SYSTEMATIC LITERATURE REVIEW ON DIGITAL TWIN-ENABLED PROCESS OPTIMISATION IN LARGE-SCALE APPAREL MANUFACTURING: FRAMEWORKS, FACTORS, AND APPLICATIONS IN DEVELOPING ECONOMIES

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Abstract

The transformation of manufacturing towards digital twin (DT) enabled systems has reshaped production process optimisation, especially within large-scale apparel industries. This study conducts a systematic literature review (SLR) to critically evaluate frameworks, influencing factors, and applications of DT-driven process optimisation with a focus on developing-economy contexts. Following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocol, 30 peer-reviewed articles published between 2018 and 2025 were examined from the database, Google Scholar. Each paper was assessed through quality screening and thematic categorisation. The analysis identified four major readiness domains: technological, organisational, human capital, and external/environmental factors that influence DT implementation for process optimisation. Findings reveal that DT enhances manufacturing efficiency through real-time monitoring, predictive simulation, and data-driven optimisation, yet adoption barriers persist in developing contexts due to infrastructure limitations, financial constraints, and workforce capability gaps. The review also synthesises recent frameworks integrating DT with Lean and Artificial Intelligence (AI) based optimisation models, presenting their relevance to operational excellence. This paper contributes to bridging the research gap by providing a consolidated perspective on DT readiness and optimisation frameworks applicable to Sri Lanka's apparel sector and similar economies. It further suggests developing context-specific maturity models and hybrid frameworks that integrate DT into continuous improvement and sustainability strategies.

Keywords: Apparel Manufacturing, developing economies, digital twin, operational excellence, process optimisation

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Introduction

The global manufacturing sector is undergoing a significant paradigm shift driven by the convergence of digital transformation and data-centric process optimisation. Within this transformation, the Digital Twin (DT), a dynamic virtual model that mirrors physical systems, has become a cornerstone of Industry 4.0 for enabling real-time simulation, predictive analytics, and decision-making (Karkaria et al. 2025). At the same time, the apparel manufacturing sector, a critical contributor to the economies of developing countries such as Sri Lanka, continues to face challenges of low productivity, high operational costs, and limited technological integration (Anthonypillailionel, 2024).

Digital Twin technology offers a novel approach to addressing these inefficiencies by integrating data-driven process visualisation, machine learning, and optimisation algorithms to enhance production control and responsiveness. Studies such as Lee and Yang, (2023) and Trauer et al., (2021) Have shown that DT frameworks significantly improve manufacturing decision-making by enabling simulation-based optimisation, fault prediction, and performance monitoring. However, in developing countries, organisational and infrastructural constraints limit the effective adoption of such technologies (Keenavinna and Wickramarachchi 2024).

In parallel, process-improvement philosophies such as Lean and Six Sigma have long been applied to reduce waste and variation within manufacturing systems. Recent research trends suggest that integrating DT technology with these continuous-improvement frameworks can lead to predictive optimisation, a proactive approach that combines virtual simulations with process analytics to achieve operational excellence (Clark et al., 2025; Mihai et al. 2022).

Despite global attention to DT applications, there remains a limited understanding of how DT-based process optimisation frameworks are conceptualised, implemented, and adapted in the context of apparel manufacturing industries in developing economies. The lack of a consolidated body of literature has created a critical research gap in identifying readiness factors, barriers, and implementation frameworks suitable for these contexts.

Hence, this study aims to conduct a Systematic Literature Review (SLR) guided by the PRISMA protocol to analyse and synthesise global research on DT-enabled process optimisation frameworks, with particular attention to apparel manufacturing industries. The review focuses on understanding the frameworks and approaches employed in DT-based optimisation, the key factors and enablers influencing DT adoption, and the applicability and implications of these frameworks for developing economies such as Sri Lanka.

By consolidating the evidence across peer-reviewed research, this paper contributes to advancing theoretical understanding and practical readiness towards DT-driven operational excellence. The insights derived from this study are expected to support policymakers, researchers, and industrial leaders in designing context-specific digital transformation strategies for sustainable manufacturing growth.

Literature Review and Theoretical Background

The concept of Digital Twin has evolved from a simulation-based engineering tool to a comprehensive framework for intelligent manufacturing and predictive optimisation. Defined as a dynamic virtual representation of physical assets and processes, a DT enables bidirectional data flow between the digital and physical worlds, allowing real-time monitoring, prediction, and optimisation (Karkaria et al. 2025). According to Zami et al. (2025), DT systems facilitate integration across industrial networks through data sharing, offloading, and real-time decision-making. Similarly, Lee and Yang (2023) demonstrate how DT-driven factories transform operational management by synchronising Internet of Things (IoT) sensor data, AI analytics, and simulation layers.

The architecture of DT frameworks typically includes five core components: the physical system, digital model, data integration layer, analytics engine, and service interface (Mihai et al. 2022). These interconnected elements allow for continuous synchronisation between cyber and physical entities, making DTs essential for high-precision process control. In manufacturing applications, DTs are frequently employed for predictive maintenance, fault detection, and simulation-based scheduling (Clark et al. 2025; Trauer et al. 2021).

Digital twin applications in manufacturing optimisation

Recent studies highlight that the application of DTs in manufacturing extends beyond equipment monitoring to include process-level optimisation and decision support. Lee and Yang (2023) proposed a simulation-enabled DT model that integrates multi-agent systems to improve production throughput, while Mihai et al. (2022) demonstrated the role of optimisation algorithms in DT frameworks to balance quality, cost, and production speed. These applications confirm that DTs serve as decision-support tools by improving responsiveness and reducing system downtime.

In a study focused on small and medium-sized enterprises (SMEs), Lee and Yang (2023) reported that only 2% of SMEs had implemented DT or Artificial Intelligence (AI) technologies due to resource constraints, indicating that readiness remains a major concern in developing regions. Meanwhile, Clark et al. (2025) emphasised real-time decision-making as a key capability of DT-driven operational management systems. Such frameworks enable predictive scheduling, resource allocation, and cost optimisation by integrating IoT sensor networks and AI-driven control systems.

Factors influencing digital twin implementation and readiness

The successful deployment of DT technologies depends on a range of internal and external factors. Synthesising findings from recent literature, four critical domains emerge: (Anthonypillailionel, 2024; Karkaria et al. 2025; Keenavinna & Wickramarachchi, 2024).

Table 1
Key factors influencing digital twin readiness

Domain	Key Factors Identified	Representative Sources
Technological Readiness	Infrastructure availability, IoT integration, interoperability, and cybersecurity	(Lee and Yang, 2023; Zami et al., 2025)
Organizational Readiness	Leadership commitment, process standardisation, and financial capacity	(Anthonypillailionel, 2024; Clark et al., 2025)
Human Capital Readiness	Workforce digital literacy, technical training, innovation culture	(Keenavinna and Wickramarachchi, 2024)
External / Environmental Factors	Market competitiveness, government policy, and global supply chain collaboration	(Karkaria et al., 2025; Zami et al., 2025)

(Source: Developed by authors based on literature (2025))

This classification aligns with prior readiness-assessment frameworks developed for Industry 4.0 and 5.0 transformations, highlighting that technological infrastructure and human capital are the most decisive factors in DT adoption within developing economies.

Conceptual linkages between digital twin frameworks and process optimisation

A recurring theme in the reviewed literature is the integration of DTs with optimisation frameworks such as Lean, Six Sigma, and AI-based control systems to achieve predictive and adaptive process management. Karkaria et al. (2025) emphasised that optimisation-centric DTs employ both offline and online algorithms to fine-tune production performance and resource efficiency. Likewise, Trauer et al. (2021) illustrated that DTs integrated with anomaly-detection algorithms can identify production defects in real time, leading to cost savings and energy efficiency.

In developing contexts such as Sri Lanka's apparel industry, the potential of DT-enabled optimisation is substantial yet underutilised. Anthonypillailionel (2024) identified a readiness gap caused by limited digital infrastructure and insufficient management awareness. This highlights the need for hybrid DT frameworks that combine simulation, predictive analytics, and process-improvement methodologies for localised industrial applications.

Summary of literature gaps

Despite a growing body of research, the following gaps persist:

1. Lack of integrated frameworks combining DT and optimisation tools for apparel manufacturing in developing economies.
2. Limited empirical evidence on organisational and workforce readiness for DT adoption.
3. Insufficient focus on contextual adaptation of global DT models to local industrial constraints.

Addressing these gaps requires developing readiness-based DT frameworks that align technological capability with human and organisational maturity, ensuring sustainable digital transformation.

Methodology

Research Design

This study adopts a Systematic Literature Review approach to examine the frameworks, factors, and applications of DT- enabled process optimisation within large-scale apparel manufacturing industries, focusing on developing-economy contexts. The review follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure a transparent, structured, and replicable process.

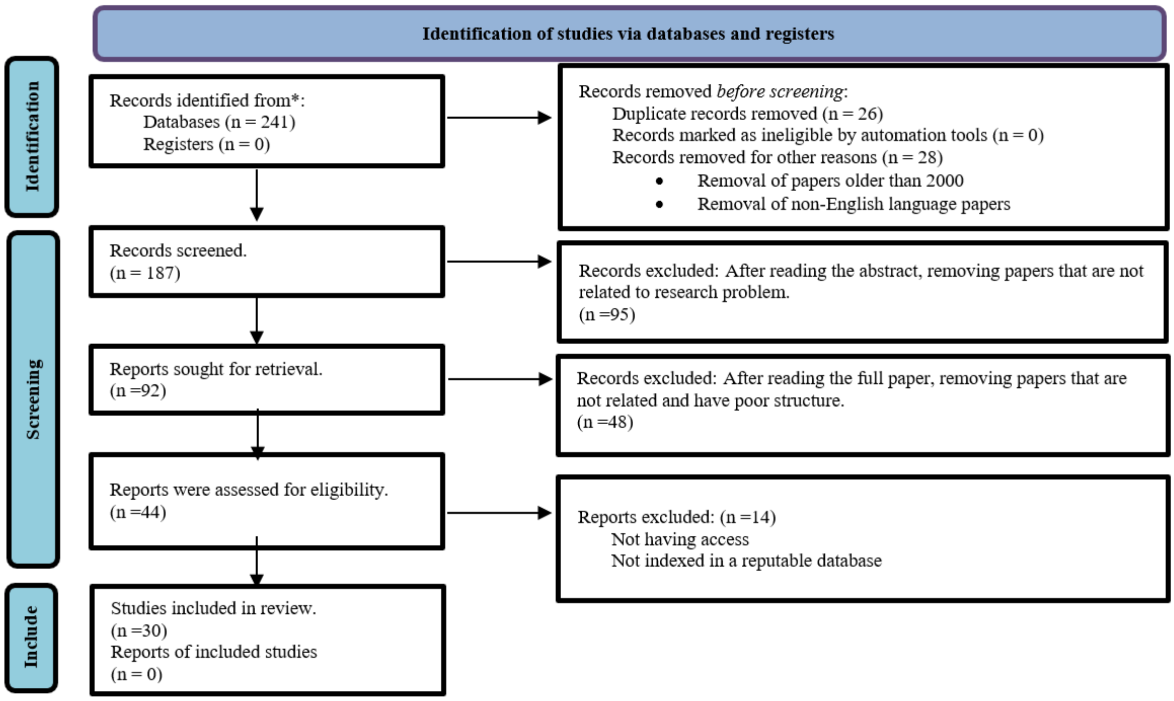
The SLR method was chosen due to its ability to synthesise dispersed evidence, evaluate research progress, and identify conceptual and practical gaps within a defined field. The review protocol was developed in alignment with the PRISMA framework, comprising four main stages: identification, screening, eligibility, and inclusion.

Data sources and search strategy

This study employed a systematic literature review approach adhering to PRISMA framework principles to ensure methodological transparency and academic rigour. The literature search was conducted using Google Scholar with a comprehensive Boolean search strategy combining keywords: ('Digital Twin' OR 'DT' OR 'Industry 4.0') AND ('production optimization' OR 'process optimization' OR 'manufacturing efficiency') AND ('Sri Lanka' OR 'developing country' OR 'emerging economy') AND ('apparel" OR 'textile' OR 'garment' OR 'fashion manufacturing') AND ('adoption' OR 'readiness OR 'implementation').

The initial search identified 241 records. Following duplicate removal (26 records) and exclusion of pre-2000 or non-English publications (28 records), 187 articles remained for screening. Title and abstract screening excluded 95 papers lacking alignment with the research problem, leaving 92 papers for full-text assessment. During full-text review, 48 papers were excluded for insufficient relevance or methodological quality, and 14 additional papers were excluded due to access limitations or indexing issues. A final set of 30 high-quality, contextually relevant studies was included, representing diverse methodological approaches including conceptual frameworks, empirical case studies, and systematic reviews.

Figure 1
PRISMA flow diagram



(Source: Developed by authors based on literature (2025))

Quality assessment

To ensure reliability, the selected studies were evaluated using a three-level quality assessment framework, adapted from Kitchenham and Charters (2007). Each paper was assessed against the following criteria:

1. Scientific Rigour – clarity of research objectives, theoretical grounding, and methodological soundness.
2. Relevance – alignment with DT-based optimisation, readiness, or apparel-industry applications.
3. Contribution – empirical or conceptual advancement to DT implementation and operational excellence.

Each study was rated on a three-point Likert scale (High = 3, Moderate = 2, Low = 1). Only studies with a cumulative score ≥ 6 out of 9 were retained for synthesis.

Limitations of the review process

Although every effort was made to ensure comprehensiveness, this review is limited by the availability of open-access resources and the exclusion of non-English studies. In addition, the rapidly evolving nature of DT research may have led to the omission of very recent publications still in press. Nevertheless, the selected studies provide a robust representation of current research trends and conceptual frameworks relevant to DT-driven optimisation in the apparel industries of developing economies.

Results and Discussion

The extracted findings were categorised into four dominant readiness domains: technological, organisational, human-capital, and external/environmental.

Table 2
Key findings and insights of readiness factors

Readiness Domain	Key Findings and Insights	Supporting Sources
Technological Factors	There is widespread consensus that DT readiness depends on IoT infrastructure, sensor interoperability, and cybersecurity mechanisms. Cloud-based integration and real-time data analytics are critical for achieving continuous optimisation.	(Zami et al., 2025; Lee and Yang, 2023; Huang et al., 2022)
Organizational Factors	Managerial commitment, financial investment, and process standardisation strongly influence DT adoption success. Integration with Lean and Six Sigma frameworks enhances process predictability.	(Clark et al., 2025; Karkaria et al., 2025)
Human-Capital Factors	Digital literacy, multidisciplinary collaboration, and employee readiness remain barriers in developing economies. Workforce training programs are highlighted as critical enablers.	(Anthonypillailionel., 2024; Keenavinna and Wickramarachchi, 2024)
External Factors	Market competitiveness and policy incentives are key external drivers. Lack of government support and poor inter-firm collaboration slow DT transformation.	(Karkaria et al., 2025; Zami et al., 2025)

(Source: Developed by authors based on literature (2025))

The results confirm that technological infrastructure and organisational leadership act as primary readiness enablers, while workforce capability and policy support remain the main constraints in emerging economies.

Frameworks and approaches for digital twin-enabled optimisation

A critical insight emerging from the review is that DT adoption rarely occurs as a standalone technology; instead, it is often integrated within optimisation frameworks such as Lean, Six Sigma, and AI-based predictive control.

Karkaria et al. (2025) proposed an optimisation-centric DT model combining multi-objective algorithms and machine-learning-driven control to enhance process adaptability.

Trauer et al. (2021) demonstrated an anomaly-detection-based DT system for real-time defect identification in aluminium extrusion, showing measurable gains in energy efficiency and cost reduction.

Clark et al. (2025) presented a DT-driven operational management framework for smart factories using edge computing and real-time IoT analytics, enabling predictive scheduling and reduced downtime.

Collectively, these studies reveal a strong trend towards hybrid integration, where DTs serve as virtual enablersof optimisation cycles rather than as isolated tools.

Comparative discussion with prior research

Compared with early DT adoption studies, contemporary frameworks place greater emphasis on predictive analytics, AI integration, and sustainability alignment. Early works (Trauer et al., 2021) mainly focused on single-machine optimisation, while recent approaches (Karkaria et al., 2025; Zami et al., 2025) extend the scope to enterprise-wide and networked DT ecosystems.

In developing economies, however, adoption remains fragmented. Anthonypillailionel (2024) noted that Sri Lankan apparel manufacturers exhibit low technological readiness and limited awareness of DT's long-term benefits. Similarly, Keenavinna and Wickramarachchi (2024) identified financial constraints and inadequate training as barriers to Industry 5.0 readiness. These findings align with Lee and Yang (2023), who emphasise that smaller manufacturers lack the capital to invest in real-time data systems.

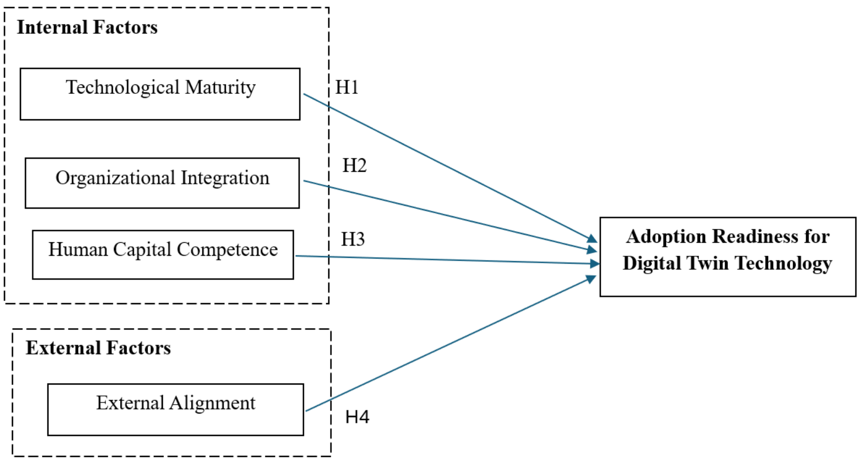
Thus, while developed nations advance towards interconnected DT ecosystems, developing countries remain constrained by resource availability and policy frameworks. Bridging this divide requires developing localised readiness models that balance cost, capability, and strategic alignment.

Integration of findings into the conceptual framework

Based on the thematic synthesis, a conceptual framework was developed to explain how the identified readiness domains collectively support DT-enabled process optimisation. The framework, depicted in *Figure 2*, illustrates interconnections between technological infrastructure, organisational support, human-capital development, and external environmental influence.

Figure 2

Conceptual framework for Digital Twin-enabled process optimisation readiness.



(Source: Developed by authors based on literature (2025))

The framework emphasises that successful DT adoption requires:

1. Technological maturity – availability of IoT architecture, data management, and simulation capabilities.
2. Organisational integration – leadership commitment, financial investment, and process governance.
3. Human-Capital competence – digital-skills development and change management.
4. External alignment – supportive policy environment and industrial collaboration.

These components interact dynamically, forming a cyclical readiness model that drives continuous improvement and predictive optimisation in apparel manufacturing.

Discussion summary

The results collectively confirm that DT technologies deliver substantial benefits in efficiency, cost, and decision accuracy, yet their success depends on multi-dimensional readiness. Further supports the argument that DT adoption in developing countries requires not only technological upgrades but also organisational transformation and policy-level support.

In the Sri Lankan context, the synthesis provides evidence that DT implementation can significantly contribute to learner production, quality consistency, and sustainable competitiveness if supported by targeted training, cross-sector collaboration, and national-level digital infrastructure development.

Conclusion and future research directions

This study systematically reviewed the integration of Digital Twin technology within process-optimisation frameworks, with a specific focus on applications and readiness in large-scale apparel manufacturing industries in developing economies. Guided by the PRISMA methodology, the review consolidated evidence from 30 peer-reviewed studies published between 2018 and 2025.

The synthesis revealed that DT technologies significantly enhance operational efficiency, process reliability, and decision-making accuracy through real-time data exchange, simulation-based optimisation, and predictive analytics. However, the adoption of DT systems remains constrained by multi-dimensional readiness challenges that encompass technological, organisational, human-capital, and external environmental factors.

From a technological perspective, inadequate data infrastructure, limited IoT connectivity, and low interoperability hinder real-time analytics and continuous improvement. Organizationally, a lack of strategic vision, leadership support, and financial investment weakens digital transformation initiatives. Human-capital barriers, particularly digital-skills shortages and low innovation culture, further slow implementation. Externally, weak policy frameworks and limited cross-industry collaboration exacerbate these limitations.

The review highlights that integrating DT with Lean and Six Sigma frameworks supports predictive optimisation by combining continuous improvement with simulation-based insight. This alignment can drive measurable gains in productivity and sustainability, especially within resource-constrained manufacturing sectors such as Sri Lanka's apparel industry.

Theoretical and practical implications

Theoretically, this paper contributes to the growing body of knowledge on DT readiness by consolidating fragmented literature into a unified conceptual model. It positions DT-enabled process optimisation as a cross-disciplinary paradigm that blends cyber-physical system design, organisational behaviour, and continuous-improvement theory.

Practically, the findings provide a roadmap for policymakers, industrial managers, and technology strategists in developing economies. The proposed conceptual framework can guide investment prioritisation, capacity-building, and policy formulation to support phased DT implementation. By addressing the identified readiness dimensions, apparel manufacturers can progress towards sustainable and data-driven operational excellence.

Study limitations and future research

This review is limited to English-language publications between 2018 and 2025 and relies solely on secondary data. Future reviews may benefit from expanding coverage to additional languages, databases, and grey literature to capture emerging empirical evidence.

Based on the observed gaps and limitations, several key avenues for future research are proposed:

1. Context-Specific Readiness Models – Develop and validate DT readiness-assessment frameworks tailored to developing-country manufacturing environments.
2. Hybrid Framework Development - Design integrated DT–Lean–AI optimisation architectures that can be empirically tested in apparel or other discrete manufacturing sectors.
3. Empirical Case Studies - Conduct longitudinal and multi-site investigations to assess the tangible performance impacts of DT adoption in production and supply-chain environments.
4. Human-Machine Collaboration Research - Explore socio-technical and behavioural aspects of workforce adaptation to DT systems, particularly in low-technology settings.
5. Policy and Sustainability Integration - Evaluate how national digital-transformation policies and sustainability regulations influence DT diffusion and industrial competitiveness.

By addressing these areas, future scholars and practitioners can accelerate the transition from conceptual understanding to measurable, context-aligned digital-twin implementation, strengthening both industrial productivity and economic resilience in emerging economies.

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