Optimizing Industrial Training in Industry 4.0: A Mixed-Methods Validation of an Integrated LMS and Six Sigma 4.0 Framework

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Hanafi Ahmad [a,b], Nurul Fadly Habidin [b], Ahzila Wahida [a], Jamilahtun Md Ghazali [a], Farah Idayu Mohd Salleh [a], Rahimah Kasim [a], Zamrin Md Zin [b,c]*
[a] *Industrial Logistic Department, UniKL Mitec, Malaysia*
[b] *University Pendidikan Sultan Idris, Tanjung Malim, Malaysia*
[c] *Johor Port Berhad, Johor, Malaysia.*
**hanafi@unikl.edu.my*

Abstract
Industrial training programs face persistent challenges due to the lack of industry-specific contextualization in Learning Management Systems (LMS) and the digital disconnect in Six Sigma methodologies, limiting their effectiveness in Industry 4.0 environments. This study addresses this gap by proposing a novel integration of LMS with Six Sigma 4.0, aiming to enhance knowledge retention, project outcomes, and operational efficiency through data-driven training optimization. Employing a mixed-methods quasi-experimental design, the research combines quantitative pre-/post-intervention assessments (n = 110 trainees) with qualitative interviews (n = 8 trainers), analyzed via statistical testing (paired t-tests) and thematic coding. Results demonstrate statistically significant improvements in knowledge retention (34%, $p < 0.001$) and project outcomes (27%, $p < 0.001$), alongside two key qualitative benefits: real-time analytics enabling agile corrective actions, and a 40% reduction in manual audits through automated Six Sigma tools. The study concludes by validating a scalable framework for industrial training innovation, contributing actionable insights for workforce development in the industry 4.0 era.

Keywords: Learning Management System, Six Sigma 4.0, Industrial Training, Quasi-Experimental Design, DMAIC, Digital Transformation.

Introduction

The Fourth Industrial Revolution has fundamentally disrupted workforce development paradigms, with 72% of manufacturing organizations reporting critical skill gaps in operational teams (World Economic Forum, 2023). As cyber-physical systems and AI-driven automation become ubiquitous (Liao et al., 2022), the demand for training solutions that simultaneously address digital fluency and process optimization has intensified. However, traditional approaches remain siloed, failing to bridge the growing divide between technological advancement and human capital readiness (Xu et al., 2021). This disconnects results in an estimated $134 billion annual productivity loss across global manufacturing sectors (Deloitte, 2023), underscoring the urgent need for integrated training frameworks.

Existing Learning Management Systems (LMS), while effective for content delivery, lack the predictive analytics and industry-specific adaptability required for Industry 4.0 environments (Zahidi et al., 2024). Concurrently, Six Sigma methodologies - though proven for process improvement - remain constrained by offline formats that prevent real-time synchronization with digital learning ecosystems (Antony et al., 2023). This dual limitation creates a persistent training efficacy gap, where only 23% of organizations achieve measurable performance improvements from their LMS investments (Thomas et al., 2025), highlighting the critical need for system integration.

While Learning Management Systems (LMS) boast 89% organizational penetration due to their scalable content delivery (Khan et al., 2025), they critically fail to meet Industry 4.0 training demands through three systemic shortcomings: (1) absence of real-time performance analytics prevents dynamic skill gap correction (Zahidi et al., 2024); (2) generic content architectures lack industry-specific adaptive pathways (Al-Fraihat et al., 2020); and (3) disconnection from quality management systems like Six Sigma undermines operational impact (Antony et al., 2023). These limitations become particularly problematic when juxtaposed with Six Sigma 4.0's own digital constraints - while its AI-enhanced DMAIC framework shows promise for training optimization (Sony & Naik,

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2024), its continued reliance on offline delivery formats creates precisely the silos that Industry 4.0's interconnected systems were designed to eliminate (Garza-Reyes et al., 2024). This dual fragmentation explains why 76% of manufacturers report stagnant workforce competency despite heavy LMS investments (Deloitte, 2023), setting the stage for our integrated solution.

While Six Sigma methodologies have successfully incorporated Industry 4.0 technologies like predictive analytics (Antony et al., 2023) and IoT-enabled process control (Sony & Naik, 2024), their application to workforce training remains limited by three critical barriers: (1) persistent reliance on offline workshop formats that prevent real-time performance tracking (Garza-Reyes et al., 2024); (2) failure to integrate with digital learning architectures, creating disconnects between skill acquisition and application (Thomas et al., 2025); and (3) inherent scalability constraints of in-person training models, which restrict deployment to only 18% of frontline workers in manufacturing settings (Khan et al., 2025). These limitations are particularly striking given Six Sigma 4.0's proven 29-42% efficiency gains in production environments (Zahidi et al., 2024), suggesting substantial unrealized potential for training optimization through digital integration.

This study bridges the research gap by proposing an innovative integration of LMS platforms with Six Sigma 4.0 methodologies, leveraging AI-enhanced DMAIC (Define-Measure-Analyze-Improve-Control) cycles to enable automated flaw detection in training programs (Sony & Naik, 2024). The unified framework delivers three transformative capabilities: (1) real-time feedback mechanisms for continuous training optimization (Garza-Reyes et al., 2024); (2) predictive analytics that enhance ROI forecasting accuracy by 38% compared to conventional systems (Khan et al., 2025); and (3) an extended Technology Acceptance Model (TAM) that incorporates Six Sigma 4.0 analytics as novel determinants of both Perceived Usefulness ($\beta = 0.72$, $p < .001$) and Perceived Ease of Use ($\beta = 0.65$, $p < .001$) in digital training adoption (Al-Emran & Abbasi, 2023). As the first empirically validated hybrid model of its kind, this research provides organizations with a scalable blueprint for HR 4.0 transformation, offering specific implementation guidelines for corporate trainers (adaptive content modules), LMS developers (embedded analytics APIs), and policymakers (integration standards for Industry 4.0 training certifications) (Thomas et al., 2025).

Research Questions

This study aims to evaluate the integration of Learning Management Systems (LMS) with Six Sigma 4.0 in enhancing training effectiveness within a quasi-experimental framework. The specific research questions are:

1. To what extent does the integrated LMS-Six Sigma 4.0 system improve training effectiveness compared to traditional LMS.
2. How do the system's integrated components mediate training outcomes?

This study aims to fill the research gap by offering a comprehensive, empirically based assessment of the integration of LMS and Six Sigma 4.0, so adding to both academic literature and practical application in industry. The study will be conducted at the port terminal area of Johor, which possesses the capacity for intensive training and ongoing process enhancement.

Literature Review

The swift progression of Industry 4.0 technologies has significantly altered workforce training needs, necessitating integrated systems that merge the scalability of digital learning with data-driven quality enhancement (Liao et al., 2022). Learning Management Systems (LMS) have become widely adopted for their content delivery capabilities (Khan et al., 2025); however, they are significantly constrained in offering industry-specific adaptive learning and real-time performance analytics (Zahidi et al., 2024). Simultaneously, Six Sigma 4.0 methodologies, while demonstrating effectiveness in process optimisation, still depend on offline training formats that do not incorporate digital learning integration (Antony et al., 2023). The ongoing disconnect between LMS platforms and Six Sigma training methodologies has created a notable research gap, as there are currently no empirical studies investigating their integrated potential to improve industrial training effectiveness (Thomas et al., 2025).

Six Sigma 4.0: Digital Transformation with Training Gaps

The integration of Industry 4.0 technologies has propelled Six Sigma methodologies into a new era of effectiveness, with IoT-enabled process monitoring and AI-driven predictive analytics now delivering 29-42% efficiency gains in defect reduction across production environments (Garza-Reyes et al., 2024). These technological advancements have transformed traditional DMAIC (Define-Measure-Analyze-Improve-Control) cycles into dynamic, data-intensive processes capable of real-time quality optimization (Antony et al., 2023). However, this operational transformation has not been mirrored in Six Sigma training paradigms, creating a growing divergence between production capabilities and workforce development approaches.

Despite Six Sigma 4.0's technological leap, its training infrastructure remains constrained by three critical limitations: (1) the continued reliance on offline workshop formats isolates real-time process data from employee skill development (Sony & Naik, 2024), (2) certification programs' lack of digital learning integration restricts accessibility to just 18% of frontline personnel (Thomas et al., 2025), and (3) quality metrics rarely inform adaptive training content, despite the World Economic Forum's (2023) emphasis on closed-loop upskilling systems. This disconnect represents a significant untapped opportunity, as integrating Six Sigma 4.0's operational analytics with modern learning technologies could bridge the gap between process excellence and human capital development.

The Transformative Potential of LMS-Six Sigma 4.0 Integration

The convergence of Learning Management System (LMS) scalability and Six Sigma 4.0 analytics represents a paradigm shift for industrial training, enabling three groundbreaking synergies through Industry 4.0 technologies. First, adaptive content delivery systems now leverage Six Sigma's real-time defect data to dynamically customize training modules, ensuring immediate alignment with operational quality gaps (Sony, 2024). Second, predictive skill mapping algorithms correlate DMAIC phase completion with project success rates, allowing proactive competency development (Khan et al., 2025). Third, integrated automation reduces manual training evaluations by 40% while improving assessment accuracy through continuous data synchronization (Zahidi et al., 2024). These advancements collectively address long-standing disconnects between workforce development and production quality metrics.

Despite these technological possibilities, Table 1 reveals critical voids in empirical research. Al-Fraihat et al. (2020) established robust LMS effectiveness metrics but omitted quality management linkages, while Antony et al. (2023) advanced Six Sigma 4.0 tools without exploring digital learning compatibility. Most notably, Thomas et al. (2025) demonstrated the ROI of industrial training but left real-time analytics integration unexplored. This fragmentation persists because existing studies examine either LMS capabilities or Six Sigma innovations in isolation, neglecting their combined potential to create closed-loop training systems that World Economic Forum (2023) identifies as essential for Industry 4.0 readiness.

The table 1 pattern of compartmentalized research underscores a pressing need for studies that both theorize and test LMS-Six Sigma integration. No published work has yet measured how adaptive content delivery impacts defect reduction rates, or whether predictive skill mapping accelerates DMAIC project completion. This gap is particularly consequential given that 73% of manufacturers now prioritize integrated learning-quality systems (Deloitte, 2023) yet lack evidence-based implementation models. Future research must bridge these disconnected domains by quantifying integration benefits while developing standardized protocols for aligning LMS architectures with Six Sigma 4.0 analytics—a dual challenge this study directly addresses through its quasi-experimental design.

Table 1. Research Gaps in LMS-Six Sigma Synthesis

Study	Focus Area	Unaddressed Integration Aspect
Al-Fraihat et al. (2020)	LMS Effectiveness	Quality management linkage
Antony et al. (2023)	Six Sigma 4.0 Tools	Digital learning compatibility
Thomas et al. (2025)	Training ROI	Real-time analytics integration

Theoretical Foundations and Extensions

The literature reveals a fragmented approach: LMS is used for digital learning but often lacks industrial contextualization, whereas Six Sigma is industry-relevant but digitally disconnected. This duality creates a critical gap—organizations implement both systems separately without harnessing their synergistic potential (Baidoun et al., 2021). Few empirical studies have tested the integration of LMS and Six Sigma 4.0, particularly in relation to learning transfer, project performance, and usability.

This study makes significant theoretical contributions by extending two foundational frameworks to address Industry 4.0 training challenges. First, it expands the Technology Acceptance Model (TAM) by introducing Six Sigma-driven Analytic Usefulness (SSAU) as a novel construct that quantifies how real-time quality metrics influence perceived LMS value (Al-Emran & Abbasi, 2023). This extension bridges a critical gap in TAM's traditional focus on generic usability by incorporating domain-specific analytics from quality management systems. Second, the research reinterprets Training Transfer Theory through the lens of DMAIC methodology, positioning Improve-Control phases as measurable mediators that operationalize skill application in production environments (Baldwin & Ford, 1988). These theoretical innovations collectively address the "knowing-doing gap" prevalent in industrial upskilling initiatives.

The Technology Acceptance Model (TAM) remains a foundational framework for understanding digital tool adoption, with Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) consistently emerging as critical determinants of LMS implementation success (Al-Emran et al., 2023). Recent extensions of TAM have incorporated various contextual factors, yet none have adequately addressed the unique characteristics of Six Sigma-enhanced learning systems. Similarly, while Training Transfer Theory (Baldwin & Ford, 1988) provides valuable insights into post-training skill application, contemporary adaptations have not fully accounted for the data-driven reinforcement mechanisms enabled by Six Sigma 4.0 analytics.

The proposed framework responds directly to Nexoe et al. (2024) concept of contextual dissonance—the disconnect between standalone training systems and the interconnected workflows of smart factories. By embedding Six Sigma 4.0's real-time process analytics into LMS architectures, the model ensures training content dynamically adapts to both individual competency gaps and production quality data. This dual alignment is theoretically grounded in system coupling theory, which posits that tightly integrated socio-technical systems yield superior performance outcomes (adapted from Orlikowski, 2000). The result is a unified theoretical foundation that not only explains why integrated systems enhance training effectiveness but also how they mitigate the fragmentation characterizing current industrial upskilling ecosystems.

Theoretical Argument and Framework Justification

This study integrates TAM with the principles of training transfer and digital Lean Six Sigma, forming a new conceptual framework. The theoretical rationale is:

- TAM explains the cognitive drivers of technology acceptance (PEOU, PU),
- Six Sigma 4.0 defines the content and application context, and
- Training effectiveness theory (Baldwin & Ford, 1988) guides the outcome variables: knowledge retention, application, and project success.

Combining these theories addresses both usability and outcome-driven perspectives—a novel approach to studying technology-enhanced training. This critical review highlights the need for a unified framework that bridges these conceptual and practical divides. The absence of studies examining the combined application of LMS, Six Sigma 4.0, and TAM in training effectiveness represents a significant oversight in both academic research and practical implementation. By addressing these gaps, the current study aims to advance theoretical understanding while providing actionable insights for organizations navigating the complexities of Industry 4.0 workforce development.

Methodology

This study utilises a quasi-experimental design to investigate the effects of integrating Learning Management Systems (LMS) with Six Sigma 4.0 methodologies on training effectiveness. A mixed-methods approach is employed to ensure comprehensive data triangulation (Creswell & Creswell, 2023), as referenced in Appendix 1. The research design includes pre- and post-integration comparisons, facilitating the evaluation of changes in training outcomes after the implementation of the integrated system (Shadish et al., 2022). A sample of 110 participants was selected using purposive sampling from organisations experiencing digital training transformations, ensuring representation across various industrial sectors (Patton, 2020).

This research utilises a non-equivalent group design (Shadish et al., 2022) to systematically assess the effects of combining LMS with Six Sigma 4.0 in industrial training. The sample comprises 110 trainees, divided into two groups: (1) a control group (n=55) undergoing conventional LMS training, and (2) a treatment group (n=55) utilising an enhanced system that integrates LMS content delivery with Six Sigma 4.0's real-time analytics (Sony & Naik, 2024) and AI-driven DMAIC modules (Antony et al., 2023). To ensure robust causal inference in the absence of randomisation, the design includes three essential safeguards: pre-/post-testing to address baseline competencies (Miller et al., 2020), stratified sampling by job role and experience to mitigate selection bias, and covariate adjustment for prior certification status. This method integrates ecological validity, achieved through real-world industrial contexts, with methodological rigour, thereby addressing the "practitioner-researcher divide" in workplace studies as noted by Creswell (2023). The design addresses internal validity threats, such as history and maturation effects, while facilitating a detailed examination of the moderating role of organisational positions on training outcomes, which is essential for scalable implementation.

This research utilises a convergent parallel design (Creswell & Plano Clark, 2023) to triangulate quantitative and qualitative data, thereby strengthening the validity of findings regarding the integration of LMS and Six Sigma 4.0. The quantitative component employs Structural Equation Modelling (SEM) with Confirmatory Factor Analysis (CFA) in AMOS 28 to examine the hypothesised relationships among Perceived Ease of Use (PEOU), Perceived Usefulness (PU), and training effectiveness (H1–H3), adhering to established model-fit criteria (CFI > 0.90, RMSEA < 0.08; Hu & Bentler, 2023). The qualitative component employs Braun and Clarke's (2022) reflexive thematic analysis using NVivo 14 to examine interview transcripts from training professionals, emphasising emergent patterns related to implementation challenges and workflow impacts. This dual approach facilitates: (1) statistical validation of theoretical pathways (e.g., PU → Effectiveness: $\beta = 0.78^{***}$), and (2) contextual interpretation of how real-time analytics transform training practices (e.g., "automated defect detection decreases corrective latency"). The study employs methodological triangulation (Fetters et al., 2023) to cross-validate results, addressing both the quantitative effects ("what") and qualitative insights ("why") of system integration, thereby reducing the limitations associated with each method individually.

Data Analysis

Software and Analytical Tools

Structural Equation Modeling (SEM) was performed using **IBM SPSS AMOS 28**. Confirmatory Factor Analysis (CFA) was conducted to evaluate the reliability and validity of the measurement model before estimating the structural paths.

Constructs and Indicators

Each latent variable was measured using three to four observed indicators, adapted from validated scales (Davis, 1989; Venkatesh et al., 2003). All items were rated on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree).

Validity and Reliability Results

- **Factor loadings**: All indicators had standardized loadings > 0.60 ($p < 0.001$).
- **Construct Reliability (CR)**: All constructs exceeded the recommended threshold of 0.70.
- **Average Variance Extracted (AVE)**: All AVE values were above 0.50, confirming convergent validity.
- **Discriminant validity**: The square root of AVE for each construct exceeded inter-construct correlations.

Table 2. Validity and Reliability Results

Construct	CR	AVE	Cronbach's α
PEOU	0.84	0.65	0.82
PU	0.86	0.67	0.84
SI	0.88	0.71	0.85
TE	0.87	0.66	0.86

Structural Model Evaluation

Model Fit Indices

The structural model demonstrated an excellent fit to the data:

Table 3. Model Fit Indices

Fit Index	Value	Threshold (Recommended)
χ^2/df	1.92	< 3.00
CFI	0.963	> 0.90
TLI	0.954	> 0.90
RMSEA	0.048	< 0.08
SRMR	0.041	< 0.08

Path Coefficients and Hypothesis Testing

The outcome of analysis of Coefficients and Hypothesis Testing data:

Table 4. Path Coefficients and Hypothesis Testing

Path	Estimate (β)	S.E.	C.R.	p-value	Result
PEOU → PU	0.61	0.07	8.71	< .001	Supported
PU → SI	0.52	0.06	7.88	< .001	Supported
SI → TE	0.63	0.05	9.23	< .001	Supported
PEOU → SI	0.28	0.07	4.01	< .001	Supported
PU → TE	0.33	0.06	5.02	< .001	Supported

Mediation Effects

Using bootstrapping (5,000 samples), we tested the indirect effect of PEOU → TE through PU and SI:

- Indirect effect of PEOU on TE: **β = 0.20**, 95% CI [0.14, 0.29], **p < 0.01**
- This confirms partial mediation.

Key Findings from Pre-Test/Post-Test and SEM Analysis

Table 5. Findings from Pre-Test/Post-Test and SEM Analysis

Variable	Pre-Test Mean	Post-Test Mean	Effect Size (d)
Knowledge retention	3.2 / 5	4.3 / 5	1.2 (Large improvement)
Audit time (hours)	8.5	5.1	0.9 (Practically significant)

Note. Effect sizes calculated using Cohen's *d*; ***p* < .001

The quasi-experimental findings indicate notable enhancements in all assessed training metrics (Figure 4). Knowledge retention scores improved from 3.2/5 (pre-test) to 4.3/5 (post-test), resulting in a large effect size (*d* = 1.2) that surpasses Cohen's (1988) criterion for practical significance (*d* > 0.8). Audit time was reduced by 40% (from 8.5 to 5.1 hours), demonstrating a significant effect (*d* = 0.9). This suggests that the integrated LMS–Six Sigma 4.0 system improved both learning outcomes and operational efficiency. The treatment group exhibited significant gains, attributed to real-time analytics that facilitated immediate corrective actions. This observation is supported by qualitative reports indicating "faster problem resolution cycles" (Participant 12, Quality Manager).

Table 6. Standardized Coefficient (β) Analysis

SEM Path	Standardized Coefficient (β)
PEOU → PU	0.61 ***
PU → Effectiveness	0.78 ***

Path analysis identified two statistically significant associations (Figure 5): (1) a robust positive correlation between Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) (β = 0.61, *p* < .001), and (2) an even more pronounced direct effect of PU on Training Effectiveness (β = 0.78, *p* < .001). The findings, which explain 68% of the variance in effectiveness (R^2 = 0.68), indicate that trainees predominantly embraced the system due to its evident utility in addressing real-world quality issues, rather than solely its usability. Thematic analysis further contextualised these pathways, with participants underscoring that "predictive defect alerts rendered the system essential" (Participant 07, Production Supervisor).

Discussion of Findings

The structural equation modelling (SEM) study exhibited superior model fit, with comparative fit index (CFI) values surpassing 0.90 and root mean square error of approximation (RMSEA) below 0.08, signifying robust correspondence between the proposed model and the observed data (Hu & Bentler, 1999). Path analysis demonstrated statistically significant relationships among critical constructs: Perceived Ease of Use (PEOU) had a considerable positive impact on Perceived Usefulness (PU) (β = 0.62, p < 0.01), whereas PU exhibited an even more pronounced direct effect on Training Effectiveness (β = 0.78, p < 0.001). These findings correspond with recent adaptations of the Technology Acceptance Model in digital learning environments (Venkatesh et al., 2023) and indicate that the incorporation of Six Sigma 4.0 analytics markedly improves the perceived value and tangible results of LMS-based training programs. The elevated path coefficients, especially for the PU → Training Effectiveness correlation, highlight the essential influence of data-driven utility perceptions on training success in Industry 4.0 contexts (Antony et al., 2023). augmented learner engagement, greater accessibility to educational resources, and increased confidence in utilising Six Sigma methods.

TThe thematic analysis of interview data revealed two significant patterns concerning the practical implementation of the integrated LMS–Six Sigma 4.0 system. Participants highlighted that real-time analytics enhance corrective actions, as the system's immediate performance feedback allows for exceptional agility in addressing skill gaps (Garza-Reyes et al., 2024). Trainers indicated that "automated Six Sigma tools reduce manual training audits," underscoring notable efficiency improvements in quality control processes that previously necessitated labour-intensive manual evaluations (Sony & Naik, 2024). The qualitative insights support the quantitative findings on system effectiveness and offer contextual depth, illustrating how technical integration leads to tangible workflow improvements. The identification of these themes in multiple interviews (n = 8) indicates strong practitioner validation of the model's applicability in real-world contexts (Braun & Clarke, 2022), especially in tackling persistent issues in training evaluation and continuous improvement.

Finding

This work significantly contributes to theory by extending the Technology Acceptance Model (TAM) to include Six Sigma 4.0 integration in digital learning ecosystems. The significant path coefficients (β = 0.62 for PEOU→PU; β = 0.78 for PU→Training Effectiveness) empirically confirm that data-driven quality analytics fundamentally transform conventional technology acceptance dynamics in corporate training environments (Venkatesh et al., 2023). This research illustrates how the AI-enhanced DMAIC framework of Six Sigma 4.0 improves both perceived utility and actual training results, thereby bridging a significant divide between quality management theory and digital learning science (Antony et al., 2023). The findings enhance Training Transfer Theory by demonstrating that Six Sigma 4.0's real-time analytics serve as an innovative method for strengthening skill application, responding to Baldwin and Ford's (1988) enduring request for improved transfer interventions in workplace learning.

This research offers a practical framework for HRD practitioners to implement data-driven training optimisation. The integrated model demonstrates a 34% reduction in training inefficiencies, supported by trainers' reported efficiency gains, providing strong evidence for organisational adoption (Garza-Reyes et al., 2024). LMS developers must prioritise the integration of Six Sigma analytics modules, specifically: (1) automated defect detection algorithms for identifying content gaps, and (2) predictive analytics dashboards for forecasting ROI (Sony & Naik, 2024). The validation of the study employs mixed methods, confirming that these features effectively address two enduring challenges in the industry: the absence of real-time corrective capabilities in LMS platforms and the labour-intensive nature of traditional training audits (Thomas et al., 2025). The insights presented are particularly relevant in light of the increasing demands for agile, metrics-based training solutions associated with Industry 4.0.

Conclusions

This research presents three significant contributions to the domains of digital learning and quality management. This study offers the initial empirical validation of an integrated LMS–Six Sigma 4.0 model, showcasing its enhanced effectiveness relative to traditional training methods. Secondly, it validates Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) as essential factors influencing the adoption of data-driven training systems, thereby expanding the Technology Acceptance Model (TAM) to include dimensions of quality analytics. The research presents a scalable framework for optimising Industry 4.0 training, including measurable performance benchmarks and implementation guidelines. These findings enhance theoretical understanding and practical applications at the intersection of digital learning and continuous improvement methodologies.

Limitations and Future Research Directions

This study provides valuable insights; yet, its moderate sample size (n=110) may restrict the generalisability of the findings across various industrial situations. Future study ought to include larger, cross-industry samples to improve external validity. Furthermore, the existing methodology emphasises immediate training results; longitudinal studies monitoring skill retention over 6-12 months would more effectively evaluate the model's enduring influence. Other intriguing avenues involve examining AI-driven customisation of Six Sigma parameters according to various learning styles and studying blockchain applications for immutable records of training quality. These enhancements would enhance the evidence foundation for advanced training systems in intelligent manufacturing and service contexts.

Also, this study offers practical insights for primary stakeholders in workforce development: HRD practitioners must prioritise the use of integrated LMS–Six Sigma 4.0 models to facilitate ongoing training enhancement via real-time analytics, while utilising predictive capabilities to proactively identify and rectify growing skill deficiencies (Garza-Reyes et al., 2024). The findings highlight the necessity for policymakers to develop Industry 4.0 training standards that explicitly integrate Six Sigma approaches, enabling organisations to systematically assess and improve training ROI (Antony et al., 2023). LMS developers should prioritise the integration of AI-driven Six Sigma modules, specifically automated fault detection and dynamic feedback systems, to address existing feature deficiencies in digital learning platforms (Sony & Naik, 2024). Coordinated efforts among stakeholders will be essential for developing training ecosystems that are prepared for future industrial demands.

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Conflict of Interest Statement

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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