6. Ethical Considerations

Ethical considerations are carefully addressed throughout all stages of this study to ensure the protection of participants and the integrity of the research process. Prior to data collection, ethical approval is obtained from the relevant institutional authority. All participants are provided with clear and comprehensive information regarding the purpose of the study, research procedures, and their roles as participants. Informed consent is obtained before participation, ensuring that individuals voluntarily agree to take part in interviews, observations, and related activities. Participants are also informed of their right to withdraw from the study at any stage without any negative consequences, reinforcing the principle of voluntary participation.

Confidentiality and anonymity are strictly maintained to protect participants' identities and sensitive information, particularly given that the study involves organizational practices and decision-making processes within learning factory environments. Personal identifiers are removed from all data, and pseudonyms are used where necessary to ensure that individuals and institutions cannot be traced. Data collected from interviews, observations, and document analysis are securely stored and accessed only by the researcher. Special attention is given to handling institutional documents and performance data to ensure that no confidential or proprietary information is disclosed. Furthermore, the study adheres to ethical principles of transparency and respect by ensuring that findings are reported accurately and without manipulation. These ethical practices not only safeguard participants but also enhance the credibility and trustworthiness of the research.

3.7. Research Validity and Reliability

To ensure the trustworthiness and rigor of the findings, this study adopts established qualitative research criteria, including credibility, transferability, dependability, and confirmability. Credibility is strengthened through methodological triangulation by integrating multiple data sources, namely semi-structured interviews, non-participant observations, and document analysis. This triangulation allows for cross-verification of findings and reduces the risk of bias by comparing insights obtained from different methods. In addition, member checking is conducted by sharing preliminary interpretations with selected participants to confirm the accuracy of the findings and ensure that they reflect participants' actual experiences and perspectives. Prolonged engagement during data collection further enhances credibility, as it enables the researcher to gain a deeper understanding of the learning factory context and decision-making practices.

Transferability is supported by providing rich and detailed descriptions of the research context, including the characteristics of learning factory environments, participant roles, and data-driven practices. These detailed accounts allow readers to assess the applicability of the findings to other similar contexts. Dependability is ensured through a systematic and well-documented research process, including clear procedures for data collection, coding, and thematic analysis. An audit trail is maintained to document all stages of the research, enabling transparency and allowing the study to be reviewed or replicated by other researchers. Confirmability is achieved by minimizing researcher bias through reflexive practices, such as memo writing and continuous reflection during the analysis process. Furthermore, the consistency of findings across multiple cases and data sources indicates a high level of reliability, demonstrating that the results are grounded in empirical evidence rather than subjective interpretation.

4. RESULTS AND FINDINGS

4.1. Overview of Data Driven Decision Making Practices in Learning Factory Environments

The findings of this study reveal that Data-Driven Decision-Making (DDDM) practices are increasingly embedded within learning factory environments as a central mechanism for enhancing both training effectiveness and operational performance. Participants consistently reported that large volumes of data are generated through learning management systems, performance monitoring tools, and analytics dashboards, capturing various dimensions of learner activity, skill development, and process efficiency. These data are not only used for retrospective evaluation but also for real-time monitoring and continuous improvement. In several cases, instructors actively utilized dashboards during training sessions to assess learner progress, while managers relied on periodic reports to evaluate program outcomes and ensure alignment with industrial standards. This indicates that data is becoming a critical asset in supporting evidence-based practices within learning factory ecosystems.

Furthermore, the study demonstrates that DDDM practices are inherently iterative and adaptive rather than linear. Decision-making processes involve continuous cycles of data collection, interpretation, implementation, and reflection. For example, when performance data indicates a decline in learner engagement, instructors adjust instructional strategies and subsequently monitor the impact of these changes through updated data. This cyclical process reflects a dynamic feedback loop that enhances responsiveness and adaptability. However, the effectiveness of these practices varies depending on the level of system integration and stakeholder capability. In environments with well-integrated data systems, decision-making processes are more efficient and coordinated, whereas fragmented systems limit the ability to generate comprehensive insights. These findings highlight that the success of DDDM depends not only on data availability but also on the alignment between technological infrastructure and organizational practices.

4.2. Stakeholder Interpretation and Utilization of Data

The analysis reveals that stakeholders interpret and utilize data differently based on their roles, responsibilities, and levels of expertise within the learning factory environment. Instructors primarily engage with detailed, learner-level data, including assessment scores, competency indicators, and participation metrics. These data are used to identify individual learning gaps, provide targeted feedback, and adapt instructional approaches to better meet learner needs. In contrast, managers and training coordinators focus on aggregated and longitudinal data, which enable them to evaluate overall program effectiveness, monitor trends, and make strategic decisions related to curriculum design and resource allocation. Data analysts and technical staff play an intermediary role by transforming raw data into accessible visualizations, thereby facilitating interpretation among other stakeholders.

In addition to role-based differences, the study highlights the importance of collaborative interpretation in transforming data into actionable insights. Observational findings indicate that stakeholders frequently engage in formal meetings and informal discussions to collectively analyze data and align their perspectives. These collaborative processes help bridge the gap between quantitative data and experiential knowledge, resulting in more contextually grounded decisions. However, variations in data literacy significantly influence how effectively stakeholders can interpret and utilize data. Participants with higher levels of analytical competence demonstrate greater confidence in applying data to decision-making, whereas those with limited skills often rely on intuition or prior experience. This disparity underscores the need for targeted capacity-building initiatives to enhance data literacy and ensure more consistent and effective use of data across all stakeholder groups.

4.3. Enabling Factors Supporting Effective Data Driven Decision Making

The findings of this study indicate that several organizational and technological factors significantly support the implementation of effective Data-Driven Decision-Making (DDDM) practices within learning factory environments. Participants emphasized that organizational culture plays an important role in encouraging stakeholders to actively engage with data and participate in collaborative decision-making processes. Learning factory environments characterized by openness, continuous improvement, and knowledge sharing were found to be more successful in integrating data into instructional and operational activities. In these environments, instructors, managers, and technical staff regularly exchanged insights obtained from analytics systems and performance reports to improve training effectiveness and learner engagement. In addition, leadership support emerged as another critical enabling factor, particularly in providing strategic direction, technological resources, and institutional commitment toward evidence-based practices. Participants explained that strong leadership support encourages stakeholders to adopt data-informed approaches more confidently and consistently.

Another important enabling factor identified in this study is the presence of adequate data literacy and integrated information systems. Stakeholders with stronger analytical competencies demonstrated greater confidence in interpreting learner performance data, monitoring training outcomes, and applying insights to improve instructional strategies. Professional development programs and technical training activities were also considered essential in strengthening stakeholders' analytical skills and improving their understanding of learning analytics systems. Furthermore, integrated information systems enabled seamless access to real-time data from multiple operational and educational platforms, reducing data fragmentation and supporting more efficient coordination among departments. Participants reported that integrated dashboards and continuous feedback mechanisms facilitated faster decision-making processes and enhanced the responsiveness of learning factory activities to changing learner and industry needs. The key enabling factors identified from the thematic analysis are summarized in Table 2.

Table 2. Key Enabling Factors Supporting Effective Data Driven Decision Making

Enabling Factor	Description	Influence on Learning Factory Environment
Organizational Culture	Promotes collaboration, openness, and evidence-based practices among stakeholders	Encourages active participation in data-driven initiatives
Leadership Support	Provides strategic direction, resource allocation, and motivation for data use	Strengthens implementation and sustainability of DDDM practices
Data Literacy	Enhances stakeholders' ability to interpret and apply analytics effectively	Improves the accuracy and quality of decision-making
Integrated Information Systems	Enables seamless access to real-time data from multiple platforms	Reduces data fragmentation and supports operational efficiency
Continuous Feedback Mechanisms	Facilitates ongoing evaluation and reflective improvement processes	Supports adaptive learning and continuous training enhancement

As presented in Table 2, the effectiveness of DDDM implementation in learning factory environments is influenced by the interaction between organizational culture, leadership commitment, analytical competence, and technological integration. These factors collectively create conditions that support collaborative interpretation of data, continuous improvement, and adaptive learning processes. The findings further suggest that organizations capable of aligning human, organizational, and technological dimensions are more likely to achieve sustainable improvements in training effectiveness, learner engagement, and operational performance. Consequently, strengthening these enabling factors is essential for institutions seeking to maximize the benefits of data-driven practices and maintain the relevance of learning factory environments in responding to evolving industrial and educational demands.

4.4. Barriers and Challenges in Implementing Data Driven Practices

Despite the growing adoption of data-driven approaches, the study identifies several barriers that hinder their effective implementation within learning factory environments. One of the most prominent challenges is the fragmentation of data across multiple systems, which limits the ability of stakeholders to obtain a holistic view of learning and operational processes. Participants reported that data stored in separate platforms often requires manual integration, leading to inefficiencies and delays in decision-making. This fragmentation reduces the usability of data and undermines its potential to support comprehensive analysis. Additionally, issues related to data quality, such as incomplete or inconsistent information, further complicate the interpretation process and reduce stakeholders' trust in data systems.

Another significant challenge is the variation in data literacy and resistance to change among stakeholders. Some participants expressed difficulty in interpreting complex analytics, which led to a reliance on intuition rather than evidence-based decision-making. Resistance to adopting new technologies and practices was also observed, particularly among individuals who are accustomed to traditional teaching methods. This resistance is often linked to perceptions of increased workload and complexity associated with data-driven approaches. Furthermore, organizational constraints such as limited resources, lack of training, and insufficient technical support exacerbate these challenges. These findings highlight the need for comprehensive strategies that address both technical and human factors, including improving system integration, enhancing data quality, and fostering a supportive organizational culture.

4.5. Impact of Data Driven Decision Making on Learning Outcomes and Training Effectiveness

The findings demonstrate that data-driven decision-making practices have a significant positive impact on learning outcomes and training effectiveness in learning factory environments. Participants reported that the use of data enables more personalized and adaptive learning experiences, allowing instructors to tailor their teaching strategies to individual learner needs. By analyzing performance data, instructors can identify areas where learners struggle and provide targeted interventions, thereby improving learning outcomes. This personalized approach not only enhances skill acquisition but also increases learner engagement and motivation, as learners receive timely and relevant feedback.

In addition to pedagogical improvements, data-driven practices also contribute to enhanced operational efficiency and strategic alignment. Managers utilize data to optimize resource allocation, improve scheduling, and ensure that training programs align with industry requirements. This alignment enhances the relevance and applicability of training, preparing learners more effectively for real-world challenges. Moreover, the continuous use of data supports iterative improvement, enabling organizations to evaluate the effectiveness of their strategies and make informed adjustments over time. As a result, learning factory environments become more adaptive and responsive to evolving technological and industrial demands, reinforcing their role as effective platforms for workforce development.

4.6. Validation of Findings Through Triangulation

To ensure the credibility, consistency, and trustworthiness of the findings, this study applies methodological triangulation by integrating data obtained from semi-structured interviews, non-participant observations, and document analysis within learning factory environments. The triangulation process enables the researcher to compare and validate information from multiple sources, thereby reducing the possibility of bias and strengthening the overall rigor of the study. Semi-structured interviews provide detailed insights into how training managers, instructors, technical staff, and trainees interpret and utilize data in decision-making processes. These findings are then compared with observational data collected during training activities, operational meetings, and interactions with analytics dashboards to examine whether stakeholder perceptions are reflected in actual practices. In addition, document analysis involving institutional reports, learner performance records, analytics dashboards, and policy documents is conducted to verify the consistency between stakeholder narratives and formal organizational procedures. The integration of these different sources allows the study to generate a comprehensive understanding of how Data-Driven Decision-Making (DDDM) practices are implemented and sustained within learning factory environments.

In addition to triangulation, member checking is conducted to improve interpretive accuracy and ensure that the findings accurately represent participants' experiences and perspectives. Preliminary interpretations and thematic findings are shared with selected participants to confirm the relevance and authenticity of the analysis. Furthermore, reflexive memo writing is continuously applied throughout the coding and thematic analysis process to document analytical decisions and minimize subjective researcher bias. Cross-case comparisons between different stakeholder roles and learning factory contexts are also performed to identify recurring patterns and contextual differences in DDDM implementation. These validation strategies strengthen the dependability and confirmability of the findings by demonstrating that the results are consistently supported across multiple data sources and participant perspectives. Overall, the validation procedures applied in this study ensure that the findings provide a reliable and empirically grounded explanation of how organizational culture, leadership support, data literacy, and technological integration influence data-driven practices in learning factory environments.

MANAGERIAL IMPLICATIONS

The findings of this study suggest that managers in learning factory environments should strengthen data governance and integration to support effective data driven decision making. Establishing clear policies for data management, ensuring interoperability between learning analytics systems and operational platforms, and maintaining data quality are essential steps to enable reliable insights for planning and evaluation. Managers should also embed data use into routine decision processes such as training reviews, performance monitoring, and curriculum updates, ensuring that data becomes a practical tool rather than merely a reporting requirement. By doing so, organizations can improve alignment between educational activities and industrial expectations while enhancing transparency and accountability.

In addition, the study highlights the importance of investing in human capacity, particularly in developing data literacy among instructors, coordinators, and technical staff. Managers should provide continuous professional development programs that focus on interpreting analytics, applying insights to instructional design, and fostering collaborative discussions around data. Encouraging cross functional collaboration between educators and industry practitioners can help bridge gaps in understanding and promote shared ownership of improvement initiatives. Leadership commitment is also critical in shaping a culture that values evidence based practices, reduces resistance to change, and supports experimentation with new approaches to data use.

Finally, managers should leverage data insights to guide strategic decisions related to resource allocation, process improvement, and innovation within learning factories. Using data to identify skill gaps, evaluate training effectiveness, and anticipate future workforce needs can help organizations remain responsive to technological and industrial changes. Building partnerships with industry stakeholders and technology providers can further enhance the relevance and sustainability of learning programs. By adopting a strategic approach that integrates governance, capability development, and continuous improvement, managers can maximize the impact of learning factories in preparing learners with the competencies required in dynamic industrial environments.

CONCLUSION

This study concludes that data driven decision making practices play a significant role in enhancing training effectiveness, improving learner engagement, and supporting adaptive learning processes within learning factory environments. The findings demonstrate that stakeholders actively use data from learning analytics systems, performance dashboards, and institutional reports to guide instructional strategies, monitor learner progress, and optimize operational planning. The study reveals that successful implementation of data driven practices is strongly influenced by organizational culture, leadership support, data literacy, and the availability of integrated technological infrastructures. At the same time, the research highlights that decision making in learning factories is not purely technical but involves continuous reflection, collaboration, and interpretation of contextual information. Overall, the study shows that when data is effectively interpreted and integrated into daily practices, learning factories can achieve better alignment between educational outcomes and industry requirements, thereby supporting more responsive and evidence informed training environments.

This research answers the central question of how stakeholders understand and implement data driven decision making by showing that decision processes are shaped by both formal data systems and informal collaborative practices. Stakeholders interpret data differently based on their roles, yet collective discussions and feedback mechanisms help translate data into actionable insights that improve training quality. However, the study also identifies several limitations. The research is based on qualitative data from a limited number of learning factory settings, which may restrict the generalizability of findings to other contexts. Additionally, variations in technological maturity across cases may influence how data practices are perceived and implemented. The reliance on self reported experiences may also introduce subjective bias, although triangulation was used to mitigate this issue. These limitations suggest that while the findings provide valuable insights, further investigation is needed to broaden understanding across diverse environments.

Future research is recommended to expand the scope by including a larger number of learning factories across different industries and geographical contexts to enhance generalizability. Quantitative studies could complement qualitative insights by examining measurable impacts of data driven decision making on performance outcomes such as skill acquisition, productivity, and learner satisfaction. Researchers are also encouraged to explore the integration of emerging technologies such as artificial intelligence driven analytics and real time monitoring systems to better understand their potential in supporting decision processes. Additionally, longitudinal studies would provide deeper insights into how data practices evolve over time and how organizational learning influences the sustainability of data driven initiatives. Such future investigations will contribute to strengthening theoretical frameworks and providing practical guidance for institutions seeking to implement effective data informed training systems.

5. DECLARATIONS

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5.2. Author Contributions

Validation was conducted by: RA. Conceptualization was completed by: MF. The methodology was developed by: JE. Formal analysis was performed by: RA. Writing, review, and editing were carried out by: JE. Visualization was completed by: MF. All authors, including: MF, RA, and JE, have reviewed and approved the final version of the manuscript.

5.3. Data Availability Statement

The corresponding author may provide the data from this study upon request.

5.4. Funding

The research, writing, and/or publishing of this work were all done without financial assistance from the authors.

5.5. Declaration of Competing Interest

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

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