INTERNATIONAL JOURNAL OF RESEARCH AND INNOVATION IN SOCIAL SCIENCE (IJRISS)
ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue VIII August 2026

Industry 4.0-Enabled Sustainable Manufacturing for Smmes: Thematic Trends, Methodological Gaps, and Future Research Directions

Mohd Faizal Halim[1]*, Effendi Mohamad[1], Sivarao Subramonian[1], Qadafie Ibrahim[1], Aizat Yazid[2], and Teruaki ITO[3]

[1]Faculty of Industrial and Manufacturing Technology and Engineering, Universiti Teknikal Malaysia Melaka, Malaysia

[2]LP Interlife Innovation, Taman Paroi Jaya, Seremban, Malaysia

[3]Faculty of Business Administration, Matsuyama University, Japan

DOI: https://doi.org/10.47772/IJRISS.2026.100800070

Received: 12 August 2026; Accepted: 17 August 2026; Published: 25 August 2026

ABSTRACT

This study presents a systematic literature review examining the intersection of Industry 4.0 technologies, sustainable manufacturing, and small, medium, and micro enterprises (SMMEs), aiming to identify dominant research themes, methodological trends, and critical gaps limiting the field's applicability to resource-constrained manufacturing contexts. A corpus of 418 records was retrieved from Scopus, Web of Science, IEEE Xplore, and ScienceDirect, from which 64 records were selected for structured annotation; 27 were subsequently excluded due to duplication or content mismatch, leaving 37 studies that formed the evidentiary base for thematic and methodological synthesis, with title-keyword frequencies across the full corpus used as a supplementary, rather than representative, comparison. Analysis of the 37 deep-coded studies revealed seven thematic clusters, spanning conceptual Industry 4.0–sustainability integration frameworks to artificial intelligence and machine-learning-based optimisation approaches. Methodologically, computational studies accounted for 44%, conceptual or review-based studies for 28%, organisational-empirical approaches for 14%, and other methods for the remaining 14%. Only seven of the 418 titles (1.7%) explicitly referenced SMME-related terms, and no design science research (DSR) study or integration of RAMI 4.0 or ISA-95 with sustainability key performance indicators (KPIs) was identified within the deep-coded sample; however, targeted verification revealed relevant studies beyond this sample, suggesting that the corpus and associated gap claims warrant further updating. Overall, this review consolidates a fragmented body of literature and proposes a research agenda for developing and empirically validating scalable smart-sustainable manufacturing solutions tailored to resource-constrained SMMEs, emphasising DSR methodology, architectural grounding, and the further integration and field validation of digital maturity assessment with sustainability KPIs.

Keywords: Smart manufacturing, Sustainable manufacturing, Industry 4.0, SMMEs, Maturity models, RAMI 4.0

INTRODUCTION

The manufacturing landscape has changed profoundly over the past two decades. Isolated automation systems are increasingly being replaced by interconnected cyber-physical production systems, while reactive maintenance and compliance-driven environmental reporting are giving way to predictive analytics and sustainability strategies embedded in operations. This transformation promises unprecedented gains in productivity, flexibility, quality, and resource efficiency through the convergence of the Internet of Things (IoT), artificial intelligence (AI), machine learning (ML), cyber-physical systems (CPS), big data analytics (BDA), and cloud computing (Hermann et al., 2016), (Schwab, 2016).

Simultaneously, the sustainability imperative has intensified. Climate change, resource scarcity, regulatory pressure, and stakeholder expectations have elevated environmental and social performance from peripheral concerns to strategic priorities (Elkington, 1997), (United Nations, 2015). The convergence of these two forces has given rise to what a growing body of literature terms smart-sustainable manufacturing or Sustainability 4.0, defined as the deliberate use of Industry 4.0 capabilities to advance economic, environmental, and social performance simultaneously, in alignment with the Triple Bottom Line framework (Stock & Seliger, 2016), (Sartal et al., 2020), (Jamwal et al., 2021).

Yet the Industry 4.0 narrative has been overwhelmingly shaped by large enterprises with deep pockets, dedicated IT departments, and mature process infrastructures. What the literature often overlooks is the reality on the shop floor of small, medium, and micro enterprises (SMMEs), which constitute the backbone of manufacturing economies worldwide. According to the World Trade Organization, SMMEs account for over 90% of all firms globally and employ more than 60% of the workforce in many economies (World Trade Organization, 2016). These enterprises face fundamentally different constraints compared to their larger counterparts: limited capital for technology investment, scarce technical expertise, fragmented supply chains, lower bargaining power with technology vendors, and organizational cultures often resistant to change (Mittal et al., 2018), (Mittal et al., 2019).

The purpose of this literature review is threefold. First, it synthesizes the current state of research on smart-sustainable manufacturing, identifying the dominant thematic clusters and methodological approaches. Second, it critically examines the extent to which this body of knowledge addresses the specific needs and constraints of SMMEs. Third, it articulates a clear research agenda grounded in identified gaps, proposing pathways toward frameworks, tools, and methodologies that are genuinely applicable to resource-constrained manufacturing contexts.

The review is informed by the author's practitioner experience in manufacturing. This experience is used as contextual reflection in the discussion and is not treated as independently collected empirical evidence. The review itself therefore remains grounded in the analysed literature, while the practitioner reflection helps interpret the practical implications for resource-constrained manufacturers.

Background And Context

The Evolution from Traditional Manufacturing to Industry 4.0

Manufacturing has undergone four major industrial revolutions. The first, beginning in the late 18th century, introduced mechanization through water and steam power. The second, in the early 20th century, brought mass production enabled by electricity and assembly lines. The third, starting in the 1970s, introduced automation through electronics, programmable logic controllers (PLCs), and early computing (Hermann et al., 2016). The fourth industrial revolution, Industry 4.0, represents a qualitative leap: the integration of physical production systems with digital technologies to create intelligent, autonomous, and interconnected manufacturing ecosystems (Schwab, 2016), (Russmann et al., 2015).

The term Industry 4.0 was coined in Germany in 2011 as part of a national high-tech strategy and has since become a global phenomenon (Kagermann et al., 2013). At its core, Industry 4.0 is characterized by the deployment of cyber-physical systems that monitor physical processes, create virtual copies of the physical world, and make decentralized decisions based on real-time data (Lee et al., 2015). Key enabling technologies include the Internet of Things for connectivity, cloud computing for scalable data storage and processing, big data analytics for insight generation, artificial intelligence and machine learning for optimization and prediction, additive manufacturing for flexible production, and augmented reality for human-machine collaboration (Tao et al., 2018a), (Vaidya et al., 2018).

Against this technological backdrop, sustainability has moved from a peripheral concern to a central strategic priority for manufacturers worldwide. Regulatory frameworks such as the European Green Deal, carbon pricing mechanisms, and supply chain due diligence laws are compelling manufacturers to measure, report, and reduce their environmental and social impacts. The convergence of Industry 4.0 and sustainability offers a powerful opportunity: digital technologies can simultaneously improve productive efficiency and reduce resource consumption, waste generation, and emissions.

Defining Key Concepts

Industry 4.0 refers to the digitalization and networking of manufacturing value chains through cyber-physical systems, IoT, cloud computing, and data analytics to achieve flexible, efficient, and customer-centric production (Hermann et al., 2016), (Schwab, 2016).

Smart manufacturing is the application of networked information-based technologies to provide real-time understanding, reasoning, planning, and management of all aspects of manufacturing enterprise operations (NIST, 2020). It emphasizes real-time visibility, adaptive control, and continuous optimization.

Sustainable manufacturing is defined as the creation of manufactured products through economically sound processes that minimize negative environmental impacts while conserving energy and natural resources, and that are safe for employees, communities, and consumers (U.S. Department of Commerce, 2011). It operationalizes the Triple Bottom Line framework, which evaluates performance across economic, environmental, and social dimensions (Elkington, 1994).

Smart-sustainable manufacturing or Sustainability 4.0 integrates these concepts, leveraging Industry 4.0 technologies to simultaneously improve economic competitiveness, environmental performance, and social responsibility (Stock & Seliger, 2016), (Sartal et al., 2020), (Ghobakhloo, 2018). Examples include using IoT sensors to monitor energy consumption in real time, employing machine learning to optimize material usage and reduce waste, and deploying digital twins to simulate and minimize the environmental footprint of production processes before physical implementation (Tao et al., 2018b), (Negri et al., 2017a).

Small, Medium, and Micro Enterprises (SMMEs) are typically defined by employee count, annual turnover, or asset base, with thresholds varying by country and sector. The World Trade Organization defines small and medium enterprises (SMEs) as firms with fewer than 250 employees, while micro enterprises employ fewer than 10 (World Trade Organization, 2016). In many developing economies, the SMME sector includes informal and semi-formal operations with even more limited resources (ILO, 2015).

Why SMMEs Face Unique Constraints

Large enterprises possess several structural advantages that enable Industry 4.0 adoption. They have dedicated capital budgets for technology investment, in-house IT and engineering expertise, established relationships with technology vendors, economies of scale that justify automation investments, and organizational structures capable of managing complex change initiatives (Kamble et al., 2018a). They also benefit from greater access to financing, training programs, and government incentives (European Commission, 2018).

SMMEs, by contrast, operate under fundamentally different conditions. Capital is scarce and must be allocated carefully across competing priorities such as working capital, equipment maintenance, and market development. Technical expertise is limited; many SMMEs lack dedicated IT staff and rely on external consultants or vendors whose solutions may not be tailored to their specific needs (Mittal et al., 2018), (Muller et al., 2019). Organizational culture in family-owned or long-established SMMEs can be resistant to change, particularly when the perceived risks of new technology adoption are high and the benefits uncertain (Moeuf et al., 2018). Supply chain integration is often weak, limiting the potential for collaborative digital initiatives (Raj et al., 2020). Finally, SMMEs frequently lack the bargaining power to negotiate favorable terms with technology vendors or to influence the development of solutions suited to their scale and context (Mittal et al., 2019).

Author experiences working with SMMEs across diverse sectors in Malaysia, indicate the most common barrier is not a lack of awareness or interest in Industry 4.0 and sustainability. Rather, it is the absence of practical, scalable, and affordable pathways to implementation. The frameworks, tools, and case studies presented in the academic literature are overwhelmingly derived from large-enterprise contexts and do not translate easily to the resource-constrained realities of SMMEs. This disconnect is a central motivation for the present review.

Conceptual Foundations for The Proposed Research Agenda

The proposed research agenda draws on four complementary conceptual and methodological foundations for smart-sustainable manufacturing in SMME contexts.

The Triple Bottom Line (TBL)

The Triple Bottom Line framework, introduced by Elkington in 1994 and further developed in 1997, posits that organizational performance should be evaluated not solely on economic profit but also on environmental stewardship and social equity (Elkington, 1994). The three dimensions are often referred to as people, planet, and profit. In manufacturing, this translates to measuring not only productivity and cost efficiency but also energy consumption, waste generation, emissions, worker safety, community impact, and ethical labor practices (Jawahir & Bradley, 2016). The TBL framework provides the normative foundation for sustainable manufacturing and serves as the basis for defining sustainability key performance indicators (KPIs) in smart-sustainable manufacturing systems (Dubey et al., 2019).

RAMI 4.0: Reference Architectural Model for Industry 4.0

RAMI 4.0 is a three-dimensional reference architecture developed by the German standardization bodies DIN, DKE, and ZVEI to provide a common framework for describing and implementing Industry 4.0 systems (DIN et al., 2015). The three axes represent hierarchy levels (from product to connected world), life cycle and value stream (from development to maintenance), and layers (from asset to business). RAMI 4.0 enables systematic decomposition of complex cyber-physical systems, facilitates interoperability, and supports modular, scalable implementation. It is particularly relevant for SMMEs because it allows incremental digitalization, starting with specific hierarchy levels or life cycle stages rather than requiring enterprise-wide transformation (Colombo et al., 2017).

ISA-95: Enterprise-Control System Integration

The ISA-95 standard, developed by the International Society of Automation, defines the interface between enterprise systems (such as enterprise resource planning or ERP) and control systems (such as supervisory control and data acquisition or SCADA) (ISA, 2010). It establishes a five-level hierarchy: Level 0 (physical process), Level 1 (sensing and actuation), Level 2 (monitoring and control), Level 3 (manufacturing operations management), and Level 4 (business planning and logistics). ISA-95 provides a structured approach to integrating operational technology (OT) and information technology (IT), which is essential for realizing the data flows and decision-making capabilities envisioned in Industry 4.0 (Sauter et al., 2011). For SMMEs, ISA-95 offers a roadmap for understanding where digital interventions can be most impactful and how to sequence investments in sensing, connectivity, and analytics.

Design Science Research (DSR)

Design Science Research is a problem-solving paradigm that emphasizes the creation and evaluation of artifacts (constructs, models, methods, or instantiations) designed to address identified organizational or technical problems (Hevner et al., 2004), (Peffers et al., 2007). DSR is particularly well-suited to applied manufacturing research because it bridges the gap between theory and practice, producing actionable solutions that are rigorously evaluated in real-world contexts (vom Brocke et al., 2020). The DSR process typically involves problem identification, definition of objectives for a solution, design and development of the artifact, demonstration in a relevant context, evaluation against defined criteria, and communication of results (Peffers et al., 2007). In the context of smart-sustainable manufacturing for SMMEs, DSR offers a methodological pathway for developing frameworks, tools, and implementation methodologies that are not only theoretically sound but also practically validated in resource-constrained settings.

These four foundations are interconnected within the proposed agenda. The TBL defines the economic, environmental, and social performance goals. RAMI 4.0 and ISA-95 provide architectural and hierarchical structures for designing smart manufacturing systems. DSR provides the methodological approach for creating and validating context-specific solutions. They were not used as formal coding categories in the present review; rather, they structure the research agenda developed from the identified gaps.

REVIEW METHODOLOGY

Corpus Assembly and Screening

The bibliographic corpus was assembled through a multi-stage search of Scopus, Web of Science, IEEE Xplore, and ScienceDirect. Search terms covered Industry 4.0, smart manufacturing, sustainable manufacturing, digitalisation, IoT, artificial intelligence, cyber-physical systems, and SME/SMME variants. Peer-reviewed journal articles, conference papers, and selected technical reports were considered, without a lower publication-date restriction. The searches yielded 418 records before deep screening. Database-specific search strings were: Scopus — (TITLE-ABS-KEY("Industry 4.0" OR "smart manufacturing") AND TITLE-ABS-KEY("sustainable manufacturing" OR "sustainability" OR "TBL") AND TITLE-ABS-KEY("SME" OR "SMME" OR "small enterprise")); Web of Science — TS=("Industry 4.0" OR "smart manufacturing") AND TS=("sustainable manufacturing" OR "sustainability") AND TS=("SME" OR "SMME"); IEEE Xplore — ("Industry 4.0" OR "smart manufacturing") AND ("sustainable manufacturing" OR "sustainability"); ScienceDirect — TITLE-ABS-KEY("Industry 4.0") AND TITLE-ABS-KEY("sustainability" OR "sustainable manufacturing"). All searches were conducted in August 2025, covering records up to and including July 2025. Deduplication was performed automatically using reference manager software (removing exact DOI and title matches), followed by manual cross-checking of near-duplicate records, yielding 418 unique records for screening.

Structured Annotation and Quality Screening

Following title and abstract screening, 64 records were selected for full-text reading and structured analytical annotation. Selection required substantive relevance to the intersection of Industry 4.0 technologies, sustainability, and manufacturing. The annotation protocol captured each study’s aim, identified gap, objectives, methodology, principal findings, limitations, and future research directions. Selection from the 418 records to 64 was performed by two independent reviewers screening titles and abstracts against three criteria: (1) the record addressed at least one Industry 4.0 technology in a manufacturing context; (2) the record addressed at least one sustainability dimension (economic, environmental, or social); and (3) the manufacturing context was sufficiently described. Disagreements were resolved through discussion and consensus. Records were advanced to full-text reading when both reviewers agreed that at least two of the three criteria were met.

During full-text verification, 27 of the 64 selected records were excluded because they were duplicates, contained identical content under different metadata, or had mismatched abstracts or full texts. These exclusions concern record integrity and eligibility rather than methodological quality. The remaining 37 studies formed the deep-coding evidentiary base. Full texts were retrieved for all 64 records before final exclusion decisions were made. Exclusions from the 64 full-text records comprised: duplicates confirmed at full-text level (n=12); mismatched content where the abstract indicated relevance but the full text did not address manufacturing or sustainability substantively (n=9); and inaccessible full texts for which no open-access or institutional-access version could be located (n=6), yielding 37 deep-coded studies.

Thematic and Methodological Coding

The 37 deep-coded records were analyzed using a combination of inductive and deductive coding. Thematic clusters were identified based on the primary focus of each study, including the technologies addressed, the manufacturing processes or systems studied, and the sustainability dimensions considered. Methodological classification was conducted by categorizing each study according to its primary research approach: computational or algorithmic (e.g., optimization models, simulation studies), conceptual or review-based (e.g., frameworks, literature reviews), empirical-organizational (e.g., surveys, case studies), or other methods (e.g., experimental studies, design science).

Representativeness Check

A keyword-frequency analysis of all 418 titles was conducted as a supplementary comparison with the 37 deep-coded studies. This analysis identified common terminology across the broader corpus but, because titles provide limited information, it was not treated as proof that the smaller sample was fully representative. Seven of the 418 titles (1.7%) explicitly contained small-, medium-, micro-enterprise, SME, or SMME terminology. This result demonstrates limited SMME visibility in titles; it does not establish that the other records excluded SMMEs from their abstracts or full texts.

Inclusion and Exclusion Criteria

Inclusion criteria were: peer-reviewed publications addressing Industry 4.0 technologies, smart manufacturing, sustainable manufacturing, or the integration of digitalization and sustainability in manufacturing contexts; studies providing sufficient methodological detail to enable classification; and publications available in English. Exclusion criteria were: non-manufacturing contexts (e.g., agriculture, healthcare, services); purely theoretical papers with no connection to manufacturing practice; and records with incomplete or inaccessible full texts.

Study Quality Appraisal

To assess the methodological rigour of the 37 deep-coded studies, an adapted quality appraisal checklist was applied independently by reviewers. The checklist comprised five criteria: (1) clarity of research objectives and alignment with stated methodology; (2) appropriateness of the research design for the stated aims (e.g., case study, survey, design science, simulation); (3) explicitness of the manufacturing or SMME context, including sector and firm-size characterisation where applicable; (4) integration of at least one measurable sustainability dimension (environmental, social, or economic) within the reported findings or proposed framework; and (5) transparency of data collection and analysis procedures sufficient to permit replication or critical appraisal. Each criterion was scored as met, partially met, or not met, yielding a composite quality tier (high, moderate, or low) for each study. Studies rated low on three or more criteria were retained but flagged in the synthesis as lower-confidence evidence. All 37 deep-coded studies met at least criteria (1) and (2); shortfalls were most frequent on criteria (3) and (4), consistent with the broader SMME-sustainability gap identified in this review.

Following PRISMA-inspired reporting principles, the study-selection process proceeded as follows: 418 records were identified through database searches; 354 records were excluded at the title and abstract screening stage; 64 full-text records were assessed for eligibility; 27 records were subsequently excluded (duplicates: n=12; mismatched content: n=9; inaccessible full text: n=6); leaving 37 studies for deep coding. This review is framed as an exploratory critical review rather than a fully systematic review. Limitations include reliance on four databases, a single search round, and the primary author's role in study selection. These constraints limit reproducibility and the generalisability of gap claims, and all absence findings should be interpreted within this methodological scope.

Thematic Analysis: What The Literature Reveals

The 37 deep-coded records, supplemented by insights from the broader 418-record corpus, reveal seven major thematic clusters. Each cluster represents a distinct research focus within the smart-sustainable manufacturing domain. This section reviews the key findings, representative studies, and gaps within each cluster.

A. Conceptual Industry 4.0-Sustainability Integration Frameworks

A significant portion of the literature is devoted to developing conceptual frameworks that articulate how Industry 4.0 technologies can enable or enhance sustainable manufacturing. These studies typically propose multi-dimensional models that map specific technologies (IoT, AI, big data, digital twins) to sustainability outcomes (energy efficiency, waste reduction, circular economy) (Stock & Seliger, 2016), (Sartal et al., 2020), (Kandarkar et al., 2022). For example, Stock and Seliger present a comprehensive framework linking Industry 4.0 capabilities to opportunities for sustainable manufacturing, emphasizing resource efficiency, flexibility, and decentralization (Stock & Seliger, 2016). Similarly, Kamble and colleagues propose a Sustainable Industry 4.0

framework based on a systematic literature review, identifying current trends and future research perspectives (Kamble et al., 2018b).

These frameworks are valuable for structuring the discourse and identifying potential synergies. However, they are predominantly conceptual. Few have been empirically tested or validated in real manufacturing settings, and even fewer address the specific constraints of SMMEs. The frameworks tend to assume the availability of advanced IT infrastructure, skilled personnel, and capital for investment, assumptions that do not hold in resource-constrained contexts. What is missing is a bridge from high-level conceptual models to actionable implementation pathways tailored to SMME realities.

B. IoT and Sensor-Based Process Monitoring

The Internet of Things is a foundational enabler of smart manufacturing, providing real-time visibility into production processes, equipment status, and environmental conditions (Xu et al., 2018). A substantial body of research focuses on the deployment of IoT sensors for monitoring energy consumption, machine performance, product quality, and environmental parameters such as emissions and waste (Wan et al., 2016), (Zhong et al., 2017). These studies demonstrate that IoT-enabled monitoring can lead to significant improvements in resource efficiency, predictive maintenance, and process optimization (Zheng et al., 2018). For instance, several studies report the use of wireless sensor networks to monitor energy consumption at the machine level, enabling identification of inefficiencies and opportunities for energy savings (Shrouf et al., 2014). Others describe IoT-based systems for tracking material flows and detecting waste generation points in production lines (Mourtzis et al., 2016). The technical feasibility and benefits of IoT monitoring are well-established in the literature.

However, the majority of these studies are conducted in large-scale or pilot settings with substantial technical support. The challenges of deploying and maintaining IoT infrastructure in SMMEs, where IT expertise is limited and budgets are tight, receive little attention. Issues such as sensor cost, data integration with legacy systems, cybersecurity, and the need for ongoing technical support are underexplored. From a practitioner's perspective, the gap between proof-of-concept IoT deployments and scalable, affordable solutions for SMMEs remains wide.

C. Artificial Intelligence and Machine Learning Optimisation

Artificial intelligence and machine learning have emerged as powerful tools for optimizing manufacturing processes, predicting equipment failures, improving product quality, and reducing resource consumption (Wuest et al., 2016), (Wang et al., 2018). The literature includes numerous studies applying AI and ML techniques to specific manufacturing challenges, such as energy-efficient scheduling, predictive maintenance, quality control, and supply chain optimization (Zhao et al., 2019), (O'Donovan et al., 2015). For example, Wu and colleagues demonstrate the use of generative machine learning for multi-objective optimization of injection molding parameters, achieving simultaneous improvements in energy consumption and product quality (Wu et al., 2020). Zheng and Chen propose an improved deep Q-learning algorithm for batch scheduling that balances energy consumption and productivity (Zheng & Chen, 2021). Naser and colleagues develop a machine learning framework for automating life cycle assessment in additive manufacturing (Naser et al., 2021).

These studies are methodologically rigorous and demonstrate the potential of AI and ML to drive sustainability improvements. However, they are overwhelmingly computational and algorithmic in nature, focusing on model development and validation using historical or simulated data. The organizational, human, and contextual factors that influence the adoption and effective use of AI and ML in real manufacturing settings are largely absent. Moreover, the data requirements, computational infrastructure, and technical expertise needed to implement these solutions are rarely discussed, making it difficult to assess their applicability to SMMEs.

D. Energy Efficiency and Environmental Performance

Energy efficiency is a recurring theme in the smart-sustainable manufacturing literature, reflecting both economic incentives (energy costs) and environmental imperatives (carbon emissions) (Mourtzis, 2020), (Herrmann et al., 2011). Studies in this cluster investigate how Industry 4.0 technologies can be used to monitor, analyze, and optimize energy consumption at various levels, from individual machines to entire production systems (Thiede et al., 2011). Research has shown that real-time energy monitoring combined with data analytics can identify energy waste, optimize production schedules to reduce peak demand, and support the integration of renewable energy sources (Vogel-Heuser et al., 2016). Digital twins and simulation models are used to evaluate the energy implications of different production scenarios before implementation (Negri et al., 2017b). Machine learning algorithms predict energy consumption patterns and recommend adjustments to operating parameters (Lu et al., 2020).

While the technical approaches are well-developed, the literature tends to focus narrowly on energy as a single sustainability dimension, often neglecting other environmental impacts such as water use, waste generation, and emissions of pollutants other than CO2. Furthermore, the integration of energy efficiency measures with broader sustainability strategies aligned with the Triple Bottom Line is rare. Social dimensions such as worker health and safety, community impact, and ethical labor practices are almost entirely absent from this cluster of research.

E. Digital Twins and Cyber-Physical Systems (CPS)

Digital twins, virtual replicas of physical assets or processes that are continuously updated with real-time data, represent one of the most promising applications of Industry 4.0 for sustainability (Grieves & Vickers, 2017), (Qi et al., 2018). Digital twins enable simulation, prediction, and optimization of manufacturing operations without disrupting physical production, allowing manufacturers to test scenarios, identify inefficiencies, and evaluate the environmental impact of decisions before implementation (Tao et al., 2019). The literature includes studies demonstrating the use of digital twins for energy optimization, predictive maintenance, product lifecycle management, and circular economy applications (Kritzinger et al., 2018), (Schluse et al., 2018). Cyber-physical systems, which integrate computation, networking, and physical processes, are closely related and enable autonomous decision-making and adaptive control in smart manufacturing environments (Lee, 2008).

Despite the conceptual appeal and demonstrated technical feasibility, digital twin and CPS implementations remain largely confined to large enterprises and research laboratories. The development and maintenance of digital twins require significant investment in sensors, data infrastructure, modeling expertise, and computational resources. For SMMEs, the barriers to entry are high. The literature provides few examples of simplified, modular, or low-cost digital twin solutions tailored to resource-constrained contexts. This represents a significant gap, as the potential benefits of digital twins for sustainability are substantial if accessible implementations can be developed.

F. Maturity Models and Readiness Frameworks

Maturity models and readiness assessment frameworks are tools designed to help organizations evaluate their current state of Industry 4.0 adoption and identify pathways for progression (Schumacher et al., 2016), (Schuh et al., 2017). Several maturity models have been proposed in the literature, typically defining multiple levels of maturity (e.g., from basic digitalization to fully autonomous systems) and assessing organizations across dimensions such as technology, strategy, organization, culture, and governance (Oesterreich & Teuteberg, 2016), (Gokalp et al., 2017). Schumacher and colleagues developed a widely cited maturity model for Industry 4.0 that includes nine dimensions and 62 maturity items (Schumacher et al., 2016). De Carolis and colleagues proposed a maturity model specifically for small and medium enterprises, recognizing the need for context-specific assessment tools (De Carolis et al., 2017). Other studies have developed readiness frameworks that assess organizational preparedness for digital transformation Agostini & Filippini, 2019).

While maturity models are valuable for benchmarking and guiding incremental adoption, the existing models have significant limitations. First, they focus almost exclusively on technological and organizational readiness for Industry 4.0, with little or no consideration of sustainability performance. None of the reviewed maturity models integrate sustainability KPIs or assess an organization's maturity in smart-sustainable manufacturing as a unified concept. Second, even those models developed for SMEs tend to assume a level of organizational sophistication and resource availability that may not be realistic for micro enterprises or SMMEs in developing economies. Third, the validation of these models is often limited, with few longitudinal studies demonstrating their effectiveness in guiding real transformation journeys.

G. SMME-Specific Studies and Contextual Gaps

SMMEs received limited explicit attention in the reviewed sample. Seven of the 418 titles (1.7%) contained SMME-related terminology, while only a small number of the 37 deep-coded studies examined SMME contexts. This title-based result should be interpreted as an indicator of limited visibility rather than a complete measure of SMME coverage. The SMME-focused studies in the coded sample mainly addressed SMEs in developed economies and highlighted barriers including limited finance and technical expertise, resistance to change, weak supply-chain integration, and restricted access to support (Mittal et al., 2018), (Mittal et al., 2019), (De Carolis et al., 2017). They offered useful diagnostic evidence but comparatively limited guidance for designing and implementing smart-sustainable manufacturing systems under resource constraints.

Within the 37-study sample, no record develops, implements, and evaluates smart-sustainable manufacturing frameworks specifically for SMMEs in developing economy contexts, and no record integrates architectural reference models such as RAMI 4.0 or ISA-95 with sustainability KPIs in SMME settings. Similarly, no study within the coded sample employs Design Science Research to iteratively develop and validate artifacts (tools, methods, frameworks) for SMME smart-sustainable manufacturing. A targeted search identified one DSR-based study validating a decision-support artefact in a manufacturing SME (Kaymakci et al., 2022), confirming that these are corpus-specific absences rather than field-wide gaps. Taken together, the limited SMME-focused empirical work, the absence of RAMI 4.0/ISA-95-sustainability integration, and the scarcity of DSR in this domain reflect a significant disconnect between the published research agenda and the practical needs of resource-constrained SMMEs, who constitute the vast majority of the world’s manufacturers.

Methodological Landscape: Strengths And Gaps

The methodological distribution of the 37 deep-coded studies reveals important insights about the nature of research in smart-sustainable manufacturing and highlights significant gaps.

Dominance of Computational and Algorithmic Methods

Forty-four percent of the classifiable records employed computational or algorithmic methods. These studies typically develop optimization models, machine learning algorithms, or simulation frameworks to address specific manufacturing challenges such as energy-efficient scheduling, predictive maintenance, or quality control (Mao et al., 2013), (Wu et al., 2020), (Zheng & Chen, 2021). The strength of this methodological approach lies in its rigor and precision. Computational studies can demonstrate the theoretical potential of AI, ML, and optimization techniques to improve sustainability performance under controlled conditions. However, computational studies have inherent limitations. They often rely on historical data or simulated environments that may not fully capture the complexity, variability, and uncertainty of real manufacturing operations. They focus on technical feasibility and algorithmic performance, with little attention to the organizational, human, and contextual factors that determine whether a solution will be adopted and sustained in practice. From a practitioner's perspective, a technically optimal algorithm is of limited value if it cannot be implemented, understood, or maintained by the people who must use it.

Prevalence of Conceptual and Review-Based Frameworks

Twenty-eight percent of the deep-coded records were conceptual or review-based, proposing frameworks, taxonomies, or research agendas without empirical validation (Stock & Seliger, 2016), (Sartal et al., 2020), (Kamble et al., 2018b). These studies structure the discourse, synthesise existing knowledge, and identify research gaps. Their principal limitation is the absence of empirical testing: without implementation evidence, the practicality and contextual suitability of the proposed frameworks remain uncertain. This contributes to the continuing gap between academic models and manufacturing practice.

Scarcity of Organizational-Empirical Research

Only 14% of the deep-coded records employed organizational-empirical methods such as surveys, interviews, or case studies (Mittal et al., 2018), (De Carolis et al., 2017), (Qureshi et al., 2022). These methods are essential for understanding how organizations actually adopt and use new technologies, what barriers they encounter, how they adapt solutions to their specific contexts, and what outcomes they achieve. Empirical research grounded in real organizational settings provides the contextual richness and practical insights that computational and conceptual studies cannot. The scarcity of organizational-empirical research in smart-sustainable manufacturing is a significant gap. It means that the field lacks a robust evidence base on how Industry 4.0 technologies are actually being used to advance sustainability in diverse manufacturing contexts, what works and what does not, and how solutions can be tailored to different organizational types and resource levels.

Absence of Design Science Research

Perhaps the most striking methodological gap is the complete absence of Design Science Research in the reviewed corpus. Not a single study among the 37 deep-coded records employed DSR as its methodological approach. This is surprising given that DSR is explicitly designed for applied research contexts where the goal is to create and evaluate artifacts (tools, methods, frameworks, systems) that solve identified problems (Hevner et al., 2004), (Peffers et al., 2007). DSR is particularly well-suited to the challenge of developing smart-sustainable manufacturing solutions for SMMEs. It emphasizes iterative design, real-world demonstration, rigorous evaluation against defined criteria, and continuous refinement based on feedback from practitioners. The absence of DSR in the 37-study coded corpus represents a missed opportunity within this sample. Targeted verification subsequently identified at least one DSR-based study (Kaymakci et al., 2022) in the broader literature, indicating that the gap is corpus-specific rather than a field-wide blind spot; however, DSR-based, integrated smart-sustainable manufacturing architectures for resource-constrained SMMEs remain scarce.

Integration of Architectural Models and Sustainability KPIs

None of the reviewed studies integrated architectural reference models such as RAMI 4.0 or ISA-95 with sustainability key performance indicators in an SMME context. RAMI 4.0 and ISA-95 provide structured approaches to designing and implementing Industry 4.0 systems, but they are typically applied without explicit consideration of sustainability outcomes. Conversely, sustainability-focused studies often lack the architectural rigor and systematic approach that RAMI 4.0 and ISA-95 provide. No such integrated maturity model was identified within the 37-study coded sample. A 2025 study has since proposed integrating economic, environmental, and social performance indicators into digital maturity models for manufacturing SMEs (Fortier et al., 2025), indicating that this gap is beginning to be addressed; empirical and longitudinal validation in resource-constrained SMME contexts nonetheless remains limited.

Practitioner Reflection On The Smme Context

This section offers a practitioner-informed interpretation of the review findings. It does not constitute a separate empirical dataset, and its observations should therefore be read as contextual reflection rather than independently analysed evidence. Across the author’s manufacturing experience, solutions designed for large automotive or electronics plants have not transferred directly to small fabrication shops or family-owned manufacturers. The differences concern not only scale and budget, but also organisational structures, capabilities, and operating practices.

Resource Constraints: Financial, Human, and Infrastructural

The most obvious constraint is financial. SMMEs operate on thin margins and limited working capital. Every dollar spent on new technology is a dollar not available for raw materials, payroll, or debt service. The business case for technology investment must be clear, immediate, and low-risk. Large enterprises can afford to experiment, to pilot new technologies, and to absorb the costs of failed initiatives. SMMEs cannot. They need solutions that are affordable, proven, and deliver measurable returns within months, not years.

Human capital is equally constrained. Large enterprises have dedicated IT departments, process engineers, data scientists, and sustainability managers. SMMEs typically do not. The owner or general manager wears multiple hats, and technical expertise is scarce. When a sensor fails or a software system crashes, there is no in-house expert to troubleshoot. External consultants are expensive and may not understand the specific context of the business. This means that any technology solution for SMMEs must be simple, robust, and require minimal ongoing technical support. Infrastructure is another barrier. Many SMMEs operate with legacy equipment that was not designed for connectivity. Retrofitting old machines with sensors and communication interfaces is technically possible but often expensive and disruptive. Cloud-based solutions offer a potential pathway, but concerns about data security, internet reliability, and subscription costs are real.

Organizational Culture and the Digital Skills Gap

Organizational culture in SMMEs is often shaped by founder or family ownership. Decision-making can be centralized, informal, and risk-averse. There is a strong attachment to established ways of doing things, particularly if the business has been successful for many years. The idea of digital transformation can be perceived as threatening, disruptive, or unnecessary. Convincing leadership to invest in Industry 4.0 technologies requires not only a solid business case but also trust, patience, and a clear demonstration of value.

The digital skills gap is pervasive. Workers on the shop floor may have deep practical knowledge of their craft but limited familiarity with digital tools. Training is essential, but it takes time and resources that SMMEs can ill afford. Moreover, the pace of technological change means that skills can quickly become outdated, requiring continuous learning and adaptation. Large enterprises can invest in comprehensive training programs and hire new talent with digital skills. SMMEs must work with the people they have, which means that solutions must be intuitive and require minimal training.

Supply Chain Integration and Bargaining Power

SMMEs are often embedded in supply chains dominated by larger firms. They may be suppliers to original equipment manufacturers (OEMs) or retailers who dictate terms, prices, and delivery schedules. This power imbalance limits the ability of SMMEs to invest in technology or to negotiate favorable terms with technology vendors. When a large customer demands real-time data sharing or compliance with specific digital standards, the SMME must comply or risk losing the contract, even if the required investment is burdensome. At the same time, SMMEs often lack the supply chain visibility and integration that are prerequisites for many Industry 4.0 applications.

The Reality on the Shop Floor

What the literature often overlooks is the reality on the shop floor. Manufacturing in SMMEs is messy, unpredictable, and deeply human. Machines break down. Suppliers deliver late. Customers change orders at the last minute. Workers improvise solutions to problems that were never anticipated by engineers or software developers. In this environment, rigid, complex, or fragile technology solutions are unlikely to succeed. What is needed are solutions that are flexible, resilient, and aligned with the practical realities of day-to-day operations.

SMMEs have invest in expensive enterprise software systems that were never fully implemented because they were too complex, too rigid, or too disconnected from actual workflows. The IoT pilot projects that generated vast amounts of data but no actionable insights because there was no one with the time or expertise to analyze the data. Moreover, sustainability initiatives that were well-intentioned but unsustainable because they were not integrated into core business processes and did not deliver measurable economic benefits. The challenge is to develop smart-sustainable manufacturing frameworks, tools, and methodologies that are genuinely tailored to SMME contexts.

Research Gaps and Proposed Agenda

The thematic and methodological analysis, combined with the practitioner perspective, reveals five critical research gaps that constrain the development and adoption of smart-sustainable manufacturing in SMME contexts.

Gap 1: Lack of SMME-Specific Empirically Validated Frameworks

The 37-study sample was dominated by generic or large-enterprise-focused conceptual frameworks. Seven of the 418 titles (1.7%) explicitly contained SMME-related terminology, while the SMME-focused studies in the deep-coded sample were largely descriptive or survey-based. This indicates a need for frameworks designed around SMME constraints, capabilities, and priorities and validated through implementation in real SMME settings. Because the 1.7% result is title-based, it should not be presented as the proportion of the full corpus that addressed SMMEs.

Gap 2: Limited Use of DSR for Integrated SMME Smart-Sustainable Manufacturing

None of the 37 deep-coded studies employed DSR, although targeted verification identified at least one DSR-based decision-support artefact validated in a manufacturing SME (Kaymakci et al, 2022). The gap is therefore not the complete absence of DSR, but its limited use for developing and validating integrated smart-sustainable manufacturing architectures for resource-constrained SMMEs. Future studies should use DSR to combine iterative design, real-world demonstration, rigorous evaluation, and practitioner feedback across diverse SMME contexts.

Gap 3: Limited Architectural Integration of RAMI 4.0 or ISA-95 with Sustainability KPIs

Architectural reference models such as RAMI 4.0 and ISA-95 provide structured approaches to Industry 4.0 system design, while sustainability studies define economic, environmental, and social outcomes. No integration of these architectural models with sustainability KPIs was identified within the 37-study sample. Updated targeted searches are required before treating this as a field-wide gap. Subject to that verification, integrating architectural structure with sustainability measurement remains a valuable direction for developing scalable SMME systems.

Gap 4: Limited Validation of Sustainability-Integrated Maturity Models

Many established maturity models assess Industry 4.0 readiness across technology, strategy, organization, and culture while giving limited attention to sustainability outcomes. However, a 2025 study proposed integrating economic, environmental, and social performance indicators into digital maturity models for manufacturing SMEs (Fortier et al, 2025). The remaining gap concerns empirical and longitudinal validation, contextual adaptation to resource-constrained SMMEs, and connection of such assessments to implementation architectures and measurable transformation pathways.

Gap 5: Limited Longitudinal or Case-Study Evidence from Developing Economy SMMEs

The vast majority of empirical research in smart-sustainable manufacturing is conducted in developed economies and in large-enterprise or pilot settings. There is a critical shortage of longitudinal studies or in-depth case studies from SMMEs in developing economies, where resource constraints are most acute and the potential impact of smart-sustainable manufacturing is greatest. Without such evidence, it is impossible to know what works, what does not, and how solutions must be adapted to different contexts.

Proposed Research Agenda

To address these gaps, this study propose a research agenda centered on the development of a dynamically scalable, DSR-based, architecturally grounded smart-sustainable manufacturing framework for resource-constrained SMMEs, evaluated through an integrated maturity model with embedded sustainability KPIs. The key elements of this agenda are as follows.

First, employ Design Science Research as the methodological foundation. This means iteratively designing, developing, demonstrating, and evaluating artifacts (frameworks, tools, methods) in real SMME settings, with continuous feedback from practitioners. The DSR process ensures that solutions are not only theoretically sound but also practically validated and refined based on real-world experience.

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue VIII August 2026

Second, ground the framework in established architectural reference models, specifically RAMI 4.0 and ISA-95. Use these models to provide a structured, modular, and scalable approach to designing smart manufacturing systems. Adapt the models to SMME contexts by identifying which hierarchy levels, life cycle stages, and layers are most relevant and feasible given resource constraints.

Third, integrate sustainability key performance indicators aligned with the Triple Bottom Line framework into every level of the architecture. This means defining and measuring economic, environmental, and social performance indicators at the machine, process, and enterprise levels, and embedding these indicators into decision-making processes.

Fourth, develop an integrated maturity model that assesses both Industry 4.0 readiness and sustainability performance in a unified framework. The maturity model should be tailored to SMME contexts, with realistic benchmarks and progression pathways that reflect the constraints and capabilities of resource-constrained manufacturers.

Fifth, validate the framework and maturity model through longitudinal case studies in diverse SMME contexts, with particular emphasis on developing economies. Document implementation processes, challenges, adaptations, and outcomes in detail. Use these case studies to refine the framework and to generate practical guidance, tools, and best practices that other SMMEs can adopt.

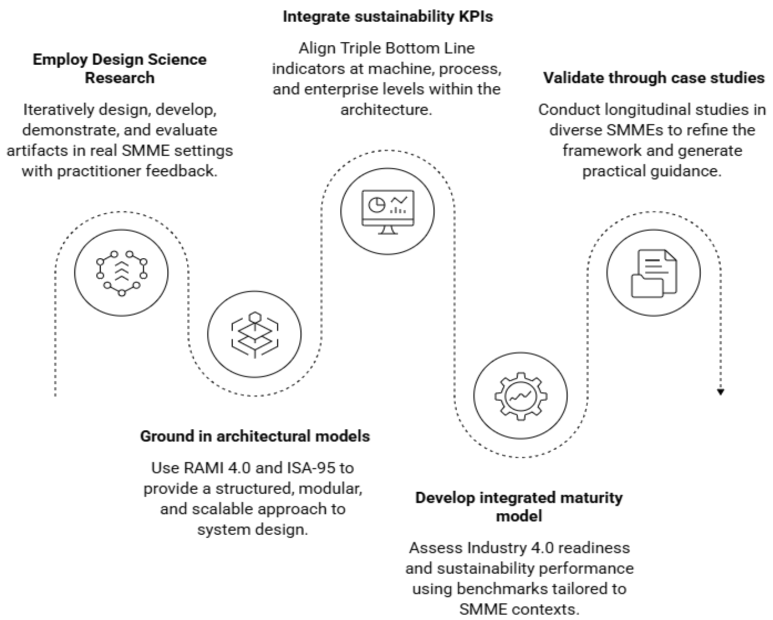

Figure 1. Integrative Framework for Industry 4.0-Enabled Sustainable Manufacturing in SMMEs

CONCLUSION

This literature review has synthesized research at the intersection of Industry 4.0 technologies, sustainable manufacturing, and small, medium, and micro enterprises. The analysis of 418 records, with deep coding of 37 studies, reveals a field that is rich in technological innovation and conceptual ambition but limited in its attention to the contexts, constraints, and needs of the vast majority of the world's manufacturers.

Seven thematic clusters were identified: conceptual frameworks; IoT and sensor-based monitoring; artificial intelligence and machine learning; energy efficiency; digital twins and cyber-physical systems; maturity models; and SMME-specific studies. Computational and conceptual approaches dominated the 37-study sample, while organisational-empirical research was limited. No DSR study or RAMI 4.0/ISA-95 integration with sustainability KPIs was identified within that sample. Seven of the 418 titles explicitly contained SMME-related terms. Targeted verification nevertheless identified relevant DSR and sustainability-integrated maturity studies outside the sample [73], [74], reinforcing the need to update the corpus and frame all absence claims cautiously.

From a practitioner's perspective, grounded in twenty years of working with manufacturers, the disconnect between the research agenda and the realities of resource-constrained manufacturing is clear. SMMEs face fundamentally different constraints than large enterprises: limited financial resources, scarce technical expertise, weak infrastructure, risk-averse cultures, and limited bargaining power. Solutions developed for large enterprises do not simply scale down. What is needed are frameworks, tools, and methodologies that are specifically designed for SMME contexts, empirically validated in real settings, and continuously refined based on practitioner feedback.

The proposed research agenda addresses these gaps by calling for Design Science Research-based development of a dynamically scalable, architecturally grounded smart-sustainable manufacturing framework for SMMEs, integrated with a maturity model that embeds sustainability KPIs. This agenda is not merely an academic exercise. It is a response to the urgent need to make the benefits of Industry 4.0 and sustainable manufacturing accessible to the enterprises that employ the majority of the world's manufacturing workforce and that are essential to inclusive economic development.

The challenge is significant, but so is the opportunity. Smart-sustainable manufacturing has the potential to transform not only the competitiveness of SMMEs but also their environmental and social impact. Realizing this potential requires a shift in the research agenda, from technology-centric and large-enterprise-focused studies to context-sensitive, practitioner-engaged, and empirically grounded research that addresses the real needs of resource-constrained manufacturers. This review is a call to the academic and practitioner community to embrace that shift and to work together toward a more inclusive, sustainable, and equitable manufacturing future.

REFERENCES

1. Hermann, M., Pentek, T., & Otto, B. (2016). Design principles for Industrie 4.0 scenarios. In Proceedings of the 49th Hawaii International Conference on System Sciences (HICSS) (pp. 3928–3937). IEEE.
2. Schwab, K. (2016). The fourth industrial revolution. World Economic Forum.
3. Elkington, J. (1997). Partnerships from cannibals with forks: The triple bottom line of 21st-century business. Environmental Quality Management, 8(1), 37–51.
4. United Nations. (2015). Transforming our world: The 2030 agenda for sustainable development. United Nations.
5. Stock, T., & Seliger, G. (2016). Opportunities of sustainable manufacturing in Industry 4.0. Procedia CIRP, 40, 536–541.
6. Sartal, A., Bellas, J. C., Mejias, A. M., & Garcia-Collado, A. (2020). The sustainable manufacturing concept, evolution and opportunities within Industry 4.0: A literature review. Advances in Mechanical Engineering, 12(5), 1–17.
7. Jamwal, A., Agrawal, R., Sharma, M., & Luthra, S. (2021). Developing a sustainability framework for Industry 4.0. Procedia CIRP, 98, 430–435.
8. World Trade Organization. (2016). World trade report 2016: Levelling the trading field for SMEs. WTO Publications.
9. Mittal, S., Khan, M. A., Romero, D., & Wuest, T. (2018). A critical review of smart manufacturing & Industry 4.0 maturity models: Implications for small and medium-sized enterprises (SMEs). Journal of Manufacturing Systems, 49, 194–214.
10. Mittal, S., Khan, M. A., Romero, D., & Wuest, T. (2019). Smart manufacturing: Characteristics, technologies and enabling factors. Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture, 233(5), 1342–1361.
11. Russmann, M., Lorenz, M., Gerbert, P., Waldner, M., Justus, J., Engel, P., & Harnisch, M. (2015). Industry 4.0: The future of productivity and growth in manufacturing industries. Boston Consulting Group.
12. Kagermann, H., Wahlster, W., & Helbig, J. (2013). Recommendations for implementing the strategic initiative INDUSTRIE 4.0. Industrie 4.0 Working Group.
13. Lee, J., Bagheri, B., & Kao, H.-A. (2015). A cyber-physical systems architecture for Industry 4.0-based manufacturing systems. Manufacturing Letters, 3, 18–23.

14. Tao, F., Qi, Q., Liu, A., & Kusiak, A. (2018). Data-driven smart manufacturing. Journal of Manufacturing Systems, 48, 157–169.
15. Vaidya, S., Ambad, P., & Bhosle, S. (2018). Industry 4.0 – A glimpse. Procedia Manufacturing, 20, 233–238.
16. National Institute of Standards and Technology. (2020). Smart manufacturing operations planning and control program. NIST.
17. U.S. Department of Commerce. (2011). Sustainable manufacturing initiative. U.S. Department of Commerce.
18. Elkington, J. (1994). Towards the sustainable corporation: Win-win-win business strategies for sustainable development. California Management Review, 36(2), 90–100.
19. Ghobakhloo, M. (2018). The future of manufacturing industry: A strategic roadmap toward Industry 4.0. Journal of Manufacturing Technology Management, 29(6), 910–936.
20. Tao, F., Cheng, J., Qi, Q., Zhang, M., Zhang, H., & Sui, F. (2018). Digital twin-driven product design, manufacturing and service with big data. International Journal of Advanced Manufacturing Technology, 94, 3563–3576.
21. Negri, E., Fumagalli, L., & Macchi, M. (2017). A review of the roles of digital twin in CPS-based production systems. Procedia Manufacturing, 11, 939–948.
22. International Labour Organization. (2015). Small and medium-sized enterprises and decent and productive employment creation. ILO.
23. Kamble, S. S., Gunasekaran, A., & Gawankar, S. A. (2018). Sustainable Industry 4.0 framework: A systematic literature review identifying the current trends and future perspectives. Process Safety and Environmental Protection, 117, 408–425.
24. European Commission. (2018). Digital transformation scoreboard 2018: EU businesses go digital. European Commission.
25. Muller, T., Jager, S., & Aurich, J. C. (2019). Barriers to the adoption of Industry 4.0 technologies in manufacturing SMEs. In Proceedings of the 52nd CIRP Conference on Manufacturing Systems (pp. 864–869).
26. Moeuf, J., Pellerin, R., Lamouri, S., Tamayo-Giraldo, S., & Barbaray, R. (2018). The industrial management of SMEs in the era of Industry 4.0. International Journal of Production Research, 56(3), 1118–1136.
27. Raj, A., Dwivedi, G., Sharma, A., Lopes de Sousa Jabbour, A. B., & Rajak, S. (2020). Barriers to the adoption of Industry 4.0 technologies in the manufacturing sector: An inter-country comparative perspective. International Journal of Production Economics, 224, Article 107546.
28. Jawahir, I. S., & Bradley, R. (2016). Technological elements of circular economy and the principles of 6R-based closed-loop material flow in sustainable manufacturing. Procedia CIRP, 40, 103–108.
29. Dubey, R., Gunasekaran, A., Childe, S. J., Papadopoulos, T., Fosso Wamba, S., & Hazen, B. T. (2019). Can big data and predictive analytics improve social and environmental sustainability? Technological Forecasting and Social Change, 144, 534–545.
30. DIN, DKE, & ZVEI. (2015). Reference architecture model Industrie 4.0 (RAMI 4.0). DIN.
31. Colombo, A. W., Karnouskos, S., Kaynak, O., Shi, Y., & Yin, S. (2017). Industrial cyberphysical systems: A backbone of the fourth industrial revolution. IEEE Industrial Electronics Magazine, 11(1), 6–16.
32. International Society of Automation. (2010). ANSI/ISA-95.00.01-2010 (IEC 62264-1 Mod) enterprise-control system integration – Part 1: Models and terminology. ISA.
33. Sauter, T., Soucek, S., Kastner, W., & Dietrich, D. (2011). The evolution of factory and building automation. IEEE Industrial Electronics Magazine, 5(3), 35–48.
34. Hevner, A. R., March, S. T., Park, J., & Ram, S. (2004). Design science in information systems research. MIS Quarterly, 28(1), 75–105.
35. Peffers, K., Tuunanen, T., Rothenberger, M. A., & Chatterjee, S. (2007). A design science research methodology for information systems research. Journal of Management Information Systems, 24(3), 45–77.
36. vom Brocke, J., Hevner, A., & Maedche, A. (2020). Introduction to design science research. In J. vom Brocke, A. Hevner, & A. Maedche (Eds.), Design science research: Cases (pp. 1–13). Springer.

37. Kandarkar, S., Agrawal, A., & Sharma, R. (2022). Integrating Industry 4.0 and sustainability toward attaining smart manufacturing systems. Journal of Cleaner Production, 380, Article 135010.
38. Kamble, S. S., Gunasekaran, A., & Sharma, R. (2018). Analysis of the driving and dependence power of barriers to adopt Industry 4.0 in Indian manufacturing industry. Computers in Industry, 101, 107–119.
39. Xu, L. D., Xu, E. L., & Li, L. (2018). Industry 4.0: State of the art and future trends. International Journal of Production Research, 56(8), 2941–2962.
40. Wan, J., Tang, S., Shu, Z., Li, D., Wang, S., Imran, M., & Vasilakos, A. V. (2016). Software-defined industrial Internet of Things in the context of Industry 4.0. IEEE Sensors Journal, 16(20), 7373–7380.
41. Zhong, R. Y., Xu, X., Klotz, E., & Newman, S. T. (2017). Intelligent manufacturing in the context of Industry 4.0: A review. Engineering, 3(5), 616–630.
42. Zheng, P., Wang, H., Sang, Z., Zhong, R. Y., Liu, Y., Liu, C., Mubarok, K., Yu, S., & Xu, X. (2018). Smart manufacturing systems for Industry 4.0: Conceptual framework, scenarios, and future perspectives. Frontiers of Mechanical Engineering, 13, 137–150.
43. Shrouf, F., Ordieres, J., & Miragliotta, G. (2014). Smart factories in Industry 4.0: A review of the concept and of energy management approached in production based on the IoT paradigm. In Proceedings of the IEEE International Conference on Industrial Engineering and Engineering Management (pp. 697–701). IEEE.
44. Mourtzis, D., Vlachou, E., & Milas, N. (2016). Industrial big data as a result of IoT adoption in manufacturing. Procedia CIRP, 55, 290–295.
45. Wuest, T., Weimer, D., Irgens, C., & Thoben, K.-D. (2016). Machine learning in manufacturing: Advantages, challenges, and applications. Production & Manufacturing Research, 4(1), 23–45.
46. Wang, J., Ma, Y., Zhang, L., Gao, R. X., & Wu, D. (2018). Deep learning for smart manufacturing: Methods and applications. Journal of Manufacturing Systems, 48, 144–156.
47. Mao, Y., Wang, Y., & Wang, X. (2013). Energy-efficient scheduling for a flexible flow shop using an improved genetic-simulated annealing algorithm. Robotics and Computer-Integrated Manufacturing, 29(5), 418–429.
48. Zhao, R., Yan, R., Chen, Z., Mao, K., Wang, P., & Gao, R. X. (2019). Deep learning and its applications to machine health monitoring. Mechanical Systems and Signal Processing, 115, 213–237.
49. O'Donovan, P., Leahy, C., Bruton, K., & O'Sullivan, D. T. J. (2015). An industrial big data pipeline for data-driven analytics maintenance applications in large-scale smart manufacturing facilities. Journal of Big Data, 2(25).
50. Wu, Y., Feng, Y., Peng, S., Mao, Z., & Chen, B. (2020). Generative machine learning-based multi-objective process parameter optimization towards energy and quality of injection molding. Journal of Manufacturing Processes, 56, 1030–1042.
51. Zheng, X., & Chen, Z. (2021). An improved deep Q-learning algorithm for a trade-off between energy consumption and productivity in batch scheduling. Journal of Manufacturing Systems, 58, 259–272.
52. Naser, A. Z., Defersha, F. M., Xu, X., & Yang, S. (2021). Automating life cycle assessment for additive manufacturing with machine learning. Journal of Cleaner Production, 321, Article 128956.
53. Mourtzis, D. (2020). Simulation in the design and operation of manufacturing systems: State of the art and new trends. International Journal of Production Research, 58(7), 1927–1949.
54. Herrmann, C., Thiede, S., Kara, S., & Hesselbach, J. (2011). Energy oriented simulation of manufacturing systems – Concept and application. CIRP Annals, 60(1), 45–48.
55. Thiede, S., Herrmann, C., & Kara, S. (2011). State of research and an innovative approach for simulating energy flows of manufacturing systems. In Glocalized solutions for sustainability in manufacturing (pp. 335–340). Springer.
56. Vogel-Heuser, B., Hess, D., & Bauer, T. (2016). Guest editorial Industry 4.0 – Prerequisites and visions. IEEE Transactions on Automation Science and Engineering, 13(2), 411–413.
57. Negri, E., Perotti, S., Fumagalli, L., Marchet, M., & Garetti, M. (2017). Modelling internal logistics systems through ontologies. Computers in Industry, 88, 19–34.
58. Lu, Y., Xu, X., & Wang, J. (2020). Smart manufacturing process and system automation – A critical review of the standards and envisioned scenarios. Journal of Manufacturing Systems, 56, 312–325.
59. Grieves, M., & Vickers, J. (2017). Digital twin: Mitigating unpredictable, undesirable emergent behavior in complex systems. In F. Kahlen, S. Flumerfelt, & A. Alves (Eds.), Transdisciplinary perspectives on complex systems (pp. 85–113). Springer.

60. Qi, Q., Tao, F., Zuo, Y., & Zhao, D. (2018). Digital twin service towards smart manufacturing. Procedia CIRP, 72, 237–242.
61. Tao, F., Zhang, H., Liu, A., & Nee, A. Y. C. (2019). Digital twin in industry: State-of-the-art. IEEE Transactions on Industrial Informatics, 15(4), 2405–2415.
62. Kritzinger, W., Karner, M., Traar, G., Henjes, J., & Sihn, W. (2018). Digital twin in manufacturing: A categorical literature review and classification. IFAC-PapersOnLine, 51(11), 1016–1022.
63. Schluse, M., Priggemeyer, M., Atorf, L., & Rossmann, J. (2018). Experimentable digital twins – Streamlining simulation-based systems engineering for Industry 4.0. IEEE Transactions on Industrial Informatics, 14(4), 1722–1731.
64. Lee, E. A. (2008). Cyber physical systems: Design challenges. In Proceedings of the 11th IEEE International Symposium on Object and Component-Oriented Real-Time Distributed Computing (ISORC) (pp. 363–369). IEEE.
65. Schumacher, A., Erol, S., & Sihn, W. (2016). A maturity model for assessing Industry 4.0 readiness and maturity of manufacturing enterprises. Procedia CIRP, 52, 161–166.
66. Schuh, G., Anderl, R., Gausemeier, J., ten Hompel, M., & Wahlster, W. (Eds.). (2017). Industrie 4.0 maturity index: Managing the digital transformation of companies. Herbert Utz Verlag.
67. Oesterreich, T. D., & Teuteberg, F. (2016). Understanding the implications of digitisation and automation in the context of Industry 4.0: A triangulation approach. Computers in Industry, 83, 121–139.
68. Gokalp, M., Sener, U., & Eren, P. E. (2017). Development of an assessment model for Industry 4.0: Industry 4.0-MM. In Software process improvement and capability determination (pp. 128–142). Springer.
69. De Carolis, A., Macchi, M., Negri, E., & Terzi, S. (2017). A maturity model for assessing the digital readiness of manufacturing companies. In Advances in production management systems (pp. 13–20). Springer.
70. Agostini, M., & Filippini, R. (2019). Organizational and managerial challenges in the path toward Industry 4.0. European Journal of Innovation Management, 22(3), 406–421.
71. Qureshi, K. M., Mewada, B., Kaur, S., & Qureshi, M. R. N. N. (2022). Assessing Lean 4.0 for Industry 4.0 readiness using PLS-SEM towards sustainable manufacturing supply chain. Sustainability, 14(19), Article 11715.
72. Rahman, A. U., Wen, F., & Amjad, F. (2023). Role of sustainable business model, Industry 4.0, crowdfunding, and stakeholders pressure toward firm sustainability: A SEM-ANN approach. Environmental Science and Pollution Research, 30, 28328–28343.
73. C. Kaymakci, S. Wenninger, P. Pelger, and A. Sauer, "A systematic selection process of machine learning cloud services for manufacturing SMEs," Computers, vol. 11, no. 1, Art. no. 14, 2022, doi: 10.3390/computers11010014.
74. J. Fortier, S. Gamache, and C. Fonrouge, "Integrating sustainable performance into the digital maturity models for SMEs in manufacturing," Applied Sciences, vol. 15, no. 7, Art. no. 4041, 2025, doi: 10.3390/app15074041.