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Development of Product and Process Innovation through the Integration of Lean Methodologies, Advanced Digitalization, and Sustainability

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ABSTRACT

This research project investigates the integration of three key paradigms, namely Lean Manufacturing (LM), advanced digitalization - with a specific focus on Artificial Intelligence (AI) - and social sustainability, within the context of small and medium-sized enterprises (SMEs). The main aim of the study is to advance the interdisciplinary knowledge on these intersecting domains and to provide managers, policymakers, and practitioners with empirically grounded insights into how such integration can drive responsible, inclusive, and resilient innovation in contemporary industrial settings. While LM, digitalization, and sustainability have each received considerable independent scholarly and managerial attention, their synergistic potential remains underexplored, particularly within SMEs, which, despite structural constraints, exhibit unique capacities for agility, contextual responsiveness, and human-centered innovation, making them an ideal context for investigation. Adopting a multi-level, interpretive approach, the study addresses three interrelated gaps: i) a systemic and theoretical gap, concerning the fragmented understanding of how LM, Industry 4.0 technologies, and social sustainability interact; ii) an operational gap, regarding the limited evidence on how AI-enabled tools can support Lean transformations while preserving inclusivity and employee well-being; and; iii) a strategic gap, focused on how AI influences international decision-making and competitiveness in SMEs. By linking these dimensions, the thesis develops a multi-layered understanding of how innovation unfolds through the dynamic alignment of social, technological, and managerial factors. To address these gaps, the thesis is structured around five main chapters, three of which consist of interrelated academic studies, each representing a different level of analysis: systemic, operational, and strategic. Specifically, Chapter I - *Context of analysis, theoretical foundations, and methodological notes* - first introduces the methodological framework and outlines the epistemological and conceptual foundations of the research. It frames the investigation within contemporary debates on Industry 4.0, sustainability-oriented innovation, and organizational transformation. Second, Chapter II - *A systematic integration of Industry 4.0 and Lean manufacturing for social sustainability: developing a comprehensive framework* - representing the first academic study of the thesis, addresses the first systemic gap through a systematic literature review that examines the intersection of Lean, Industry 4.0, and social sustainability through 43 peer-reviewed publications. The findings reveal that while environmental and economic dimensions have been widely studied, the social pillar remains underrepresented. The chapter thus develops a conceptual framework illustrating how the integration of Lean and digital technologies can strengthen human-centered values and contribute to socially sustainable innovation. Subsequently, Chapter III - *Exploring AI-driven training for Lean manufacturing: a case study on social sustainability in an SME* - developing the second article of the thesis, addresses the second operational gap through an in-depth

case study of an Italian SME implementing an AI-driven training platform within a Lean transformation journey. The analysis shows that AI can democratize knowledge and enhance participation, y*et al*so introduces tensions such as digital anxiety, skill gaps, and perceived monitoring. Therefore, the study underscores that achieving social sustainability in digital transformation requires participatory implementation, transparent communication, and the preservation of human agency. Chapter IV - *The role of Artificial Intelligence in international strategic decision-making for SMEs* - which constitutes the third academic article of the research, further explores the third strategic gap through a multiple-case study of six Italian SMEs, analyzing how AI supports international strategic decision-making. The results show that AI enhances foresight, partner evaluation, and risk management, positioning it as a strategic and cognitive infrastructure rather than a mere efficiency tool. However, its benefits depend on organizational readiness, ethical awareness, and alignment with human-centered principles. Lastly, Chapter V - *Concluding remarks and future research avenues* - integrates findings from all three studies into a multi-level synthesis linking process-level learning and improvement with organizational culture and strategic decision-making. The chapter emphasizes that meaningful innovation in SMEs emerges not from technology alone but from the systemic alignment of Lean principles, digitalization, and social sustainability. Overall, the thesis offers a comprehensive set of theoretical, methodological, and managerial contributions and implications that collectively advance the understanding of innovation as a socio-technical and human-centered process in SMEs. Theoretically, it provides five main advances. First, it reconceptualizes LM-Industry 4.0 convergence as a socio-technical, ethically anchored system, demonstrating that Lean principles, particularly "respect for people", serve as a cultural infrastructure for inclusive digital transformation. Second, it extends the Lean 4.0 paradigm by positioning social sustainability as an integral component of industrial resilience. Third, it conceptualizes innovation in SMEs as a multi-level and emergent process that links micro-level learning and participation with organizational and operational culture and macro-level strategic foresight. Fourth, it redefines SMEs as contextually adaptive, human-centered innovation agents, repositioning them as active actors of integrated innovation rather than structurally constrained. Finally, it reframes AI as a socio-organizational phenomenon that reshapes decision-making and learning rather than merely automating tasks. Methodologically**,** the thesis contributes a robust multi-level qualitative design that integrates a systematic literature review with single and multiple case studies. This triangulated approach demonstrates how interpretive, cross-method research can generate context-sensitive insights into the complex interdependencies of Lean, AI, and sustainability, offering a transferable framework for studying socio-technical change in other SME contexts. Managerially**,** the research provides an actionable roadmap for implementing responsible innovation within SMEs. It translates theoretical insights into practical guidelines for aligning technological adoption with ethical, human,

and sustainability principles. Specifically, it proposes strategies for integrating AI into Lean systems through participatory governance, inclusive training, and transparent communication; for embedding social sustainability metrics into performance evaluation; and for leveraging AI-driven decision tools to enhance strategic agility without eroding human judgment. Finally, the thesis delivers a distinctive cross-level synthesis, merging theoretical, operational, and strategic perspectives into an integrated model of human-centered innovation. This framework illustrates how the systemic alignment of Lean methodologies, digitalization, and social sustainability principles enables SMEs to achieve technological advancement that is not only efficient but also ethically responsible, socially inclusive, and strategically adaptive. In doing so, the research contributes to ongoing debates on digital and sustainable transformation, positioning SMEs as key actors in the pursuit of a more resilient and human-centered industrial future.

Keywords: Lean Manufacturing; Industry 4.0; Artificial Intelligence; Social Sustainability; Digital Transformation; SMEs; Inclusive Innovation.

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INTRODUCTION

This research project is situated at the intersection of innovation management, organizational studies, and sustainability, with a specific focus on small and medium-sized enterprises (SMEs) operating in the manufacturing sector. Positioned within the broader discourse of industrial transformation, the thesis explores how emerging paradigms such as Industry 4.0 (I4.0), sustainability, and Lean production methodologies reconfigure business practices and value creation mechanisms.

In the contemporary landscape marked by rapid industrial evolution and increasing complexity, firms are prompted to innovate not only in terms of products and production processes but also in their core organizational structures through which they operate and interact with the wider socio-institutional environment (Capriati and Divella, 2022). This need emerges from the intersection of critical global trends, including the accelerating degradation of ecological systems, the intensification of transnational competitive pressures, and the exacerbation of socio-economic inequalities (Iqbal *et al*., 2022). In response to these converging pressures, firms are increasingly required to reconfigure their organizational models and strategic orientations to maintain competitiveness, address stakeholder demands, and ensure long-term sustainability (Knoke, 2019; Kharkheli and Gavardashvili, 2022).

These multidimensional conditions are driving a significant rethinking of how innovation is conceptualized, pushing firms to adopt more complex and socially embedded innovation practices (Littunen *et al*., 2021). In this evolving scenario, innovation is no longer conceived as a set of optional enhancements but rather as a strategic necessity that must permeate business models and organizational structures (Velu, 2024). The innovation process now extends beyond traditional domains such as research and development (R&D) or mere technological advancement, encompassing instead the reconfiguration of value creation logics and the integration of context-responsible organizational practices (Sareen and Pandey, 2021; Fonseca, 2014). This broader understanding of innovation reflects a shift toward a holistic and sustainable transformation model, in which economic goals are deliberately reconciled with environmental responsibility and social equity (Forsman, 2015; Fleacă *et al*., 2023). Consequently, to remain adaptive and competitive, modern firms need to be restructured as dynamic socio-economic systems, capable of long-term planning, effective resource deployment, and structural flexibility (Dereli, 2015).

Within this evolving industrial and socio-economic context, the so-called “triple challenge”, comprising the imperatives of operational efficiency, digital transformation, and environmental sustainability, has emerged as a central point of scholarly discourse and a guiding framework for policy formulation, particularly within the European Union (Fagerberg *et al*., 2016; Phoomsavarth, 2023). This interconnected set of priorities reflects the multifaceted pressures contemporary industries face to optimize resource utilization, integrate digital technologies, and align their strategies with long-term ecological objectives (Horobeț *et al*., 2024; Gómez, 2022). In response, key strategic initiatives such as the European Green Deal and the forthcoming European Competitiveness Deal underscore the imperative to set up a coherent policy architecture that simultaneously increases innovation, enhances competitiveness, and advances sustainability (Osorio, 2025; Ala-Lahti, 2024). These efforts seek to ensure the long-term resilience of European industry by embedding sustainability as a core lever of industrial renewal and technological progress (Rowan and Casey, 2021; Phoomsavarth, 2023).

Representing central actors in the European industrial scenario, SMEs are at the forefront of addressing the interconnected challenges of operational efficiency, digitalization, and sustainability. Globally, they account for 90% of all businesses, they contribute to 50% of employment, and generate two out of every three jobs (The World Bank, 2023; Melo *et al*., 2023). However, SMEs are also particularly vulnerable to the converging pressures of globalization, technological transformation, and sustainability transitions (Pufinas, 2018). These firms face an increasingly complex landscape in which they are expected to remain competitive in volatile global markets, build resilience to systemic shocks, and integrate environmental and social sustainability into their core strategies (Jayasundara and Rajapakshe, 2020; Prasanna *et al*., 2019; Malik and Jasińska-Biliczak, 2018).

While they face clear structural constraints, among which limited access to capital, skilled labor, and advanced technologies, these small realities also exhibit inherent strengths that position them as strategic agents of transformation (Unegbu *et al*., 2024). For instance, their relatively small scale and agile organizational structures often translate into greater adaptability, enabling them to respond rapidly to changing market conditions and adopt innovative practices. These qualities are particularly evident when SMEs are supported by targeted training initiatives and collaborative frameworks, which strengthen their capacity for innovation (Hamburg, 2020; Balder *et al*., 2024).

In this respect, recent studies highlight how agile business models and iterative development strategies enhance SMEs' resilience and responsiveness in volatile environments (Omowole *et al*., 2024). Their intrinsic flexibility and openness to change enable them to absorb shocks more effectively and adjust their operations accordingly (Homayoun *et al*., 2024). Moreover, their digital and agile collaboration mechanisms have proven effective in strengthening product development processes and inter-organizational knowledge exchange (Balder *et al*., 2024). These attributes not only contribute to innovation capacity but also reinforce SMEs' potential role in advancing both green and digital transitions (Kesidou and Ri, 2021; Harrington *et al*., 2016).

As such, despite their limitations, SMEs are increasingly recognized as key enablers in the transition toward a more inclusive, sustainable, and innovation-driven economy, positioning them as potential laboratories for transformative innovation (Klewitz and Hansen, 2014). Indeed, when they pursue innovation and digitalization simultaneously, SMEs can achieve gains in resource efficiency, expand into new markets, and better align with emerging sustainability demands (Ziaei and Roshani, 2024). In this respect, research demonstrates that different forms of eco-innovation, including eco-process, eco-product, and eco-organizational innovation, positively influence SMEs' sustainable performance across environmental, social, and economic dimensions (Oduro, 2024; Singh and Chakraborty, 2021). Furthermore, these benefits are amplified when eco-innovation is combined with strong digital capabilities and supported by effective management systems and leadership commitment (Liu and Javaid, 2025; Le and Ikram, 2021). For these reasons, SMEs operate within a delicate balance of risk and opportunity: although structurally disadvantaged in many respects, their flexibility, embeddedness in local economies, and openness to experimentation make them uniquely suited to catalyze the innovation needed for a more sustainable and resilient industrial future (Eusebio, 2024; Bucheli-Calvache *et al*., 2023).

Significantly, in this scenario, the onset of the Fourth Industrial Revolution, commonly referred to as Industry 4.0 (I4.0), has intensified existing pressures on firms by introducing a set of digital technologies created to fundamentally transform industrial processes and organizational architectures (Boz and Ibrahimağaoğlu, 2022). It represents more than a mere technological upgrade, entailing an important shift driven by the convergence of cyber-physical systems (CPS), Artificial Intelligence (AI), the Internet of Things (IoT), and Big Data Analytics (Zubrzycki *et al*., 2021). These technologies collectively enable the emergence of "smart factories," which are characterized by flexible, automated, and data-driven production systems that can dynamically adapt to changing operational contexts and market demands (Mosleuzzaman *et al*., 2024; Gabsi, 2024).

The integration of these digital capabilities facilitates real-time monitoring, predictive maintenance, resource optimization, and greater responsiveness (Sharma *et al*., 2020; Serôdio *et al*., 2024). The implementation of I4.0 has shown measurable impacts on employee productivity, organizational agility, and innovation capacity, particularly when paired with appropriate digital training and leadership strategies (Nurrohmat *et al*., 2024). The shift is evident across sectors, including pharma and logistics, where these technologies have enabled real-time optimization, automated quality control, and personalized production (Soni and Patel, 2024; Ravshan and Ogunmola, 2025). Specifically, AI and IoT enable real-time data processing, predictive maintenance, and enhanced production customization, empowering firms to increase productivity, reduce downtime, and better align with sustainability goals (Mali *et al*., 2024; Shovon *et al*., 2024). In parallel, Big Data enhances decision-making by enabling companies to uncover patterns and optimize resources across the supply chain (Ghani, 2024).

Despite its transformative potential, the transition to I4.0 remains inconsistent, particularly among SMEs, due to barriers such as high initial investment costs, skills shortages, and cyber-security risks (Shovon *et al*., 2024). Nevertheless, the strategic adoption of these technologies is seen as essential not only for operational competitiveness but also for long-term resilience and sustainable industrial development for such small realities.

Moreover, the mere availability of advanced technologies does not guarantee meaningful or sustainable innovation. Indeed, their true potential can only be unlocked when they are embedded in coherent managerial philosophies and organizational cultures rooted in human-centered and strategic thinking (Sony and Naik, 2019). In this regard, Lean Manufacturing (LM) presents a valuable complementary framework. Developed to minimize waste and maximize value, LM is grounded in principles such as continuous improvement (*kaizen*), employee involvement, and long-term value creation (Womack and Jones, 1996). Beyond operational efficiency, LM is increasingly recognized for its potential to bridge the digitalization-sustainability gap, particularly in relation to the social pillar of sustainability, which remains relatively underexplored in both research and practice (Elkington, 1997; Ghaithan *et al*., 2023; Vinodh *et al*., 2020). This lack of attention is particularly evident in the fact that Lean discourse has extensively addressed the environmental and economic dimensions of sustainable development, while paying comparatively less attention to the social pillar, including employee well-being, workplace safety, inclusivity, and empowerment (Bonilla *et al*., 2018).

Despite the limited academic focus, several studies have shown that Lean principles, such as employee engagement, standardized work, and visual management, can positively affect job satisfaction, organizational trust, and workplace safety, thereby contributing directly to social sustainability (Angelis *et al*., 2011; Conti *et al*., 2006). In addition, Lean's focus on respect for people lays the cultural foundation needed to successfully implement digital technologies and support inclusive and adaptive organizational change (Dombrowski and Mielke, 2013). This alignment is especially relevant in the context of Lean 4.0, which integrates Lean principles with I4.0 technologies, where firms are expected not only to automate and optimize but also to develop socio-technical systems that are ethical, resilient, and human-centered (Rossini *et al*., 2019). Thus, by enhancing continuous improvement and employee empowerment, Lean 4.0 can serve as a unifying framework that reconciles efficiency with equity and innovation with sustainability.

Taking a problematization approach, it is evident that further knowledge on the intersection between Lean methodologies, I4.0, and social sustainability is needed to fully understand their interplay and potential to drive product and process innovation in SMEs. Such understanding is crucial to supporting them in deciding how to strategically integrate I4.0 tools into Lean transformations while preserving human-centered values and managing contextual constraints.

Against this backdrop, several underexplored areas in the current literature emerge. A first area of investigation concerns the intersection of AI adoption and social sustainability in industrial organizations. While AI is often celebrated for its potential to automate processes and reduce inefficiencies, less attention has been paid to its effects on participation, autonomy, and critical thinking at the shop floor level (Block, 2024). SMEs, in particular, face the dual challenge of digital skill gaps and resistance to change, which may undermine efforts to democratize technology use and enhance inclusive innovation cultures (Seppänen *et al*., 2025). Moreover, overreliance on AI systems can create unintended social risks, such as deskilling or increased stress, that conflict with the Lean emphasis on human-centered continuous improvement (Polimeni and Adrower, 2024).

A second research gap lies in the challenges of building operational knowledge and supporting organizational learning in Lean transformations. While learning is a core pillar of Lean, many SMEs struggle to transfer tacit knowledge and train employees effectively due to resource constraints and limited formal infrastructures (Zahari *et al*., 2019; Gustavsson and Lundqvist, 2015). Although AI, particularly Natural Language Processing (NLP) systems, offers new ways to scale learning and increase access to operational expertise, empirical insights into how AI-enabled training systems affect Lean-specific learning outcomes remain scarce (Adam *et al*., 2021). Furthermore, traditional Lean training methods often fail to engage different learner profiles or provide actionable, context-specific guidance (Torres *et al*., 2021), raising critical questions about how digital tools may complement, replace, or disrupt human-led learning mechanisms.

A third neglected area concerns the context-specific barriers SMEs face in adopting AI as part of their Lean journeys. Much of the literature focuses on large firms with robust digital infrastructures, overlooking the fact that SMEs often rely on informal processes, tacit routines, and limited managerial resources (Zahari *et al*., 2019). This discrepancy creates a misalignment between available AI tools and the absorptive capacity of small firms, making it essential to understand how SMEs interpret, adopt, and adapt AI technologies given their unique constraints and goals.

Thus, this study aims to contribute to these emerging areas of research by analyzing how SMEs can leverage the integration of Lean principles, AI tools, and social sustainability goals to enhance inclusive innovation. This objective gains particular relevance in a production landscape increasingly shaped by intelligent technologies and evolving social expectations. Thus, deepening knowledge on this intersection is not only academically relevant but practically urgent. In this context, investigating the evolving role of AI in Lean contexts not only opens new avenues to rethink business models, worker engagement, and operational sustainability but also provides insights into how industrial ecosystems might reconfigure around human-AI complementarity rather than substitution.

The need to build further knowledge on the convergence of digitalization, Lean methodologies, and sustainability, particularly within the context of SMEs is further evidenced by the increasing number of recent calls for papers and special issues in different journals. These initiatives underscore the relevance of exploring how emerging technologies such as AI, Big Data, and the IoT can be strategically integrated with human-centered and sustainability-oriented and LM practices. For example, the journal *Sustainability* launched the special issue "Industry 4.0 for SMEs - Smart Manufacturing and Logistics" which focuses on how small firms can leverage smart technologies while embedding social and organizational sustainability (Rauch *et al*., 2020[1]). A second special issue from the same journal, titled "SMEs in Industry 4.0: Collaborative Networks in the Value Chain," highlights the role of collaborative innovation ecosystems in facilitating digital and sustainable transformation among SMEs (Ferreira *et al*., 2023[2]). Additionally, the special issue "Digital Supply Chain and Sustainable SME Management" focuses on integrating digital supply chains and sustainability strategies, emphasizing human, organizational, and technological dynamics in SME contexts (Ahmed *et al*., 2024[3]). Further confirming this trend, the *International Journal of Cleaner Production* issued a call for papers on "Sustainability and SMEs," calling for studies that investigate how innovation, digital tools, and managerial strategies promote sustainable performance in small enterprises (Pizzi *et al*., 2021[4]). The *Review of Managerial Science* also released a special issue on "Resilience in SMEs," inviting contributions that explore how small firms build organizational adaptability and resilience through innovation and digital transformation (Beermann *et al*., 2023[5]). Moreover, the *Journal of International Economics and Management* announced a special issue titled "Digital Transformation and Sustainability in Emerging Economies," which seeks to understand how digital innovation supports inclusive, ESG-driven growth under structural and institutional constraints, an especially relevant lens for smaller firms (Nguyen *et al*., 2024[6]). Finally, the *R & D Management Journal* (Wiley) is currently hosting a call for papers on "Circular Economy and Digital Technology Enabled Innovation," inviting empirical and theoretical work on how digital tools contribute to circular and sustainable innovation processes (Tura *et al*., 2024[7]). Collectively, these initiatives reflect an increasing scholarly recognition that the technological evolution of SMEs cannot be disentangled from issues of organizational learning, social sustainability, and human-centric innovation. They confirm the timeliness and academic relevance of investigating how Lean and digital practices can be strategically integrated within SMEs to support inclusive and sustainable transformation.

Based on these premises, the thesis pursues a dual objective. On the one hand, it aims to expand academic discourse at the intersection of Lean methodologies, AI, and social sustainability by addressing specific and underexplored research gaps through three distinct studies. The intent is

[1] https://www.mdpi.com/journal/sustainability/special_issues/Smart_Manufacturing_Logistics?utm
[2] https://www.mdpi.com/journal/sustainability/special_issues/N45R8W4HR7
[3] https://www.mdpi.com/journal/sustainability/special_issues/TT75NO7G43
[4] https://www.anzam.org/wp-content/uploads/2021/12/Sustainability-and-SMEs-CALL-FOR-PAPERS-JMO-Special-Issue.pdf
[5] https://link.springer.com/journal/11846/updates/27701212
[6] https://www.emeraldgrouppublishing.com/calls-for-papers/call-papers-journal-international-economics-and-management-special-issue-digital
[7] https://onlinelibrary.wiley.com/pb-assets/assets/14679310/RADM_SI_CFP_CE%20and%20Digital%20technology%20enabled%20innovation-1673972575843.pdf

to enrich the awareness on these themes in identified new research areas. On the other hand, the research project is oriented toward supporting practitioners and SME managers in managing the complexities of AI adoption. By providing analytical tools and empirical insights grounded in real cases, the study aims to support informed decision-making on how to integrate Lean, digital technologies, and social responsibility into coherent innovation strategies. Therefore, the overall aim of this thesis is the following:

Investigate how product and process innovation can be developed in manufacturing SMEs through the integration of Lean methodologies, advanced digital technologies such as Artificial Intelligence, and social sustainability principles.

To this aim, the work is structured as a collection of three scientific articles, each addressing a distinct but interrelated aspect of this transformation. These articles are part of a conceptual and empirical architecture that spans multiple levels of organizational analysis, namely theoretical, operational, and strategic, each corresponding to a specific level of analysis and scholarly contribution.

Specifically, the first article (Chapter II) lays the conceptual groundwork, presenting a systematic literature review (SLR) on the integration of LM and I4.0 technologies in relation to social sustainability, a dimension often overlooked in traditional industrial paradigms (Martínez-Conesa *et al*., 2017; Buer *et al*., 2021). By mapping existing research and identifying emergent themes, this study constructs a theoretical framework that clarifies how Lean and I4.0 can jointly enhance or hinder social sustainability outcomes in SMEs.

The second article (Chapter III) shifts the focus from theory to operational and organizational practice, exploring how AI-driven training platforms are used to support Lean implementation in a real SME context. Through an in-depth case study of an Italian manufacturing firm, the article examines how AI-based learning tools impact employee engagement, knowledge accessibility, and perceptions of autonomy and inclusion. It reveals how such technologies can act as instruments for democratizing knowledge, while also introducing new challenges such as digital skill gaps and psychological pressure. In doing so, the study foregrounds the importance of embedding digital tools within socially conscious and participatory frameworks.

The third article (Chapter IV) expands the lens to the strategic level, investigating how AI supports international strategic decision-making processes (ISDMPs) in SMEs. Through a multiple-case study of Italian SMEs operating internationally, the research examines how AI tools assist in identifying new markets, selecting entry modes, and managing uncertainty in global contexts. The study demonstrates that AI is not only an enabler of operational efficiency but also a strategic asset that enhances data-driven agility and foresight, thereby strengthening SMEs' capacity to compete globally in an increasingly volatile environment.

Methodologically, the thesis adopts a multi-level qualitative approach, combining systematic literature review, single and multiple case study analysis, and empirical data collection in real-world SME contexts. The triangulation of these methods enables a comprehensive examination of innovation dynamics at theoretical, operational, and strategic levels. This methodological framework underpins the article-based structure of the dissertation, in which each article addresses specific research questions through distinct methods and data sources. At the same time, the thesis as a whole is guided by a unifying research goal: to understand how Lean practices and advanced digital technologies, when strategically integrated with social sustainability values, can generate innovation in SMEs.

The core contribution of this work lies in its ability to bridge conceptual, methodological, and practical divides in the existing literature. Indeed, despite the growing interest in both digital transformation and sustainability, the current body of research remains fragmented and marked by several important gaps. First, while the environmental and economic dimensions of sustainability have been widely investigated, the social pillar, which includes employee well-being, inclusivity, participation, and equity, remains relatively underexplored. Second, digital technologies and Lean methodologies are often examined in isolation, with limited attention to their synergistic potential. Third, studies disproportionately focus on large enterprises, underestimating the unique characteristics and constraints of SMEs. Fourth, much of the literature on AI in industry adopts a techno-centric view, paying little attention to how these tools impact human roles, learning processes, and organizational culture.

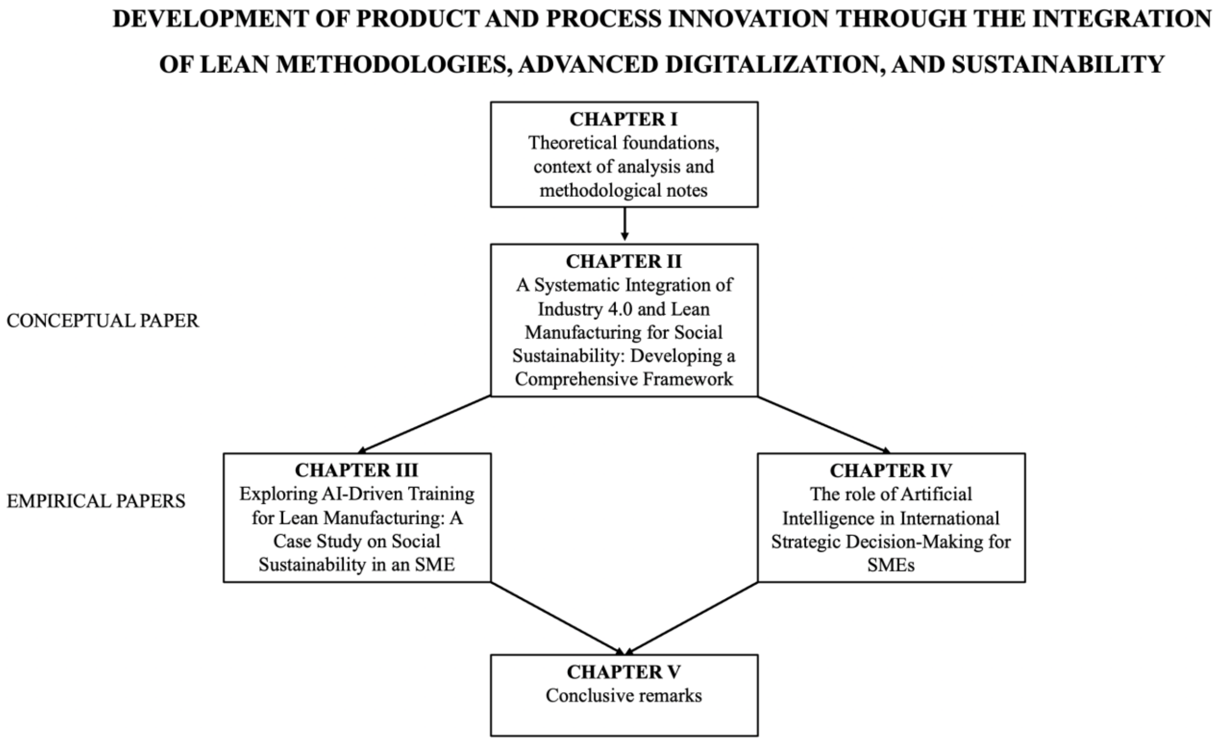
Thus, this dissertation addresses these gaps by adopting a multi-level, interdisciplinary approach that spans from systemic-theoretical models (Chapter II) to human-centered training practices (Chapter III), to strategic internationalization dynamics (Chapter IV). Therefore, the thesis is situated within an evolving research landscape that increasingly calls for integrative and interdisciplinary approaches. Moreover, this thesis advocates for a paradigm of innovation that is not only technologically enabled but also ethically responsible, socially inclusive, and organizationally embedded.

By focusing on SMEs, organizations that are both vulnerable and adaptive, it also underscores the importance of tailored, context-sensitive strategies capable of driving meaningful and lasting transformation. In doing so, it responds to the urgent need for more integrative and humanistic approaches to industrial innovation in the age of AI and beyond.

Beyond its academic relevance, this research project aims to provide actionable insights for practitioners and policymakers seeking to enhance SME competitiveness and resilience in the era of I4.0. By exploring the integration of Lean methodologies, advanced digital technologies (e.g., AI-driven systems), and social sustainability principles, the research offers concrete guidance for SME managers seeking to innovate responsibly and inclusively. Moreover, the results are expected to support institutional actors and industrial policy designers in developing more targeted, participatory, and context-sensitive interventions, positioning SMEs not only as beneficiaries of innovation policy, but as active agents of socio-technical transformation toward a more equitable and sustainable industrial ecosystem.

Figure 1 graphically represents the thesis structure by chapters and illustrates the connections between each article and the overarching research objective.

Figure 1. Structure and outputs of the research project.



Source: Author’s own elaboration.

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CHAPTER I - CONTEXT OF ANALYSIS, THEORETICAL FOUNDATIONS AND METHODOLOGICAL NOTES

1. CONTEXT OF ANALYSIS AND THEORETICAL BACKGROUND

In recent years, the global industrial and economic landscape has been profoundly reshaped by the convergence of technological innovations, rapidly evolving market structures, and increasing environmental and societal pressures. Technological advancements, particularly in automation, digitalization, and artificial intelligence, have significantly altered production systems, employment structures, and global connectivity (Duan, 2023; Komissarova *et al.*, 2020). Simultaneously, growing environmental awareness and social demands have driven industries to adopt more sustainable models and practices, as seen in the ongoing transformation of sectors such as the chemical and petroleum industries (Habrylevych, 2024). These trends are further compounded by shifts in global market dynamics and business models, requiring enterprises to continuously adapt to globalization, regulatory changes, and changing consumer expectations (Pavlov *et al.*, 2024). Moreover, these transformations are not isolated but embedded in deeper socio-economic and ecological cycles that characterize the evolution of industrial societies (Brand, 2018).

As a result of these interconnected changes, traditional business models have been challenged by several global factors, including resource scarcity, climate change, and shifting societal expectations (Goni *et al.*, 2021; Lopez-Torres *et al.*, 2022; Urbancová and Vrabcová, 2023). These evolutions have profoundly reshaped the conditions under which firms must operate, since businesses must progressively strike a balance between social responsibility, environmental preservation, and economic performance (Morioka and Carvhalo, 2016; Ashrafi *et al.*, 2020).

In this evolving context, innovation is no longer limited to product development or operational upgrades, rather, it requires redesigning entire value-creation logics, organizational models, and stakeholder relationships (Teece, 2018). This has led to the pursuit of new models that integrate greater operational effectiveness with fewer negative effects on the environment and human welfare (Parida *et al.*, 2019; Bocken and Geradts, 2020; Shakeel *et al.*, 2020; Acciarini *et al.*, 2022).

Among the frameworks emerging in response to these challenges, LM, advanced digitalization, and sustainability have emerged as key paradigms for renewing organizational processes, capabilities, and performance.

Specifically, according to Yu *et al.* (2020), Teixeira *et al.* (2021), Jum'a *et al.* (2022), and Wadood *et al.* (2023), the combination of LM and a sustainability-oriented approach has become a paradigm shift in production settings, with the potential to optimize resources, minimize waste, and generate long-term value. Businesses can create systems that are agile, adaptive, and aligned to simultaneously support both human well-being and the environment by integrating Lean concepts with the economic, environmental, and social pillars of sustainability (Kleindorfer *et al.*, 2005; Liao and Wang, 2021). This growing convergence marks a departure from earlier perspectives, where Lean and sustainability were traditionally studied as distinct domains. Today, they are increasingly conceptualized as mutually reinforcing frameworks which, when integrated, can enhance firms' ability to remain both efficient and socially responsible in volatile and uncertain environments (Sony and Naik, 2020; Kamble *et al*., 2020; Bonilla *et al*., 2018).

Among the forces reshaping modern production and organizational systems, also advanced digitalization plays a central role. In this scenario, I4.0 technologies are widely recognized as transformative drivers of innovation, sustainability, and strategic agility across production and organizational systems. Indeed, they enable firms to optimize operations, reduce waste, and respond more effectively to dynamic market conditions and sustainability goals, while also promoting new, flexible, and human-centered business models (Gitau, 2025). Significantly, this transformative potential goes beyond a simple upgrade of the automation system: it entails the deep integration of technologies such as AI, IoT, cyber-physical systems, digital twins, and data analytics into value-creation processes. Within supply chains, digitalization supports real-time monitoring, traceability, and optimization of energy and material use, aligning technological innovation with environmental and social objectives (Radi *et al*., 2024).

For SMEs in particular, digital transformation provides tools to overcome structural limitations and adopt scalable, intelligent, and sustainable production models. Case studies in the UK demonstrate how SMEs can successfully leverage technologies such as IoT, AI, and collaborative robotics to pursue both Environmental, Social and Governance (ESG) goals and business performance (Khan, 2024). Indeed, this digital shift is not isolated from other management paradigms: when integrated with LM and sustainability strategies, advanced digitalization acts as a multiplier of efficiency, innovation, and adaptability (Buer *et al*., 2018). It enables organizations to move toward resilient and future-oriented models, redefining the strategic role of technology in organizational design and continuous improvement.

This research project is situated within this intersectional space. Precisely exploring this interconnection as a fertile ground for innovation and transformation in the contemporary manufacturing firms, it aims to contribute to a growing but still fragmented body of knowledge by examining how the integration of Lean principles, digital technologies, and sustainability practices can enable SMEs to develop product and process innovations that are resilient, inclusive, and future-oriented (Buer *et al*., 2021).

1.1 Lean Manufacturing: efficiency, flexibility, and human centrality

In the manufacturing industry, LM is a management philosophy that emphasizes waste elimination to increase process efficiency and generate value for customers (Shah and Ward, 2003; Holweg, 2007; Gupta and Jain, 2013; Belhadi *et al*., 2017; Nwanya and Oko, 2019). Lean practices are widely acknowledged as a successful way to lower costs, enhance quality, and boost competitiveness in industrial settings (Čiarnienė and Vienažindienė, 2012; Bhamu and Singh Sangwan, 2014; Verma and Sharma, 2017; Ben Ruben *et al*., 2019; Palange and Dhatrak, 2021). It represents a broad concept that encompasses all company operations and promotes a continuous improvement culture across all organizational levels (Kassem *et al*., 2023). In industries other than manufacturing and automobiles, such as construction, textiles, healthcare, hospitality, and education, this strategy has proven particularly advantageous (Danese *et al*., 2018; Yadav *et al*., 2022; Pinto *et al*., 2022). Indeed, it is widely recognized as a key strategic approach for companies aiming to optimize operations, eliminate waste, and respond effectively to emerging market challenges in an increasingly competitive and rapidly evolving global environment (Deshmukh *et al*., 2022; Adebayo *et al*., 2024).

LM disseminated globally across industries thanks to the industrial engineer Taiichi Ohno, who developed this method to streamline manufacturing by detecting and removing waste, thereby enhancing business performance and increasing total value (Čiarnienė and Vienažindienė, 2012; Das *et al*., 2014; AlManei *et al*., 2017). Originally codified within the Toyota Production System (Pavnaskar *et al*., 2003; Shah and Ward, 2007), Krafcik (1998) coined the term "Lean" to refer to the alternative production method that Toyota has embraced (Shah and Ward, 2007; Mostafa *et al*., 2013). The Machine that Changed the World, by Womack *et al*. (1990), expanded on this idea, popularizing the notion of "Lean Production" and reshaping the conceptualization of industrial production (Bhamu and Singh Sangwan, 2014; Alkhoraif *et al*., 2019; Jaiswal *et al*., 2021). The term "Lean Production" was replaced by the more popular "Lean Manufacturing" as the strategy gained traction in the broader manufacturing setting (Osman *et al*., 2020).

Even if the Lean concept has evolved in many ways, at its core, it promotes the elimination of waste, continuous improvement (kaizen), and the maximization of the customer value (Verrier *et al*., 2014; Ben Ruben *et al*., 2019; Rodrigues *et al*., 2019). This foundational emphasis on waste reduction is operationalized through the classification of seven major types of waste, initially identified by Taiichi Ohno: overproduction, waiting time, transportation, inventory, motion, defects, and over-processing, collectively referred to as "muda" in Japanese (Jasti and Kodali, 2015; Soliman, 2017; Nwanya and Oko, 2019). Additionally, the underutilization of human potential - i.e., the underuse of employee skills, creativity, and decision-making capacity - has been increasingly recognized as the eighth type of waste in Lean thinking (Nwanya and Oko, 2019; Patel *et al*., 2022; Tanasic *et al*., 2022). Unlike the original seven wastes, which primarily address material inefficiencies, this additional category emphasizes the socio-organizational dimension of waste, highlighting how overlooking workers' abilities can undermine continuous improvement and limit innovation. As also Özen and Ventura (2017) highlight, the "waste of talent" reflects the failure to harness employees' knowledge, skills, and capacities, a factor that directly impacts organizational learning and operational efficiency. In this respect, standardized leadership approaches have been shown to reduce this form of waste by actively involving employees in problem-solving and improvement efforts (Nel *et al*., 2020). Therefore, recognizing and addressing this “eighth waste” becomes essential for aligning operational excellence with human-centered innovation and long-term organizational resilience.

To systematically address all forms of waste identified - “material” and “human” - the Lean approach is guided by five core principles (Womack and Jones, 1996), which provide the foundation for designing efficient and value-driven processes. These principles include:

(i) Value: it consists of understanding the value that the customers associate with the product, focusing exclusively on activities that meet their needs and expectations.

(ii) Value stream mapping: it implies an in-depth analysis of processes, identifying the activities that add value, those that do not add value but are necessary for the process, and those that do not generate value and can be eliminated.

(iii) Flow: it ensures that the value stream flows without interruption, ensuring that each phase proceeds continuously, from initial planning to customer.

(iv) Pull: it implies producing only according to customer demand, thus avoiding overproduction and unnecessary inventory.

(v) Pursue perfection: it refers to the continuous improvement of processes, progressively reducing waste and optimizing the production cycle to maximize value creation.

Translating these guiding principles into practice requires the use of specific Lean tools and techniques which support companies in operationalizing the Lean philosophy across different functional areas (Alefari *et al*., 2017; Kovilage, 2021; Kumar *et al*., 2022). For instance, the study by Salonitis and Tsinopoulos (2016) separated the main Lean strategies into five groups in accordance with Panizzolo’s (1998) taxonomy. The first is about equipment and processes, including Cellular Manufacturing, Lean Six Sigma, Continuous Flow, Waste Identification, Poka-Yoke, Value Stream Mapping (VSM), Total Productive Maintenance (TPM), Kaizen, 5S, and Single Minute of Exchange of Die (SMED). These tools are used to maximize operational efficiency and minimize waste. The second category focuses on production planning and control and includes tools such as Heijunka, Visual Control, Kanban, and Workforce Engagement that improve scheduling and workflow management. Workforce Commitment, Employee Involvement, and Quality Circles are some of the strategies in the third category, which focuses on active employee participation, and are part of the human resources strategy. To improve the flow between the business and its suppliers, the fourth category focuses on supplier relations and includes Just-in-Time (JIT), Lean Supply Chain, and Supplier Quality. The fifth category focuses on customer interactions and aims at improving customer satisfaction through higher-quality products or services, but it does not include specialized Lean methods.

LM as a philosophy has changed dramatically over time, and its use has spread beyond conventional manufacturing procedures (AlManei *et al*., 2017). Indeed, it is no longer a simple toolkit for process optimization; it is a socio-technical system grounded in human engagement, learning, and organizational culture (Shah and Ward, 2007). Despite its operational effectiveness, the success of Lean transformation is often contingent upon organizational culture and human capital development (Marodin *et al*., 2018; Tortorella *et al*., 2020). The human-centered component of LM is not secondary but integral to its long-term impact and is increasingly linked to broader discussions on social sustainability. Indeed, research increasingly emphasizes that successful Lean transformations depend not only on technical execution, but also on the development of human capabilities, trust, and a culture of shared responsibility (Tortorella *et al*., 2020; Marodin *et al*., 2018). Importantly, LM's emphasis on "respect for people" and employee participation positions it as a bridge to social sustainability goals, particularly in enhancing job quality, psychological safety, and continuous learning (Vinodh *et al*., 2020).

This human-centered orientation has become even more salient in light of the digital revolution, where the integration of AI and other technologies threatens to displace or deskill workers unless mediated by inclusive practices and participatory frameworks (Rana *et al*., 2021).

1.2 Advanced Digitalization and Artificial Intelligence in Industry 4.0 for operational and strategic objectives

The Fourth Industrial Revolution (I4.0) marks a fundamental transformation in the organization of industrial value chains, driven by the integration of advanced digital technologies into manufacturing and business processes. At the heart of this transformation lies the ambition to create smart factories and data-driven enterprises capable of dynamic adaptation, autonomous decision-making, and continuous self-optimization (Sheshadri, 2024; Banjanović-Mehmedović and Jahic, 2022; Kagermann *et al*., 2013; Liao *et al*., 2017). Unlike previous industrial paradigms, I4.0 introduces a cyber-physical convergence, where operational technology (OT) and information technology (IT) are no longer parallel but deeply interconnected, forming a platform for cognitive production systems that can sense, reason, and act in real time (Banitaan *et al*., 2023; Walas and Redchuk, 2021).

Moreover, advanced digitalization redefines organizational boundaries and hierarchies by enabling decentralized production control and inter-organizational collaboration through smart supply chains (Mubarik *et al*., 2024). Technologies such as cloud computing, blockchain, and AI-enabled analytics converge to create cognitive ecosystems where machines, suppliers, and human operators interact through intelligent interfaces and autonomous systems (Urgancı and Çevik, 2023). These ecosystems exhibit emergent properties, resilience, flexibility, antifragility, that were previously unattainable in traditional manufacturing setups (Mubarik *et al*., 2024). Such digitally infused networks, empowered by real-time information flows and multi-agent AI systems, enable not only operational optimization but also the creation of new strategic capabilities such as mass customization, demand-driven production, and rapid reconfiguration (Banitaan *et al*., 2023; Banjanović-Mehmedović and Jahic, 2022).

Among these technologies, AI stands out as a general-purpose technology capable of transforming both operational workflows and strategic processes. AI is central in this landscape, serving as both a strategic enabler and an operational driver. At the strategic level, AI supports data-driven decision-making by uncovering patterns and insights across complex datasets, enabling firms to anticipate market trends, personalize offerings, and allocate resources more effectively (Sony and Naik, 2020; Del Giudice *et al*., 2021). For instance, AI enables dynamic decision-making processes by offering predictive insights into customer behaviors, improving demand forecasting, and guiding strategic resource allocation (Wang, 2024; Mahabub *et al*., 2025), thus reshaping traditional planning cycles and enabling continuous strategic alignment with dynamic market shifts (Zheng *et al*., 2024; Abir, 2024). Moreover, it plays a critical role in facilitating servitization and mass customization strategies by enhancing firms' ability to adapt quickly to market needs and deliver personalized, high-value services and products (Sjödin *et al*., 2023; Bustinza *et al*., 2024). These capabilities transform AI from a purely operational tool into a central driver of innovation and long-term competitive advantage.

At the operational level, AI-driven systems empower predictive maintenance, adaptive production scheduling, and real-time quality control, thereby reducing machine downtime, improving yield, and increasing overall equipment effectiveness (OEE) (Fantozzi *et al*., 2025; Kraus *et al*., 2022). It enables real-time anomaly detection, predictive maintenance, and adaptive control, enhancing efficiency, responsiveness, and reliability (Zhou *et al*., 2015; Tortorella *et al*., 2021). Also AI-integrated Digital Twins, for example, enable continuous mirroring and simulation of physical assets, enabling firms to model future scenarios, test hypotheses, and anticipate failures with high accuracy (Fantozzi *et al*., 2025).

In the context of Lean transformation, AI can enhance process visibility, anomaly detection, and employee training, enabling a more data-driven and agile approach to continuous improvement (Sony and Naik, 2020; Tortorella *et al*., 2021). The implications for sustainability and resilience are equally important. AI-enabled process optimization supports the efficient use of energy and materials, thus contributing to environmental sustainability and aligning with the principles of the circular economy (Zheng *et al*., 2024; Abir, 2024). Additionally, integrating AI with big data analytics (BDA) allows firms to simulate and monitor environmental impact, thereby enabling the design of more sustainable and compliant operations (Zheng *et al*., 2024). At a macro level, digitalization also democratizes industrial innovation by lowering entry barriers for SMEs, creating distributed manufacturing models, and accelerating time-to-market through digital prototyping and agile production (Kraus *et al*., 2022).

Thus, the convergence of advanced digitalization and AI within the I4.0 paradigm represents a paradigm shift, not only in how manufacturing operations are optimized, but in how firms generate value, compete, and evolve strategically. The dual role of AI as both an optimizer of current operations and a driver of future capabilities positions it as a cornerstone technology for intelligent, resilient, and sustainable industrial systems (Sheshadri, 2024; Banitaan *et al*., 2023; Zheng *et al*., 2024).

However, despite its potential, the implementation of AI in SMEs remains uneven and fraught with barriers. Technological complexity, high upfront investment costs, limited digital competencies, and organizational resistance frequently hinder adoption (Moeuf *et al*., 2018; Rezaei *et al*., 2024).

Moreover, these technological advancements are not without challenges. The adoption of AI in industrial contexts entails significant complexity related to data quality, infrastructure readiness, legacy system integration, and workforce adaptation (Khoruzhy *et al*., 2022). There is a growing consensus in the literature that digital transformation must be approached as a socio-technical system, where technological implementation is intrinsically tied to human capabilities, organizational culture, and governance structures (Murugesan *et al*., 2023; Zheng *et al*., 2024). In fact, studies show that the full benefits of Industry 4.0 are rarely realized without complementary investments in digital literacy**,** cross-functional collaboration, and change management practices (Banitaan *et al*., 2023). The rise of AI further introduces a set of ethical and social concerns including algorithmic bias, surveillance, and job displacement that challenge the legitimacy and sustainability of digital transformation efforts (Dignum, 2019).

In light of these complexities, this dissertation frames AI not only as a tool for automation and optimization, but as a potential enabler of human-centered innovation. When designed and implemented within participatory frameworks, AI can increase inclusive learning, democratize access to knowledge, and support broader involvement in both strategic and operational decision-making processes (Rana *et al*., 2021). Reframing digitalization in these terms is essential to ensure that the adoption of I4.0 technologies in SMEs is not only efficient but also resilient, sustainable, and socially legitimate.

This broader perspective on digitalization naturally intersects with the evolving understanding of sustainability, particularly its social dimension, which remains less explored yet increasingly central to discussions on organizational transformation and long-term value creation.

1.3 Social Sustainability: beyond efficiency

The idea of sustainability gained prominence in the latter part of the 20th century as people became more conscious of how human activity affects the environment and society (Mebratu, 1998; Du Pisani, 2006; Glavič and Lukman, 2007; Ahern, 2011). There were concerns about resource depletion, environmental degradation, and social inequality brought on by non-inclusive development during this time, as economic and industrial models predicated on the heavy use of natural resources began to show their flaws (Hopwood *et al*., 2005; Tomislav 2018; Fernández *et al*., 2021). A new strategy that balanced environmental, social, and economic concerns became necessary as a result (Taylor, 2016; Mensah, 2019; Purvis *et al*., 2019; Li *et al*., 2021).

In light of the growing awareness of environmental and social consequences of human activity, sustainable development has become a central topic in global policy, organizational strategy, and civil society discourses (Topple *et al*., 2017). The concept was first formally introduced at the 1972 United Nations Conference on the Human Environment in Stockholm (Purvis *et al*., 2019). However, it gained widespread recognition with the publication of the 1987 Brundtland Report by the World Commission on Environment and Development (WCED). This report offered the widely cited definition of sustainable development as that which "*meets the needs of the present generation without compromising the ability of future generations to meet their own needs*" (WCED, 1987, p. 41). This definition emphasized the importance of balancing social justice, environmental preservation, and economic progress (Taylor, 2016; Li *et al*., 2021).

Since the seminal definition provided by the WCED (1987), the concept of sustainability has evolved into a multifaceted framework, taking on different meanings depending on the context in which it is applied (Bilan, 2013). A widely recognized and integrative approach is the Triple Bottom Line (TBL), introduced by Elkington (1997), which conceptualizes sustainability as the balanced pursuit of three interconnected dimensions: economic prosperity, environmental quality, and social equity. According to this framework, businesses are expected to embed sustainability not only in their environmental and economic strategies but also in their social practices, thereby aligning corporate performance with broader societal goals (Hourneaux *et al*., 2019; Loviscek, 2020; Schaltegger *et al*., 2022). In pursuit of this triple objective of sustainability, firms are encouraged to adopt bottom-up decision-making and investment models that account for all three pillars simultaneously (Lozano, 2020; Spallini *et al*., 2021). In this view, the economic, environmental, and social pillars are not standalone objectives but mutually reinforcing foundations of sustainable development (Pawłowski, 2008; Barbosa *et al*., 2014; Mensah, 2019). This triadic structure continues to serve as a cornerstone for both academic research and managerial practice in defining, measuring, and implementing sustainability (Giovannoni and Fabietti, 2013; Strezov *et al*., 2017; Ranjbari *et al*., 2021).

Specifically, the ability of businesses to generate long-term value and guarantee financial performance is referred to as the economic dimension (Eslami *et al*., 2019; Sartal *et al*., 2020; Ahmad *et al*., 2023). It entails creating laws that support the economic and responsible use of resources while offering income and job possibilities (Moore *et al*., 2017; Giovannoni and Fabietti, 2013; Eslami *et al*., 2019; Mensah, 2019).

By implementing cleaner manufacturing methods, effective waste management, and optimal resource utilization, environmental sustainability aims to reduce its ecological impact (Chang *et al*., 2017; Hegab *et al*., 2018; Machado *et al*., 2020). This dimension is concerned with protecting the environment and preserving the integrity of natural ecosystems (Morioka and Carvalho, 2016; Salvioni and Almici, 2020). It further encourages actions such as the use of renewable energy and prudent resource management that minimize ecological impacts (Roscoe *et al*., 2019).

Lastly, the social component addresses the welfare of employees, communities, and all other stakeholders (Digalwar *et al*., 2020; Henao *et al*., 2021; Yip *et al*., 2023). By guaranteeing equitable access to basic rights like security, health, and education, the dimension focuses on social justice and equity (Gupta and Vegelin, 2016; Eizenberg and Jabareen, 2017; Ajmal *et al*., 2018; Leal Filho *et al*., 2019).

However, the mere acknowledgment of these pillars is not sufficient. Effectively integrating them into corporate strategies requires a profound cultural and organizational shift across sectors. Businesses must adopt more responsible perspectives along the entire value chain, from design and production to distribution and consumption (Faulkner and Badurdeen, 2014; Sajadieh *et al*., 2022). This transition is often hindered by significant challenges, including the need to engage different stakeholders, manage transition costs and investments, optimize processes and resources, and adopt new technologies (Gbededo *et al*., 2018; Mathiyazhagan *et al*., 2019; Malek and Desai, 2019; Orji, 2019; Virmani *et al*., 2021).

Despite this conceptual broadening, the social pillar, encompassing workplace safety, equity, inclusion, job satisfaction, and democratic governance, remains underdeveloped in both scholarship and practice (Martínez-Jurado and Moyano-Fuentes, 2014; Ejsmont *et al*., 2020). This neglect is particularly problematic in digital and Lean transformations, which can generate new forms of workplace stress, skill inequality, and job insecurity if not implemented carefully (Barley *et al*., 2017). Accordingly, social sustainability becomes in this sense not only an ethical imperative, but also a strategic asset: companies that invest in inclusive, empowering work environments are more resilient, adaptive, and innovative over time (Ceschin and Gaziulusoy, 2016).

In this research project social sustainability is not just a thematic concern but a core analytical lens through which the integration of Lean and AI is assessed. The central hypothesis is that technological and managerial innovation, when disconnected from people’s needs and aspirations, particularly in the vulnerable context of SMEs, is likely to fall short of generating long-term value. Conversely, embedding socially inclusive practices into digital and Lean transformation initiatives can create synergies that improve employee engagement, enhance resilience and continuous innovation (Vinodh *et al*., 2020). The present thesis thus explicitly foregrounds social sustainability as both a research object and an evaluative lens for studying Lean and AI integration in SMEs.

1.4 Small and Medium-Sized Enterprises: a strategic context for study

Small and Medium-sized Enterprises (SMEs) represent approximately 90% of all businesses worldwide, employ between 60% and 70% of the global workforce, and contribute significantly to economic growth, accounting for around 50% to 60% of value added or GDP in many countries (UN, 2024[8]; OECD, 2024[9]). Their vital role in economic development, innovation, and territorial cohesion makes them a strategic context for investigating organizational transformation, particularly as they manage increasing technological complexity and societal demands. SMEs exhibit distinctive characteristics that influence how they experience and respond to technological and organizational change.

Although SMEs are widely praised for their agility, flexibility, and proximity to customers, an extensive body of research reveals indeed that these advantages coexist with persistent structural, cultural, and managerial constraints that undermine their ability to achieve sustained innovation and digital transformation. Their innovation processes are often shaped by resource limitations, informal organizational structures, and high sensitivity to environmental changes (Lee *et al*., 2001; Bianchi *et al*., 2021; Pearce *et al*., 2018). Indeed, typically operating with limited financial and human resources, they tend to adopt informal management structures and scarce human resources, which collectively pose significant challenges to implementing complex initiatives such as AI or Lean transformations (Moeuf *et al*., 2018). Moreover, they rely on intuitive or experience-based decision-making rather than formalized strategic planning (Lee *et al*., 2001; Bianchi *et al*., 2021). Recent systematic reviews and empirical studies underscore that limited financial resources, managerial informality, low absorptive capacity, and cultural resistance to change are the most consistent inhibitors of transformation across different contexts and sectors (Krismajayanti *et al.,* 2024; Omowole *et al.,* 2024; Judijanto *et al.,* 2025; Clemente-Almendros, 2024). For instance, numerous studies identify financial scarcity and inadequate human resources as critical bottlenecks for SMEs attempting to adopt digital and Lean technologies. Systematic literature reviews highlight that SMEs frequently lack the capital required to invest in advanced technologies, as well as the internal competencies to

[8] https://www.un.org/en/observances/micro-small-medium-businesses-day?utm
[9] https://www.oecd.org/en/topics/sub-issues/sme-indicators-benchmarking-and-monitoring.html?utm

manage digital projects effectively (Boonmee *et al.,* 2025). These deficiencies create a strong bias toward short-term operational survival over strategic innovation. Clemente-Almendros (2024) further shows that even when financial support exists, weak organizational coordination and limited strategic vision prevent SMEs from capturing the full value of digital transformation.

Beyond resources, SMEs are often characterized by centralized decision-making and informal governance, which constrain experimentation and learning. Bibliometric and empirical analyses confirm that organizational rigidity, lack of standardized procedures, and absence of cross-functional collaboration significantly hinder transformation success (Judijanto et al., 2025; Brink and Packmohr, 2025). In the context of Lean and Lean 4.0 initiatives, similar obstacles emerge: El Amine and El Hadri (2022) and Qureshi *et al*. (2025) demonstrate that managerial informality and unclear roles within SMEs limit the institutionalization of Lean practices, while fragmented communication structures slow the integration of digital tools into continuous-improvement routines.

Cultural and behavioral dimensions constitute perhaps the most pervasive constraints. Empirical studies reveal that SME employees often display digital anxiety, low innovation orientation, and fear of technological displacement, leading to passive or resistant attitudes toward change (Justy *et al.,* 2023; Chandani *et al.,* 2025). A bibliometric review of transformation barriers emphasizes that resistance to change, lack of leadership commitment, and insufficient training are recurring inhibitors across industries (Judijanto *et al.,* 2025). Likewise, Krismajayanti *et al.* (2024) find that cultural inertia, manifested through hierarchical structures and weak learning cultures, reduces SMEs' responsiveness to digital opportunities.

Moreover, SMEs' reliance on informal, experience-based learning further restricts their innovation capability. Jewapatarakul and Ueasangkomsate (2024) demonstrate that digital organizational culture, readiness, and knowledge acquisition strongly determine SMEs' transformation success, yet few firms invest systematically in knowledge management systems. This finding aligns with preprint meta-analyses showing that insufficient learning infrastructure is one of the top five barriers to digital transformation in SMEs (Kargas *et al.,* 2025).

Consequently, these features can be both a limitation and a strength. On the one hand, SMEs face structural disadvantages in accessing digital innovation and implementing sustainability-oriented change. On the other hand, their organizational agility, decentralized decision-making, and openness to experimentation make them highly responsive to rapid transformation, especially in turbulent or uncertain contexts (Voss and Rytter, 2007; Brunswicker and Vanhaverbeke, 2015). However, while the flexibility of SMEs makes them well-suited to Lean implementation and rapid digital adoption, they continue to encounter significant barriers in accessing external expertise, funding, and technologies (Moeuf *et al*., 2018).

In this scenario, the human resource dimension in SMEs is often underdeveloped, with limited formal training structures and unequal access to decision-making processes (Voss and Rytter, 2007). Limited access to formal training, asymmetries in knowledge between owner-managers and employees, and restricted opportunities for employee participation in strategic decisions hinder both innovation capacity and social sustainability outcomes (Durst and Edvardsson, 2012). Without targeted interventions to address these gaps, especially in learning, inclusion, and participation, efforts at digital or Lean transformation may reproduce existing inequalities rather than resolve them.

These dynamics make SMEs an ideal context to study the real-world integration of Lean, AI, and social sustainability, and offer the opportunity to generate insights that are both theoretically valuable and managerially actionable.

Therefore, this dissertation explicitly argues that SMEs represent an ideal empirical and theoretical setting for exploring how Lean principles, AI-based technologies, and social sustainability can interact. Their scale, resource constraints, and human-centric nature make them uniquely positioned to generate grounded, actionable insights on the dynamics of inclusive innovation. Moreover, by focusing on SMEs, this research addresses a persistent gap in the literature, where transformation strategies are often modeled on large enterprises, and offers policy-relevant contributions aimed at creating more democratic, resilient, and context-sensitive models of digital transformation (Bianchi *et al*., 2021; Müller *et al*., 2018).

1.5 Adopted perspectives on the integration of Lean, AI, and social sustainability in SMEs

The convergence of LM, AI, and Social Sustainability in SMEs is an emergent but still underdeveloped research field. While Lean methodologies have long been associated with operational efficiency through waste reduction and process optimization (Buer *et al*., 2018), recent literature suggests their potential synergies with AI technologies and social sustainability initiatives, particularly in SMEs, where constraints on resources and capabilities are often more pronounced (Siegel *et al*., 2019; Hussain *et al*., 2024). However, a theoretically coherent and empirically grounded framework that integrates these three dimensions remains largely absent.

Scholars have attempted to investigate this triadic relationship from two primary analytical perspectives: the first adopts an intraorganizational lens, while the second focuses on an interorganizational level.

The intraorganizational perspective focuses on the internal effects of Lean-AI integration on process performance, decision-making, and human-centered outcomes such as worker autonomy, safety, engagement, and skill development. For example, studies such as those by Souza and Alves (2018) and Kosasih *et al*. (2023) illustrate how combining Lean with digital tools (e.g., real-time monitoring, predictive analytics) creates more agile and socially responsible workflows, especially when employee empowerment is emphasized through participatory models. The proposed LIMSSI framework (Lean-Integrated Management System for Sustainability Improvement), in particular, highlights how internal structures can simultaneously drive efficiency and social value creation by embedding principles of occupational health, resource rationalization, and continuous learning (Souza and Alves, 2018). Empirical evidence further underscores the need to consider not only economic and environmental gains, but also social metrics when integrating AI into Lean practices. Hussain *et al*. (2024) propose the "Ergo-Green Lean" model, which places ergonomic well-being and social responsibility alongside digital transformation, suggesting that technology-enabled Lean systems must be designed with human adaptability and safety in mind. Similarly, Sajan *et al*. (2017) find that Lean implementation in Indian SMEs positively contributes to the social dimension of sustainability, as measured by improved labor conditions and employee development, when properly aligned with strategic sustainability goals.

The interorganizational perspective explores how the Lean-AI-social sustainability nexus shapes SME relationships across their value chains and ecosystems. This view considers how collaborative digital platforms, data-sharing systems, and smart supply chain strategies facilitate sustainable practices beyond the firm's boundaries. Ciccullo *et al*. (2018) propose six modes of integration between Lean, agile, and sustainable paradigms, many of which involve rethinking supplier-customer relationships through technologies that enable traceability, responsiveness, and stakeholder inclusion. Particularly in SME networks, such digital integrations must account for asymmetries in resources, capabilities, and sustainability maturity levels.

Despite these advancements, fragmentation remains a defining feature of the literature. There is a significant lack of unified frameworks that systematically explain how Lean, AI, and social sustainability interact, especially in SMEs. Several studies adopt isolated case-based or conceptual approaches (Choudhary *et al*., 2019; Wu *et al*., 2015), often without a robust theoretical grounding. For instance, while the integration of AI into Lean processes is frequently justified from a performance-enhancement viewpoint, its implications for social sustainability (e.g., job design, workforce empowerment, equity in digital access) are rarely addressed in depth or through longitudinal empirical analysis.

Recent contributions advocate for a multi-level, systems-oriented methodology that captures both operational (micro-level) and strategic (macro-level) dynamics of this integration (Siegel *et al*., 2019; Hussain *et al*., 2024). This approach supports the co-design of human-centered AI tools that are embedded in Lean systems and aligned with sustainability values. Furthermore, Gopi and

Saleeshya (2022) emphasize the need for conceptual frameworks that account the unique constraints of SMEs, including financial constraints, low digital readiness, and resistance to organizational change. Such frameworks provide a foundation for designing context-sensitive interventions that integrate Lean, AI, and social sustainability not merely as parallel efforts but as mutually reinforcing components of a broader sustainable transformation.

Therefore, while the theoretical potential of integrating Lean, AI, and social sustainability in SMEs is increasingly recognized, empirical studies and unified frameworks remain scarce. The current body of literature calls for more interdisciplinary, context-aware research that can bridge existing gaps and create a comprehensive understanding of this integration, capable of informing both academic debates and practical implementations in resource-constrained SME environments.

In light of the theoretical fragmentation outlined above, this dissertation positions itself at the intersection of Lean, AI, and social sustainability by proposing a multi-level, integrative research agenda. Building upon the dual perspectives that dominate current literature, namely, intraorganizational and interorganizational approaches, this thesis aims to bridge the gap between micro-level operational transformations and macro-level strategic decision-making within SMEs.

2. OPEN QUESTIONS AND RESEARCH OBJECTIVES: A MULTI-LEVEL PERSPECTIVE ON INNOVATION

Understanding how Lean methodologies, advanced digital technologies, and sustainability interact to generate innovation in SMEs requires a theoretical and analytical framework that accommodates complexity, interdependence, and contextual sensitivity. Traditional linear models of innovation are increasingly inadequate for capturing the dynamic and multi-faceted nature of contemporary transformation processes (Baregheh *et al.*, 2009), particularly in resource-constrained and human-centered environments such as SMEs. Although LM, advanced digitalization through I4.0 technologies, and social sustainability are increasingly discussed as interdependent paradigms, significant conceptual and empirical gaps remain in understanding their systemic integration within SMEs.

First, while the integration of LM and I4.0 technologies, commonly referred to as "Lean 4.0", has been widely framed as a strategy to enhance productivity and operational efficiency (Ghobakhloo and Fathi, 2020; Liao *et al.*, 2017), there remains a notable absence of theorization regarding the social sustainability dimension of such integration. Most studies focus on cost reduction, defect minimization, and process optimization (Buer *et al.*, 2018), yet fail to unpack how specific LM practices (e.g., Kaizen, VSM, TPM) interact with digital tools (e.g., IoT, AI, CPS) to influence workplace factors such as autonomy, participation, safety, well-being, and motivation. Moreover, where social outcomes are mentioned, they are often treated superficially or reported as side effects

(Vinodh *et al*., 2019; Yadav and Gahlot, 2022). Theoretical mappings rarely theorize causal mechanisms, and mediating or moderating factors (e.g., leadership style, team climate, skill asymmetries) are underexplored (Ghobakhloo, 2020). This absence is particularly critical in SME contexts, where human capital is limited, hierarchies are flatter, and informal processes dominate decision-making (Amrina *et al*., 2021).

Trying to address this research gap, this thesis advances the following research question (RQ):

RQ 1:

What is the effect of I4.0 tools and LM practices on the social sustainability functions?

A second research gap concerns the micro-foundations of AI-enabled learning processes in Lean transformation. While AI, especially Natural Language Processing (NLP), is increasingly explored for its capacity to enhance knowledge dissemination, skill acquisition, and performance monitoring (Pratap and Venkatesh, 2024; Ibrahim and Kumar, 2024), there is limited understanding of how these tools affect learning dynamics, particularly in SMEs. Although the literature acknowledges the potential of AI-based training systems to democratize access to Lean knowledge and reinforce continuous improvement cultures (Boursali *et al*., 2024), a deeper empirical understanding remains lacking. Specifically, little is known about how features such as algorithmic personalization, data-driven feedback, and real-time adaptation influence key enablers of effective learning, such as learner autonomy, psychological safety, and intergenerational knowledge transfer. For instance, early findings suggest that while AI training can enhance engagement and self-paced learning (Maity, 2019), it can also generate techno-stress, perceived surveillance, or exclusion of senior workers with lower digital proficiency (Wilson and Velden, 2022). Furthermore, the organizational governance of such systems, how firms design, monitor, and ethically implement them, remains under-theorized, especially in resource-constrained firms. To address these gaps, this dissertation advances two interrelated research questions aimed at unpacking the role of AI-driven training in Lean transformations within SMEs, both from an operational and a social sustainability perspective:

RQ 2:

How can AI-driven training effectively support LM adoption in SMEs?

RQ3:

What is the impact of AI-driven training on social sustainability outcomes in an LM environment?

Finally, at a strategic level, there is a growing, but still nascent, literature on how SMEs incorporate AI into their international strategic decision-making processes (ISDMPs) (Suljic, 2025). While the transformative potential of AI in improving decision speed, data-driven analysis, and opportunity recognition is well established in large firms (Gomaa, 2025), few studies examine how SMEs adapt these capabilities within their resource, cultural, and governance constraints. The literature lacks a granular understanding of how AI adoption affects the core dimensions of SDMPs, such as decentralization, communication, formalization, and value alignment (Lutfi *et al*., 2022). Recent work emphasizes the need for ethical AI governance, leadership support, and organizational readiness (Suljic, 2025; Kumarasamy *et al*., 2025), but provides little guidance on how strategic AI integration feeds back into operational-level practices and worker experience.

To advance the understanding of strategic-level implications, this dissertation explores how SMEs engage with AI technologies in shaping their international strategic decision-making processes. In particular, it explores the dimensions of such decisions, formulating two guiding research questions:

RQ4:
How do SMEs' decision-makers adopt AI digital technologies in their International Strategic Decisions?
RQ5:
How does AI integration reshape Strategic Decision-Making Process dimensions in firms operating in international markets?

By addressing these interrelated questions, this dissertation contributes to an emerging research agenda that bridges theoretical, operational, and strategic levels, developing an integrated socio-technical framework for sustainable innovation in SMEs. In doing so, it not only responds to unresolved theoretical debates but also offers insights for practitioners managing the complexities of AI-augmented Lean transformation under conditions of uncertainty and constraint. Therefore, this thesis adopts a multi-level perspective on innovation, which views innovation not as a discrete event or isolated intervention, but as an emergent property of interactions across multiple, interrelated organizational levels: the theoretical-systemic level, the operational level, and the strategic-managerial level. The first level, developed in Chapter II, provides the theoretical lens for understanding synergies and tensions in practice. The second level in Chapter III explores how digitalization can act as a driver or barrier to social sustainability within SMEs. The third level, developed in Chapter IV broadens the organizational scope and links operational transformation to global competitiveness.

Each level provides unique mechanisms, constraints, and opportunities through which Lean, AI, and sustainability are enacted, negotiated, and institutionalized. This multi-level framework not only reflects the layered reality of organizational life, but also offers a robust structure for integrating the contributions of the three papers that constitute this dissertation.

Accordingly, this thesis pursues four interlinked research objectives that address these open questions while integrating the three papers into a single explanatory architecture.

The first objective is conceptual and theory-building in nature. It aims to address the current fragmentation in the literature on LM and I4.0 by developing an integrated, human-centered framework that positions social sustainability as a core evaluative dimension. The review synthesizes and categorizes existing studies to examine how LM and I4.0 jointly influence organizational and social outcomes. It highlights critical gaps in current research, especially concerning equity, well-being, participation, and calls for a shift from purely efficiency-driven frameworks to approaches that center human impacts and values. The review lays the conceptual groundwork for linking technological configurations to social functions and proposes future directions for empirical testing and refinement.

The second objective takes an operational and micro-foundational perspective. Through an in-depth case study of an Italian metalworking SME, it explores how AI-enabled training platforms, specifically Google's NLP-based Notebook LM, impact the dissemination of Lean knowledge and shape day-to-day worker experiences. The analysis reveals that AI training helps democratize access to Lean, enhances reflective problem-solving, and improves cross-functional coordination. However, it also surfaces tensions such as digital skill gaps, increased monitoring pressure, and ambiguity around autonomy and job security.

The third objective focuses on the strategic and organizational level. It develops and empirically refines a conceptual model of how AI is reshaping International Strategic Decision-Making Processes (ISDMPs) in manufacturing SMEs. Based on six Italian cases, the study analyzes how AI influences five core decision-making dimensions (speed, quality, decentralization, lateral communication, and formalization) and identifies enabling conditions and inhibitors. The research shows how AI can both democratize and recentralize strategic decisions and links these dynamics to firm-level outcomes such as the speed of international expansion, the quality of decision-making, and alignment with human-centered transformation.

The fourth research objective, developed in Chapter V of this dissertation, serves as the overarching cross-level synthesis. Its purpose is to integrate the theoretical, operational, and strategic insights generated in the previous three studies into a unified socio-technical theory of human-centered innovation in SMEs. This objective addresses the need, highlighted across all manuscripts, for analytical frameworks that can bridge the micro-level of manufacturing practices and the macro-level of strategic decision-making, capturing how feedback loops between these levels condition the success or failure of LM-I4.0 transformations. Furthermore, the objective engages directly with the policy and managerial implications of human-centered digitalization. By synthesizing context-rich findings into actionable design principles, responsible AI governance mechanisms, and scalable intervention logics, it seeks to offer evidence-based guidance for SMEs, policy-makers, and ecosystem actors managing the tensions between digital transformation, Lean efficiency, and social inclusion.

Building on these four research objectives, the thesis aims to offer a set of multi-dimensional contributions across three interrelated domains: theoretical, methodological, and managerial.

Theoretically, rather than building on a single framework, this research advances distinct yet interconnected theoretical frontiers. First, it contributes to the socio-technical literature by problematizing the underrepresentation of social sustainability in the integration of Lean and I4.0 paradigms. Second, it extends theories of workplace learning and digital training by investigating how AI-based learning tools reshape knowledge flows, autonomy, and inclusion in Lean transformations. Third, it contributes to the strategic management literature by offering an empirically grounded understanding of how AI supports international strategic decision-making in SMEs, particularly under uncertainty and resource constraints.

Methodologically, the thesis adopts a cross-level, qualitatively driven research design that triangulates systematic literature review, single and multiple case studies, and inductive theorizing. This multi-level approach demonstrates the potential of qualitative inquiry to capture complex dynamics of socio-technical change, particularly within SMEs where informal structures and contextual variability demand flexible yet rigorous methodological tools.

Managerially, the research generates actionable frameworks and empirical insights that assist SME managers in facing the social, technical, and strategic tensions of digital transformation. By focusing on real-world constraints and human dynamics, the proposed models help practitioners implement AI and Lean in socially sustainable ways, bridging operational improvement with inclusivity, empowerment, and long-term resilience.

2.1. Structure of the thesis and rationale

This research project thus adopts a paper-based structure that reflects both the complexity of the research questions and the interdisciplinary nature of the theoretical domains explored. It comprises three scientific articles that, while individually grounded in distinct methodological traditions, collectively address a unified research question: how the integrated application of Lean methodologies, advanced digital technologies (particularly Artificial Intelligence), and social sustainability principles can enhance innovation within SMEs.

The article-based approach provides the flexibility to examine the research problem through multiple methodological lenses, allowing each study to engage deeply with a specific dimension of the overall inquiry while maintaining thematic and conceptual coherence across the thesis. Each article is scientifically autonomous, contributing to its own body of literature, but their aggregation forms an integrated theoretical and empirical narrative that captures the multi-level dynamics, namely theoretical-systemic, operational, and strategic-managerial, of innovation in resource-constrained, human-centric industrial environments. A more detailed explanation of these different dynamics follows.

2.1.1 The theoretical-systemic level

At the theoretical-systemic level, innovation is shaped by the interplay between technological paradigms, management philosophies, and societal expectations. This level encompasses frameworks and conceptual models that define what counts as innovation, what goals it should serve, and how it should be evaluated. The integration of LM and I4.0 technologies is a prime example of this systemic interplay. These paradigms, though developed in different historical and disciplinary contexts, are increasingly seen as complementary: Lean provides the human-centered process discipline, while I4.0 offers the technological tools to enhance responsiveness, accuracy, and adaptability (Moyano-Fuentes *et al*., 2021). Despite this theoretical complementarity, much of the literature on Lean and I4.0 remains anchored in economic, technical, and environmental performance outcomes, often sidelining social sustainability dimensions such as equity, well-being, and inclusivity (Frank *et al*., 2019; Magruk, 2016; Ejsmont *et al*., 2020; Gallo *et al*., 2021).

The first article in this dissertation addresses this gap by conducting a Systematic Literature Review (SLR) on Lean-I4.0 integration and social sustainability. It develops a conceptual framework that maps critical tensions and highlights the ethical implications and human consequences of digitally enabled process innovations. By synthesizing contributions across disciplines, the article builds a conceptual framework that identifies specific social functions that can be enhanced through Lean-I4.0 integration, such as improved workplace safety, increased employee participation, and enhanced opportunities for learning and upskilling. This framework does not simply catalog existing knowledge but establishes an important imperative: to treat innovation not as a neutral or purely technical evolution, but as a human-centered and ethically grounded transformation process (Brozzi *et al*., 2020).

This chapter thus serves as the analytical and value-oriented lens through which the rest of the thesis is interpreted, positioning social sustainability not as a peripheral concern but as a central evaluative criterion for the future of industrial innovation in SMEs.

2.1.2 The operational level

Building upon the systemic insights of the first article, the second contribution explores the human and organizational implications of digital transformation at the operational level. Centered on an in-depth qualitative case study of an Italian manufacturing SME, the article investigates the implementation of an AI-based training platform designed to support Lean deployment and continuous improvement efforts. At the operational level, innovation is enacted by individuals and teams who engage directly with technologies, processes, and each other. Here, human capital, skill development, and organizational culture become central drivers of successful transformation. In SMEs, such innovation is often informal and emergent, yet can be highly impactful when aligned with strategic intent and supported by digital tools and appropriate technologies (Bessant *et al*., 2005).

For this reason, the empirical article examines how AI impacts learning dynamics, autonomy, and perceptions of inclusion in everyday operations. It reinforces the idea that technology must be designed and deployed to augment, not replace, human capabilities, echoing foundational principles of both Lean and sustainable innovation (Sawhney and Chason, 2005; Citybabu and Yamini, 2024). Moreover, it indicates that AI can act as a knowledge equalizer, enhancing continuous improvement and engagement, if integrated with participatory design and respect for user context. However, the study also warns against techno-deterministic approaches that overlook digital divides and emotional responses to automation (Rana *et al*., 2021). Furthermore, it highlights the centrality of workforce development in digital transformation and emphasizes the importance of structured onboarding, hybrid learning models, and transparent communication around AI's role in organizations (Papetti *et al*., 2020; Kumar *et al*., 2024; Saha *et al*., 2023). Lastly, illustrating that the operational level is not merely a site of execution, but a crucial context for co-creating innovation that is both effective and socially embedded, it also offers practical insights into how structured onboarding processes, hybrid learning models, and transparent communication can support the development of a socially sustainable digital workplace.

2.1.3 The strategic-managerial level

At the strategic level, innovation concerns how organizations plan, prioritize, and adapt to uncertainty in complex environments. For SMEs, this includes market entry strategies, resource orchestration, and technological foresight, areas increasingly mediated by AI. AI now plays a critical role in enabling strategic decision-making by enhancing data visibility, simulating competitive scenarios, and improving forecasting accuracy (Troshani *et al*., 2021).

Nonetheless, SME integration of AI for strategic purposes remains limited by organizational inertia, lack of technical infrastructure, and cognitive barriers. Trust in AI systems, interpretability of outputs, and usability in non-expert settings are all crucial factors determining adoption outcomes

(Jöhnk *et al*., 2021). For this reason, the third article contributes to the emerging discourse on AI-driven internationalization, emphasizing that digital maturity, understood not only as technological infrastructure but as strategic readiness, is becoming a critical enabler of global competitiveness in the SME sector (Dillon *et al*., 2020; Rezaei *et al*., 2024).

The article addresses this dimension through a multiple-case study of SMEs that have adopted AI tools to guide internationalization decisions. It explores how AI increases strategic cognition, supports market evaluation, and enhances agility, while also highlighting critical barriers related to trust, usability, and interpretability. These challenges are particularly acute in SMEs, where strategic decisions are often centralized and intuition-driven, and where integrating complex digital tools may require both technical investment and cultural transformation.

By positioning AI adoption within broader strategic routines, this article contributes to a more detailed understanding of how digitalization and innovation intersect at the level of business models and global competitiveness, especially in firms with limited resources and high environmental uncertainty. Specifically, it expands the scope from the operational to the strategic and international level, investigating how SMEs integrate AI tools in international strategic decision-making processes (ISDMPs). The research identifies how AI supports key decisions such as market selection, entry modes, and partner evaluation, while also uncovering barriers to adoption, including limited expertise, financial constraints, and cultural resistance (Denicolai *et al*., 2021; Francioni *et al*., 2015; Menzies *et al*., 2024). This chapter addresses the growing need for evidence-based, data-driven decision-making in international markets and emphasizes the strategic value of digital maturity for SMEs seeking global competitiveness (Rezaei *et al*., 2024; Dillon *et al*., 2020).

Through the integration of systemic, operational, and strategic levels, this thesis offers a holistic perspective on SME innovation that foregrounds value alignment, managerial agency, and human experience. While each level generates distinct insights, it is their interdependence that allows for a comprehensive understanding of how Lean, AI, and social sustainability co-evolve within real organizational contexts.

The article-based format ensures methodological rigor**,** scientific contribution, and managerial relevance in each thematic area, while allowing for integration and coherence through the overarching conceptual narrative. Despite their methodological and contextual differences, the three articles are deeply interconnected and aligned with the central research objective. They share: i) a common empirical focus on SMEs, treated as both drivers and beneficiaries of innovation under conditions of constraint; ii) a sustained emphasis on the social dimension of innovation, addressing inclusivity, participation, employee development, and organizational ethics; iii) a qualitative, context-sensitive orientation, privileging depth, interpretive richness, and situated understanding over universal generalization.

3. METHODOLOGICAL CONSIDERATIONS

The topic of this research is the transformation and innovation of SMEs through the integration of LM and I4.0 technologies, with a particular focus on how such integration can promote socially sustainable, human-centered innovation. Considering the exploratory nature of the research and the contemporary evolving events under investigation, the methodology applied is qualitative which is justified by both the features of the investigated phenomenon and the research objectives.

Indeed, the qualitative approach is particularly suited to emerging, under-theorized domains such as human-centered digital transformation in SMEs, allowing for rich, detailed exploration of mechanisms, experiences, and interdependencies that are not easily captured through quantitative methods. This methodology enables iterative theory-building, integrating conceptual development with empirical insights across multiple levels of analysis (Lindgreen *et al*., 2021; Pearse, 2021). In this sense, qualitative methodology is designed to collect rich and detailed information and build subjective findings, which are crucial in theory-building processes for mainstream, new research topics (Crick, 2021). It is well-suited for addressing relevant problems or gaps, from which to delineate strategic solutions for specific stakeholders (Epp and Otnes, 2021). Moreover, qualitative research is suitable for studies that are not limited to evaluating a phenomenon but also analyze the context and history around it (Yin, 2009; Meyer, 2001; Lindgreen *et al*., 2021).

Comprehending the contextual and temporal dynamics of Lean-I4.0 integration is essential to unpack its multilevel complexity and human implications. The transformation of SMEs through these technologies is not linear nor universal, but deeply shaped by sectoral contingencies, organizational histories, and socio-technical configurations. Interactions and interdependencies among actors such as employees, managers, technologies, and governance systems play a critical role in enabling or constraining socially sustainable outcomes; therefore, the integration of LM and I4.0 is inherently embedded in the specific context in which it unfolds (Frank *et al*., 2024).

In the field of Lean and the integration of emerging technologies, case study methodology has proven to be a powerful tool for exploring complex, multilevel dynamics, especially in highly variable contexts such as SMEs. Several studies have shown that case studies are particularly practical for examining transitions toward Lean-4.0 models, offering a deep understanding of the organizational, technological, and social challenges involved (Tetteh-Caesar *et al*., 2024; Saraswat *et al*., 2024). In particular, Frank *et al*. (2024) emphasize that qualitative, context-sensitive approaches are essential to grasp the dialectical tensions that emerge from its integration, especially regarding workforce impacts and organizational learning. Similarly, Chiarini and Kumar, 2020 use grounded theory to explore the convergence of Lean Six Sigma and I4.0, arguing for systematic, in-depth approaches to fully capture contextual complexity. Moreover, adopting the case study method is relevant to get the complexity levels involved in the investigated relationships (Halinen and Törnroos, 2005). Since the research aims to provide a deep and contextual analysis of the interconnected elements, case studies offer the opportunity for a methodical, extensive exploration. Additionally, case study methodology is beneficial for theory development in dynamic contexts (Pratt, 2009; Matthyssens and Vandenbempt, 2003); therefore, it applies to the aim of this research.

Based on the above, this dissertation adopts a combination of single and multiple case studies, as recommended by Saraswat *et al*. (2024), to gain a more comprehensive understanding of how Lean tools and AI technologies interact across organizational levels. This approach enables the investigation of operational-strategic linkages, supports theory development in dynamic environments (Frank *et al*., 2024), and facilitates the formulation of socio-technical innovation frameworks tailored to SME transformation.

Although each chapter is grounded in a distinct methodological tradition, they are unified by a shared epistemological stance: an interpretivist paradigm combined with a phenomenon-driven approach (Flyvbjerg, 2006), which prioritizes depth, contextual richness, and practical relevance over statistical generalization. This stance is particularly appropriate given the research focus on SMEs, organizations characterized by heterogeneity, embeddedness, and informal learning structures.

In light of this, a SLR was adopted as the initial step of this dissertation to clarify conceptual ambiguities, uncover implicit assumptions, and build an integrative framework capable of repositioning social sustainability functions such as participation, equity, and well-being at the center of human-centered innovation. To operationalize this intent, the literature review was not limited to a descriptive synthesis but was instead designed to advance theory by identifying key dimensions and gaps. Chapter II thus develops a conceptual framework to understand the theoretical framing. The SLR was adopted as a theory-building tool due to the fragmented and conceptually inconsistent nature of existing research on Lean-I4.0 integration. This method enables structured knowledge accumulation and critical synthesis in emerging fields (Tranfield *et al*., 2003), and is particularly well-suited for generating conceptual clarity and research agendas in underdeveloped domains (Snyder, 2019). The SLR was instrumental not only in identifying underexplored research gaps but also in formulating testable propositions grounded in real-world complexity and contextual variation, thereby laying the foundation for the empirical chapters that follow.

Building on the theoretical insights and propositions developed through the SLR, the subsequent phase of the research adopts a qualitative empirical approach to explore these dynamics in real organizational contexts. Specifically, the qualitative approach in the two empirical chapters of this research consists of a case study methodology (Yin, 1994). Chapter III introduces a single, in-depth case study of an Italian SME. The single case study has been adopted to achieve benefits as a high-quality theory, a deeper understanding of the main subject and a rich description of the examined phenomenon. In parallel, the multiple case study developed in Chapter IV provides access to benefits such as strong and reliable evidence, theory-building derived from the observation of similarities and differences between the cases, and a wide range of theoretical insights (Gustafsson, 2017).

The case studies examined along this research project followed a rigorous data collection method, with few distinctions between the two empirical chapters. In general terms, the main data sources implied are semi-structured interviews and participant observation. Interviews have been selected as the main data source since they allow rich data collection and information triangulation, bias limitation, and findings validation when combined with other data sources (Jonsen and Jehn, 2009). Interviews were in the form of one-to-one, in-depth, semi-structured, open-ended interviews (Cavana *et al*., 2001). To ensure the validity of the questions addressed during the interviews, the writing of a formal protocol preceded the interviews' actualization. The aim of the protocol is to have a standardized and uniform interview approach, to collect focused and relevant data, and to keep a high degree of flexibility (Hunter, 2012). In line with the adopted theoretical approach, in each chapter of this research the interview protocol is based on literature insights and on the research questions of the study.

Formulating the interview protocol is also key to identify the proper respondents (Aguinis and Bradley, 2014). For this reason, the selection of interviewees across the two empirical studies in this dissertation was guided by theoretical relevance and proximity to the phenomena under investigation. In each study, participants were selected for their direct involvement in Lean or I4.0 initiatives, ensuring they could offer firsthand, experience-based insights into the mechanisms of digital transformation and their social implications. They were sampled based on their involvement with the analyzed initiatives and their ability to provide a unique perspective on the initiatives' evolution (Patton, 2005). So, in Chapter III, interviewees included operators, team leaders, and HR/training managers involved in the design and implementation of AI-enabled learning pathways. These informants were chosen for their situated knowledge of how digital training tools affected inclusion, learning effectiveness, and daily operational practices. Similarly, in Chapter IV, respondents were selected from internationalization teams, senior leadership, and middle managers, whose roles directly influenced or were affected by data-enabled strategic decision-making in the international context.

The data analysis strategy adopted across the two empirical chapters of this dissertation is grounded in thematic analysis (Braun and Clarke, 2021), applied within an abductive logic (Dubois and Gadde, 2002) to iteratively connect theoretical constructs and empirical insights. This choice reflects the exploratory and theory-building nature of the research, which seeks to uncover underlying mechanisms of human-centered digitalization in SMEs. Each empirical chapter (namely, Chapter III and Chapter IV) deployed thematic coding to identify recurrent patterns, contradictions, and contextual characteristics emerging from the qualitative data. The process followed the well-established steps of thematic analysis: familiarization, coding (both deductive and inductive), theme development, review, and integration, allowing for rich interpretation and contextual anchoring of findings (Clarke and Braun, 2021). Specifically, in Chapter III data from semi-structured interviews were coded to identify how AI-driven training tools impacted empowerment, motivation, inclusion, and digital adaptation. The analysis surfaced three central themes: AI as an equalizer vs. disruptor, empowerment vs. burnout, and digital divides in LM adoption. In Chapter IV thematic analysis was applied to explore how AI-enabled data infrastructures reshape strategic decision-making dynamics in SMEs. Guided by SDMP theory, themes were derived concerning the tensions between centralization and decentralization, formalization and agility, and the enablers and inhibitors of human-centered governance. Across all studies, manual coding was adopted, which was appropriate given the structured format of case study data and the emphasis on interpretive depth. Codes were developed iteratively, balancing literature-driven categories (e.g., SDMP dimensions) with emergent, data-driven patterns. Findings were continually refined through cross-case comparisons, memo writing, and triangulation with secondary sources, following Denzin's (1978) recommendations for qualitative rigor. This rigorous, theme-based analysis approach allowed the research to move beyond surface descriptions and uncover multi-level socio-technical dynamics, capturing the ambivalent and contextual nature of digital transformation processes in SMEs.

The techniques used to frame and critically discuss the findings differ across the two empirical chapters of the dissertation, and each has been selected based on the nature of the case study, its research objectives, and the type of insights sought.

In Chapter III the analysis is framed through in-depth case reconstruction of a longitudinal intervention in a Lean SME. The discussion technique does not rely on a predefined model but builds on the thematic dimensions that emerged through abductive coding: cognitive load, inclusiveness, motivation, fairness perception, and design tensions (e.g., empowerment vs surveillance). These dimensions are grounded in the literature on AI in Human Resource Management (HRM), and Lean digitalization, to interpret the enabling and constraining roles of AI in socially sustainable knowledge diffusion.

In Chapter IV, the analysis and discussion of results are structured around a theory-informed thematic comparison of six small Italian manufacturing firms, aimed at understanding how AI adoption influences key dimensions of international strategic decision-making processes (ISDMPs), including quality, decentralization, communication, and formalization. Rather than applying a fixed analytical lens, the study follows an inductive interpretive logic, in which themes are developed through thematic analysis (Braun and Clarke, 2021) and critically connected to the SDMP literature, enabling a detailed understanding of variation across cases. This approach allows the identification of shared mechanisms (e.g., how AI improves speed and formalization) and contingent differences (e.g., how data quality or leadership styles condition decentralization and communication). It also captures how human-centric values, organizational culture, and firm-level capabilities mediate the role of AI, reflecting the socio-technical complexity of digital transformation in SMEs.

Table 1 summarizes the methodological approaches employed in the three chapters of the research to provide an overall view of the qualitative method applied.

Table 1. Methodological approach of papers.

CHAPTER	TITLE	RQS	CASE STUDY TYPE	MAIN DATA SOURCES	SECONDARY DATA SOURCES	FRAMING TECHNIQUE
CHAPTER II	A Systematic Integration of Industry 4.0 and Lean Manufacturing for Social Sustainability: Developing a Comprehensive Framework	RQ: What is the effect of I4.0 tools and LM practices on the social sustainability functions?	Systematic Literature Review (SLR)	Peer-reviewed journal articles (43 selected)	Bibliometric databases (Scopus, WoS), journal rankings, snowballing	Triple Bottom Line framework / Social sustainability
CHAPTER III	Exploring AI-Driven Training for Lean Manufacturing: A Case Study on Social Sustainability in an SME	RQ1: How can AI-driven training effectively support LM adoption in SMEs? RQ2: What is the impact of AI-driven training on social sustainability outcomes in an LM environment?	Single case study (SME, Italy)	Semi-structured interviews with operators, team leader, Lean manager, production flow manager	Internal documents, training modules, implementation reports	Human-centered LM / AI-HR integration
CHAPTER IV	The Role of Artificial Intelligence in International Strategic Decision-Making for SMEs	RQ1. How do SMEs' decision-makers adopt AI digital technologies in their International Strategic Decisions? RQ2. How does AI integration reshape Strategic Decision-Making Process dimensions in firms operating in international markets?	Multiple case study (6 SMEs, Italy)	Semi-structured interviews with key international decision-makers	Websites, company reports, external industry sources	Strategic Decision-Making Process (SDMP) theory

Source: Author's own elaboration.

Basically, to adequately capture the complex, multi-level nature of innovation processes in SMEs, the dissertation integrates a SLR, a single case study, and a multiple-case comparative analysis. These methodological choices were not made arbitrarily; rather, they follow a purposeful and sequential logic, consistent with a progressively layered investigation that unfolds across theoretical**,** operational, and strategic domains. Indeed, the sequencing of the studies follows a cumulative and layered logic, designed to mirror the complex dynamics of innovation in SMEs. This progressive layering, from systemic to operational to strategic, mirrors the real-world complexity of innovation in SMEs. It also reflects the idea that transformative change does not reside solely in technologies or tools, but in the intersections between values, routines, decisions, and people. By engaging each of these layers through distinct yet complementary methodologies, the thesis provides a comprehensive, detailed, and grounded account of how Lean, AI, and sustainability intersect in small firm contexts. This methodological orientation, rich in context, layered in structure, and flexible in design, ensures that the insights generated are not only analytically rigorous but also theoretically generative and actionable, with relevance for SME leaders, policy-makers, and innovation scholars alike.

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CHAPTER II: A SYSTEMATIC INTEGRATION OF INDUSTRY 4.0 AND LEAN MANUFACTURING FOR SOCIAL SUSTAINABILITY: DEVELOPING A COMPREHENSIVE FRAMEWORK*

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ABSTRACT

The study investigates how the integration of Industry 4.0 (I4.0) technologies and Lean Manufacturing (LM) practices enhances social sustainability, a frequently overlooked pillar of the Triple Bottom Line framework. A Systematic Literature Review (SLR) was conducted, combining quantitative bibliometric and qualitative content analyses across 43 peer-reviewed publications. The analysis led to the identification of five key social sustainability functions: i) health and safety, ii) quality of work life, iii) employee involvement, iv) communication, and v) motivation, affected by I4.0 and LM. The findings show that the synergy between these paradigms promotes safer, more equitable, and engaging work environments. The study introduces a novel conceptual framework that synthesizes how I4.0 tools (e.g., IoT, BDA) and LM methods (e.g., Kaizen, VSM) jointly improve organizational and workforce well-being. This research challenges the traditional economic-environmental focus and contributes to developing human-centered strategies for sustainable industrial transformation.

Keywords: Lean manufacturing; Industry 4.0; Social sustainability; Systematic literature review; Triple Bottom Line; Technological-managerial integration; Human-centric innovation

1. INTRODUCTION

In the current context of resource scarcity and environmental degradation, sustainable development has become a crucial topic in industrial and academic debates (Hong and Xiao, 2024). The concept gained global recognition with the 1987 World Commission on Environment and Development (WCED) report, which defined it as "*development that meets the needs of the present without compromising the ability of future generations to meet their own needs*" (WCED, 1987, p.15). This notion is often articulated around the Triple Bottom Line (TBL) framework (Elkington, 1999), which urges organizations to integrate economic, social, and environmental considerations into their operations (Asif and Searcy, 2014), allowing a synergistic approach to present and future sustainability (Geissdoerfer *et al*., 2017). The business environment has indeed become increasingly dynamic, reflecting not only economic but also increased social and environmental pressures (Ciffolilli and Muscio, 2018; Ben-Daya *et al*., 2019). Yet, traditional production models have frequently neglected these social and environmental dimensions (Bai *et al*., 2020).

In contrast and in response to this transformation, two paradigms have emerged in the manufacturing scenario: Industry 4.0 (I4.0) and Lean Manufacturing (LM). Coined by the German government, I4.0 refers to a suite of digital technologies including robotics, artificial intelligence (AI), machine learning (ML), and the Internet of Things (IoT) that are reshaping industrial processes (Kagermann *et al*., 2013; Vashishth *et al*., 2024; Khanuja *et al*., 2024). These technologies enhance data-driven decision-making, predictive capabilities, and process optimization, thereby supporting both efficiency and environmental sustainability (Beltrami *et al*., 2021; Schwab, 2017; Nara *et al*., 2021; Ansari *et al*., 2025).

LM, on the other hand, challenges traditional manufacturing by treating inventory as waste and focusing on Lean principles such as waste elimination, demand prediction, and operational excellence (Gupta and Jain, 2013; Cezar Lucato *et al*., 2014; Jum'a *et al*., 2022). It relies on continuous improvement and total employee involvement to boost performance and eliminate inefficiencies (Singh and Singh, 2024; Tasdemir *et al*., 2018; Singh *et al*., 2018), placing strong emphasis on human factors as a key element for organizational sustainability (Ghaitan *et al*., 2021).

Although the integration of I4.0 and LM is increasingly acknowledged for its positive effects on economic and environmental performance, the social dimension of sustainability, which is central to the Triple Bottom Line framework, remains relatively underexplored. Nevertheless, this integration holds significant potential to improve workplace conditions, ensure fair labor practices, and enhance community well-being (Kamble *et al*., 2020; Kolberg and Zühlke, 2015). In this regard, the literature highlights the importance of adopting human-centered approaches within LM (Sawhney and Chason, 2005; de Treville and Antonakis, 2006; Rother, 2010) and underscores the crucial role of employee behavior in determining the success of digital transformation initiatives (Alieva and Powell, 2022; Olsson *et al*., 2024).

Despite extensive studies on the economic and environmental outcomes of these paradigms, their impact on social sustainability remains insufficiently addressed (Ghaithan *et al*., 2023). This study seeks to bridge that gap by investigating how the convergence of I4.0 technologies and LM practices can enhance the social dimension of sustainability in manufacturing contexts.

1.1 Research gap and RQ

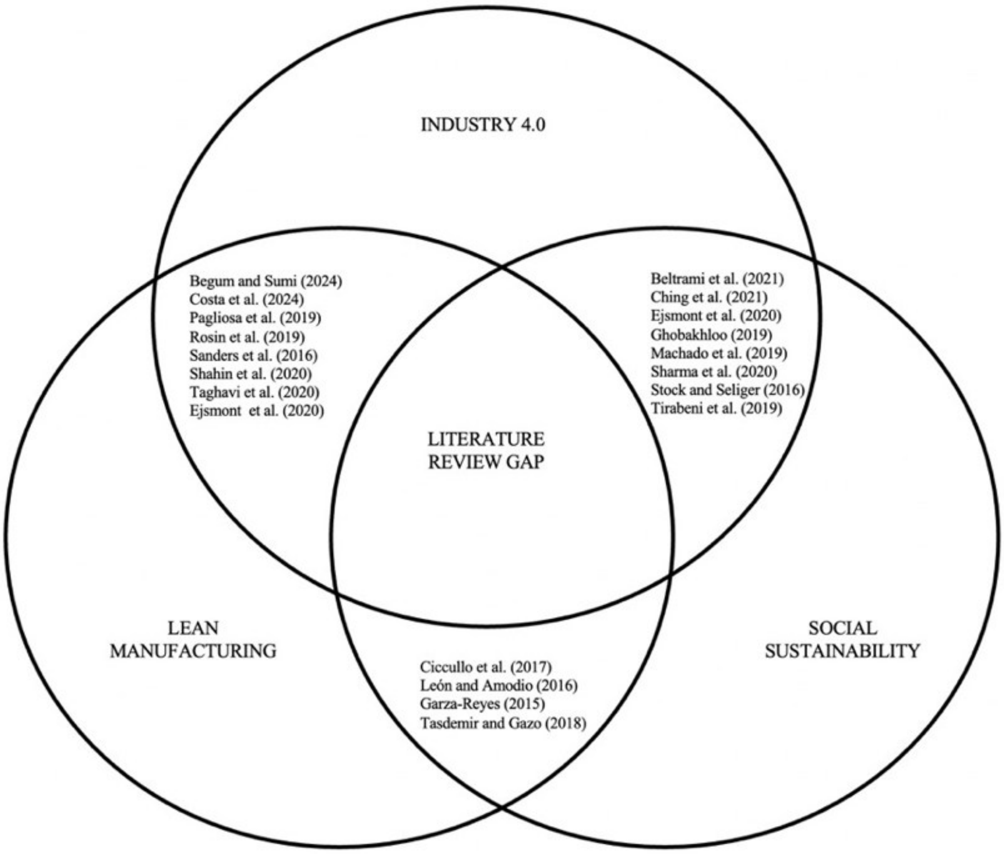
Manufacturing companies today pursue dual goals: promoting economic advancement and enhancing internal social welfare, while safeguarding environmental sustainability to ensure long-term viability (Abreu *et al*., 2021; Kumar *et al*., 2022). In this context, I4.0 and LM have emerged as key paradigms, introducing managerial innovations that are reshaping business operations. This literature review is motivated by the need to explore the interplay between LM, I4.0, and the social dimension of sustainability, an area still under-investigated despite its relevance.

Although scholarly interest in the relationship between Lean and sustainability has grown, most studies fail to fully incorporate the TBL framework, often relegating the social pillar to the background (León and Amodio, 2016). In particular, research tends to privilege economic and environmental aspects, while the social implications of I4.0 remain largely superficial (Magruk, 2016). Significant contributions by Beltrami *et al*. (2021), Ching *et al*. (2021), Ejsmont *et al*. (2020), and Machado *et al*. (2019) deepen our understanding of how I4.0 influences sustainability performance, yet give limited attention to its social impact. Similarly, contributions by Costa *et al*. (2024), Pagliosa *et al*. (2019) and Rosin *et al*. (2019), provide comprehensive models connecting LM and I4.0, but often fall short of analyzing their effects on social sustainability.

On the other hand, reviews by Garza-Reyes (2015) and Tasdemir and Gazo (2018) focus on Lean-sustainability synergies, evaluating how Lean supports sustainable initiatives. However, even these studies tend to address the social dimension only marginally, as a secondary element within broader sustainability discussions.

To the best of the authors' knowledge, no previous literature review has holistically examined the integration of LM practices, I4.0 technologies, and the social sustainability dimension (see Figure 1). This systematic literature review (SLR) aims to fill that gap by exploring the synergies between technological and managerial innovations and their implications for the social pillar of sustainability. The review offers a novel perspective, revealing overlooked interconnections and contributing to a more integrated understanding of sustainable industrial development.

Figure 1. Research gap in Literature reviews.



Source: Author's own elaboration.

Consequently, the research question guiding this investigation is:

RQ: What is the effect of I4.0 tools and LM practices on the social sustainability functions?

Addressing this question requires, first, clarifying how the social dimension of sustainability has been conceptually and empirically treated in previous research, and second, identifying how the interactions between I4.0 and LM shape social outcomes in organizational contexts. Rather than assuming predefined categories, this study adopts an inductive approach in which social sustainability functions emerge from the systematic analysis of the reviewed literature. These functions will then serve as analytical anchors to examine the effects of technological and managerial practices on the social pillar of sustainability. Specifically, the term social sustainability functions denotes the organizational and relational mechanisms through which the social dimension of sustainability becomes operational within industrial systems (Dempsey *et al*., 2011; Papetti *et al*., 2020; Asokan *et al*., 2022). Rather than representing abstract ethical values, these functions constitute the dynamic processes, practices, and interactions that mediate between technological and managerial innovations and employees' lived experiences in the workplace. Conceptually, they can be understood as the functional expressions of social sustainability: they translate the normative intent of the social pillar (e.g., equity, well-being, participation) into observable organizational behaviors and outcomes. They encompass both structural dimensions (e.g., communication flows, participatory structures) and behavioral dimensions (e.g., empowerment, motivation, trust), thus linking operational practices to human-centered performance.

From an analytical point of view, identifying these functions enables the systematic examination of how I4.0 and LM jointly shape social outcomes, clarifying not only what aspects of social sustainability are affected, but also through which organizational mechanisms such effects materialize. Accordingly, these functions serve as interpretive lenses that reveal the ways in which digital transformation and lean management contribute - positively or negatively - to the construction of socially sustainable industrial ecosystems.

With this in mind, to address the RQ, the article adopts a SLR methodology, widely recognized for its ability to structure research fields, consolidate theory, and ensure methodological transparency and rigor (da Cunha Bezerra *et al*., 2020; Tranfield *et al*., 2003).

The article is organized as follows: Section 2 details the methodological approach; Section 3 presents the findings and analysis; Section 4 discusses the development of a comprehensive framework; Section 5 outlines future research directions while the final section summarizes conclusions, limitations, and implications.

2. METHODOLOGY

This study adopts a SLR methodology to analyze publication trends, relevant research outlets, and methodological approaches, while identifying I4.0 technologies and LM tools that influence social sustainability functions. The SLR method is particularly suited to exploring emerging or under-defined research areas (Toth-Peter *et al*., 2023), offering a structured and replicable process for selecting, reviewing, and evaluating the existing body of knowledge (Ghobakhloo *et al*., 2021; Rousseau *et al*., 2008).

The review was conducted in seven main phases: (i) definition of objectives, (ii) keyword selection, (iii) database identification, (iv) development of inclusion and exclusion criteria, (v) screening, (vi) data extraction, and (vii) analysis.

To identify literature relevant to the intersection of I4.0, LM, and social sustainability, a BooLean search string was constructed using combinations such as ("industry 4.0" OR "smart industry" OR "advanced manufacturing" OR "smart manufacturing" OR "fourth industrial revolution") AND ("sustainability" OR "sustainable" OR "TBL" OR "social sustainability") AND ("Lean" OR "Lean manufacturing" OR "Lean production"). This formulation reflects regional variations in terminology, e.g., “Industry 4.0” in Europe versus “advanced manufacturing” in the Americas and Asia (Ejsmont *et al*., 2020), and thus integrates synonyms for broader coverage (Gupta *et al*., 2022). The search was limited to publications from 2011 onward, corresponding to the introduction of the term “Industry 4.0” (Kagermann *et al*., 2013; Núnez-Merino *et al*., 2020), and aligned with prior SLRs in the field (Yilmaz *et al*., 2022; Kaswan *et al*., 2022).

The databases selected were Web of Science (searching abstract and title) and Scopus (abstract, title, and keywords), chosen for their comprehensiveness and methodological reliability (Aghaei *et al*., 2013; Guz *et al*., 2009), as well as their frequent use in systematic reviews (e.g., Gallo *et al*., 2021; Yilmaz *et al*., 2022). These databases host a wide range of high-impact, peer-reviewed journals across disciplines, which enhances the validity of the review (Schätzlein *et al*., 2023).

In line with Levy and Ellis (2006) and Thomé *et al*. (2016), we applied exclusion criteria to remove duplicates and non-English publications, with detailed criteria listed in Table 1. Inclusion and exclusion filters were adapted from Lobo Mesquita *et al*. (2022). Consistent with Yilmaz *et al*. (2022), the review focused exclusively on the manufacturing context; articles not addressing this sector were excluded. Filters were applied to include only documents categorized under “Business,” “Management and Accounting,” “Social Science,” “Economics,” and “Econometrics and Finance.”

Table 1. Inclusion and exclusion criteria.

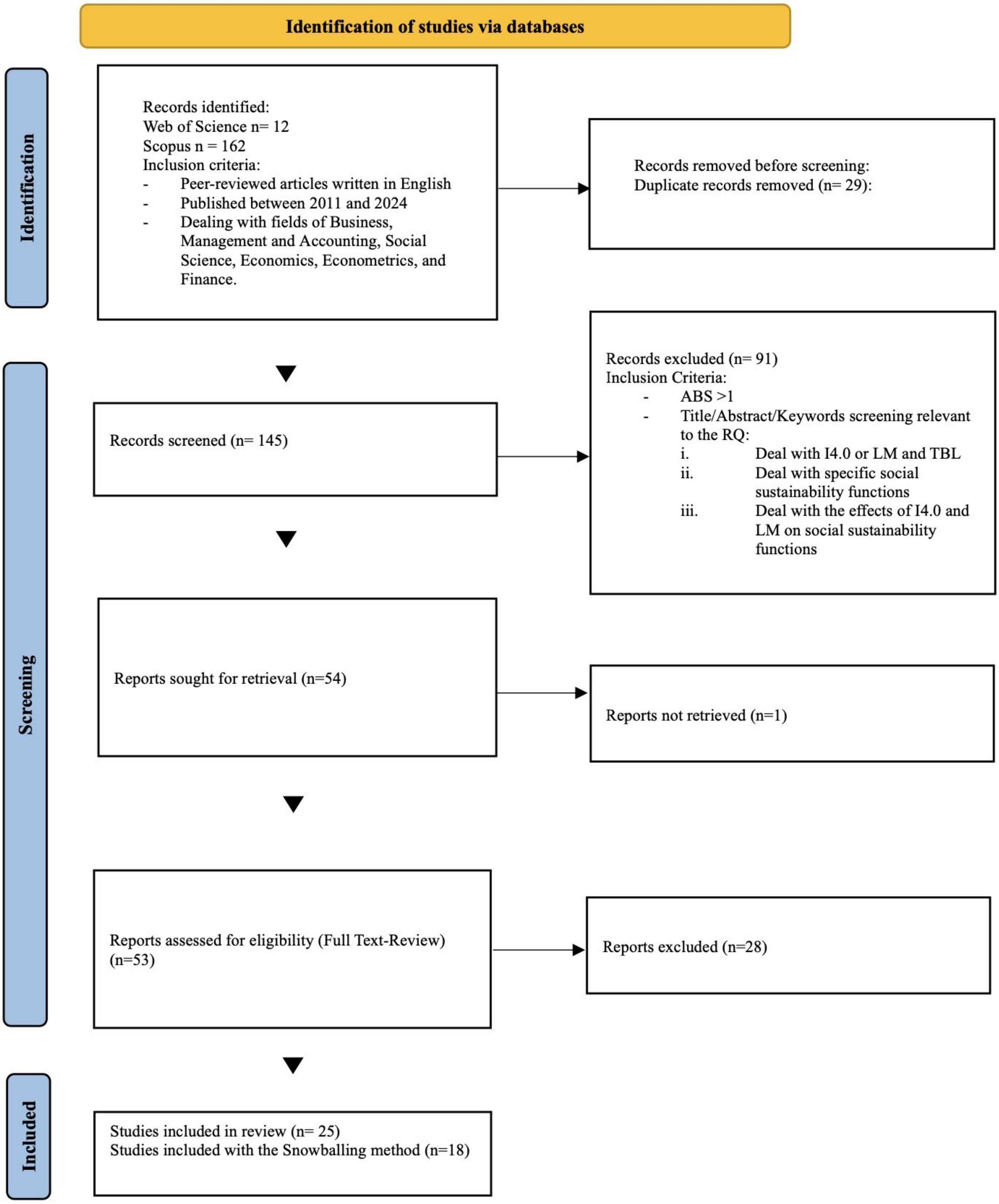
TOPIC	INCLUSION CRITERIA	EXCLUSION CRITERIA	RATIONALE
PERIOD	Published between 2011 and 2024.	Published before 2011.	This time interval has been considered appropriate to capture the specific trends referred to under the notion of "I4.0". (Kagermann *et al*. 2013; Núnez-Merino *et al.,* 2020).
SOURCE	Peer-reviewed journal articles.	Other types of documents (e.g., conference papers; books; book chapters; editorials, letters).	The focus on peer-reviewed journal articles ensures a high level of academic rigor and reliability in the sources used and it has already been done by other SLRs (e.g. Citybabu and Yamini, 2024).
THEME	Environmental, Social, or Economic sustainability; I4.0 technology or dimensions; LM/thinking.	Lean with other meanings (e.g., Lean mass).	Ensures thematic alignment with the study's focus on sustainability, including the social dimension.
FOCUS	Papers that deal with the relationships between LM, I4.0, and Social Sustainability.	Papers not addressing these relationships.	This choice aligns with the research question investigating the interplay between these three domains.
SECTOR	Business, Management and Accounting, Social Science, Economics, Econometrics, and Finance.	Sectors other than the included ones.	This selection reflects the study's targeted analysis of the manufacturing sector and its related disciplines.

Source: Author's own elaboration.

The initial search retrieved 12 articles from Web of Science and 162 from Scopus. After removing duplicates, 145 records remained. We selected papers from journals with an ABS ranking >1 to ensure a minimum level of quality. Following Martiny *et al*. (2024), unranked but relevant journals were also considered to avoid selection bias. A preliminary review of titles, abstracts, and keywords narrowed the list to 54 potentially relevant articles. One study was excluded for treating social sustainability too generically, leaving 53 articles for full review. During the screening phase, 28 papers were excluded as they did not explicitly address the social dimension of sustainability. Although many discussed sustainability in general terms, often focusing on environmental or economic outcomes, their content lacked clear reference to human-centric aspects such as occupational safety, employee well-being, participation, or ethical management. This decision is consistent with best practices in SLRs that advocate thematic alignment between research objectives and inclusion criteria (Tranfield *et al*., 2003; Thomé *et al*., 2016). An additional 18 articles were identified through snowballing, for a final corpus of 43 studies. These were chosen for their capacity to explain the specific effects of I4.0 and LM on social sustainability in manufacturing and to inform the development of a comprehensive framework.

The full process is illustrated in the PRISMA flow diagram in Figure 2**.**

Figure 2. PRISMA flowchart adapted from Martiny *et al*. (2024).



Source: Author’s own elaboration.

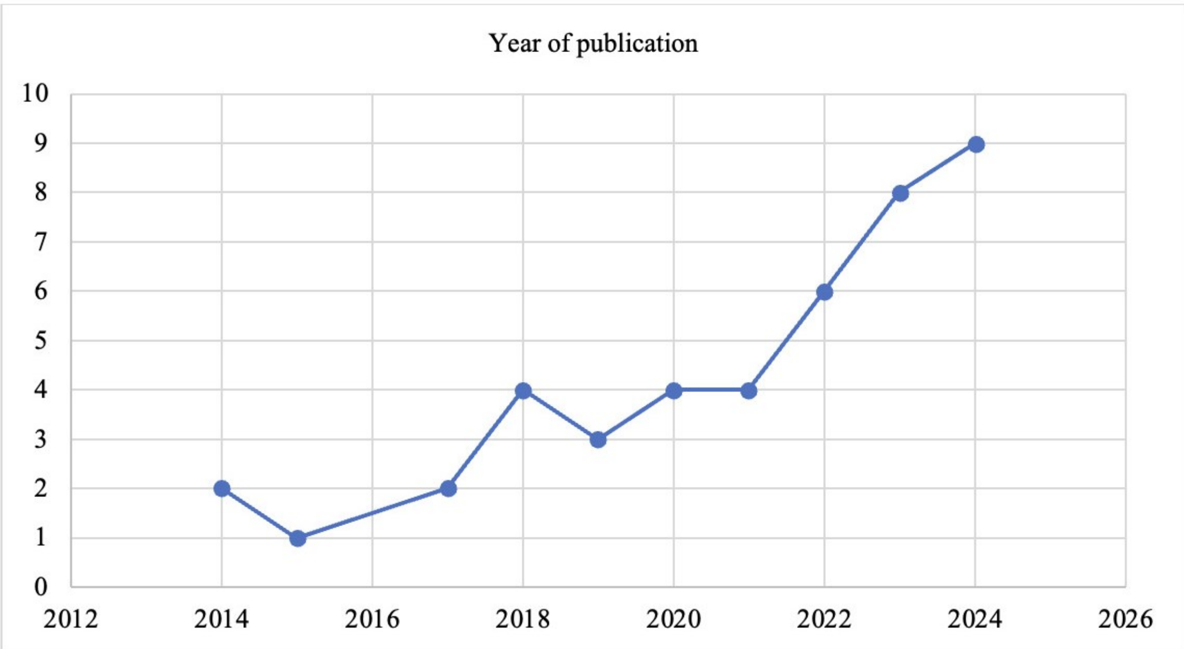
3. RESULTS AND ANALYSIS

This SLR addresses the RQ through two complementary analyses: (i) quantitative analysis examining research growth, publication sources, and methodological trends, and (ii) qualitative analysis identifying social sustainability functions, I4.0 technologies, and LM tools in manufacturing to understand their impact on social outcomes.

3.1 Quantitative analysis

This section examines the bibliometric characteristics of the 43 selected papers, outlining key research trends on I4.0, LM, and social sustainability. As shown in Figure 3, scholarly interest has increased steadily, with a significant rise after 2020. This trend is likely linked to the COVID-19 pandemic, which accelerated the adoption of automation and IoT to ensure industrial continuity (Bhatia and Diaz-Elsayed, 2023; Costa Melo *et al*., 2023). Although I4.0 was first introduced in 2011 (Kagermann *et al*., 2013), sustainability-oriented research only gained momentum from 2014, as national and industrial digitalization initiatives began to incorporate sustainability targets (Machado *et al*., 2020). The timeline suggests a progressive convergence between technological innovation, Lean practices, and sustainability goals.

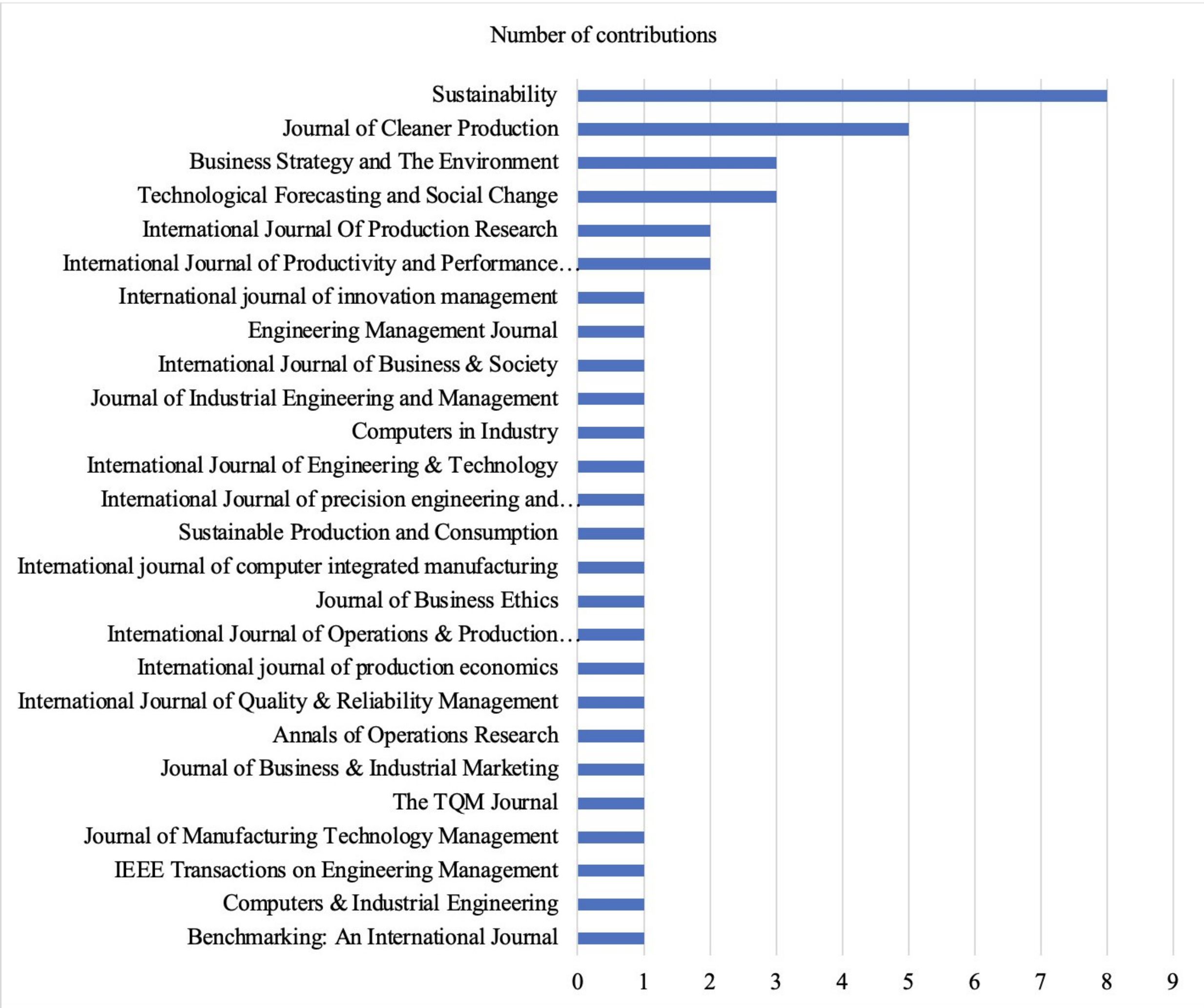
Figure 3. Contributions published between 2011 and 2024.



Source: Author's own elaboration.

The journal distribution (Figure 4) reveals that most contributions were published in *Sustainability* (8 papers), which focuses on digital technologies and their sustainability applications (Ejsmont *et al*., 2020), and in the *Journal of CLeaner Production* (6), which emphasizes environmental management and sustainable production strategies. Other journals contributed one or two articles each, demonstrating the interdisciplinary nature of this research area. These include topics such as sustainable operations, green innovation, and industrial transformation, confirming the wide academic interest in integrating I4.0 and LM into sustainability discourses (Toth-Peter *et al*., 2023).

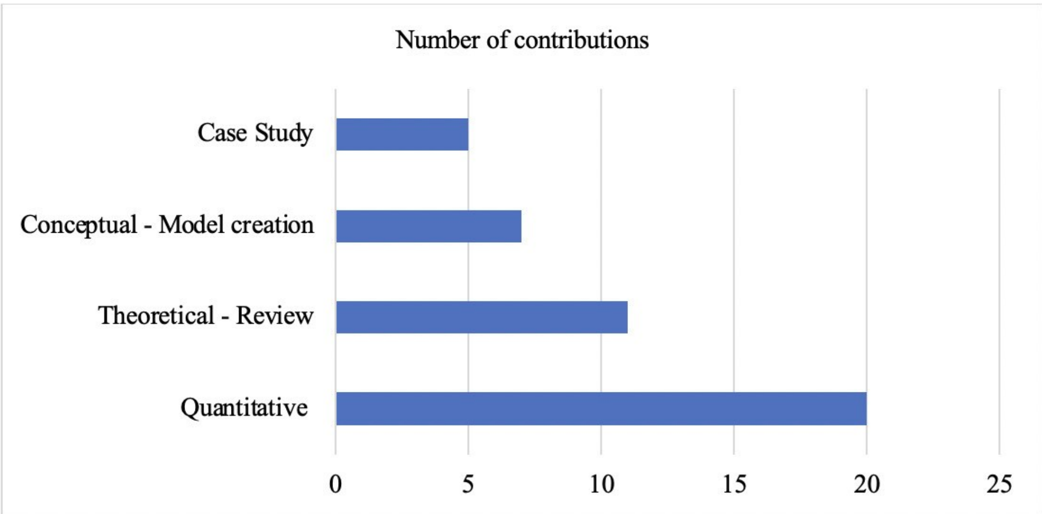
Figure 4. Publication outlets.



Source: Author’s own elaboration.

Methodologically, the corpus of 43 papers exhibits a heterogeneous composition, which provides complementary yet distinct insights into the integration of LM and I4.0. Specifically, 11 studies adopt a review-based approach (systematic or narrative), 7 propose conceptual or theoretical frameworks, and 25 report empirical evidence through quantitative surveys, case studies, or mixed methods, as summarized in Figure 5. This distribution illustrates a research field still in consolidation, where theoretical propositions increasingly inform empirical inquiry but remain only partially validated by data. Conceptual works typically emphasize the synergies between digitalization and Lean principles, while empirical studies examine how these interactions translate into tangible organizational outcomes such as enhanced safety, communication, and employee involvement. The dominance of quantitative approaches reflects the metric-driven nature of I4.0 and LM, which often rely on productivity and sustainability indicators. However, the limited number of case studies highlights a gap in exploring organizational and cultural dimensions, while the relatively few conceptual papers suggest the need for more robust theoretical integration. This imbalance calls for future research to adopt different methodological approaches to capture the complex interplay between technologies, managerial practices, and social outcomes.

Figure 5. Type of conducted studies.



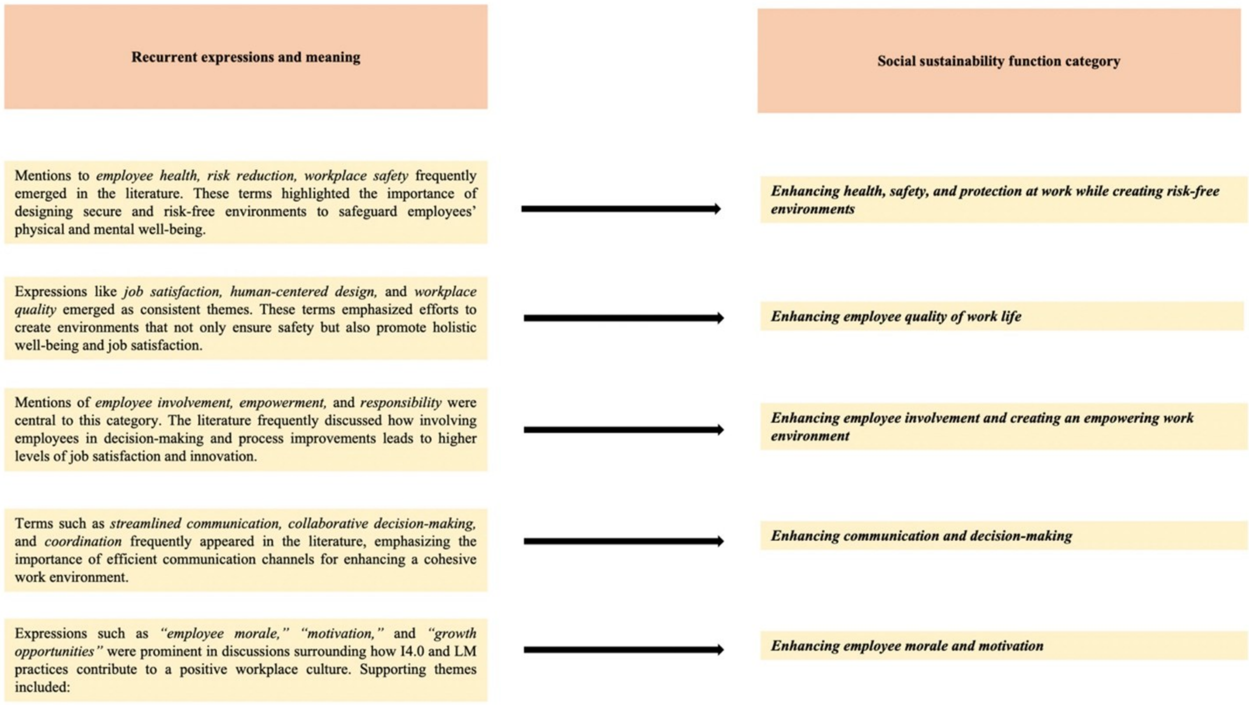
Source: Author’s own elaboration.

3.2 Qualitative analysis

A detailed qualitative analysis was conducted on the articles to identify the main social sustainability functions influenced by I4.0 and LM practices. The process involved four key steps: i) identification of recurring themes through a systematic analysis of frequently mentioned employee-focused sustainability terms, such as “well-being”, “motivation”, “participation”, “safety”, and “quality of work life”. These terms acted as conceptual anchors; ii) grouping and categorization when related concepts were organized into broader social sustainability categories. For instance, references to “employee empowerment” and “responsibility” were synthesized under the broader category of “enhancing involvement”. Similarly, mentions to “workplace safety” and “ergonomics” were grouped into a unified category focusing on safety and health; iii) validation of functions when the preliminary categories were cross-checked with the literature to ensure alignment with the primary social sustainability themes; iv) final categorization into five key social functions shaped by I4.0 and LM integration thanks to the iterative review process.

Figure 6 illustrates this process, mapping recurring expressions to the final social sustainability categories.

Figure 6. Derivation and categorization of expressions into social sustainability's functions.



Source: Author's own elaboration.

3.2.1 Social sustainability functions

Social sustainability functions are defined as social objectives that businesses can achieve using I4.0 tools and LM practices. Social sustainability aims to create healthy and livable communities where everyone is protected from discrimination and has access to universal human rights and basic amenities such as security or healthcare (Dempsey et al., 2011). This concept includes employee well-being, inclusivity, customer satisfaction, ethical business conduct, and workforce involvement (Asokan et al., 2022), improving workplace conditions, occupational health and safety, human-centered job design, and skill development (Papetti et al., 2020). The following sub-sections outline the social sustainability functions identified in the review, shaped by LM practices and I4.0 technologies.

Enhancing health, safety, and protection at work while creating risk-free environments.

The social dimension of sustainability emphasizes enhancing employee health and safety by designing work environments that minimize risks and accidents. The literature strongly supports the critical role of I4.0 technologies and LM practices in achieving this objective. Ghaithan *et al.* (2021) highlight that LM acts as a mediating variable, amplifying the impact of I4.0 technologies on sustainability performance by prioritizing the human factor. This dual approach contributes to organizational and social sustainability by emphasizing employee protection at work. For instance, delegating physically demanding and hazardous tasks to robots enhances both safety and operational efficiency. The integration of augmented reality further strengthens this shift by improving safety, process management, and quality control (Ramirez-Peña *et al*., 2020). Saha *et al*. (2023) underscore that improving workplace safety, providing tailored training, and offering incentives within LM practices directly contribute to sustainability by ensuring a secure and rewarding working environment. Furthermore, Eskandari *et al*. (2022) emphasize that LM practices enhance social sustainability by improving workplace conditions through better safety protocols, comprehensive employee training programs, and well-designed incentive structures. Similarly, I4.0 tools play a key role in enhancing safety measures, optimizing working conditions, and ultimately supporting the physical and mental well-being of employees (Brozzi *et al.,* 2020). These advancements demonstrate the potential of combining innovative technologies and Lean strategies to create a safer, risk-free work environment.

Enhancing employee quality of work life.

The enhancement of quality work-life conditions is another critical function emerging from the integration of I4.0 technologies and Lean practices. Ciano *et al*. (2019) demonstrate that comprehensive quality management initiatives significantly improve workers' overall quality of work life. In this context, the use of autonomous robots within the I4.0 framework serves as a crucial variable, exerting a strong influence on organizational outcomes. The adoption of value stream mapping (VSM) combined with simulation techniques has proven effective in improving work quality and minimizing workplace accidents (Varela *et al.,* 2019). Dotoli *et al*. (2014) identify Value Stream Mapping (VSM) as a key Lean tool for optimizing supply policies between workstations, thereby enhancing safety, efficiency, and overall working conditions. Collectively, these strategies contribute to the creation of a healthier and more satisfying work environment, ultimately improving employees' quality of life.

Enhancing employee involvement and creating an empowering work environment.

The empowerment of employees and their active involvement in workplace improvement initiatives are central to socially sustainable practices. VSM 4.0 processes demonstrate their ability to empower employees by encouraging them to take responsibility for process improvements (Citybabu and Yamini, 2024). Through continuous improvement initiatives, Lean techniques further enhance job satisfaction and a sense of empowerment among workers (Beraldin *et al*., 2019). The integration of big data analytics (BDA) strengths this dynamic by improving flexibility and employee commitment (de Mattos Nascimento *et al*., 2024). Additionally, the Industrial Internet of Things (IIoT) facilitates optimized human–machine interactions, significantly enabling greater employee involvement (Kiel *et al.,* 2017). Collectively, these strategies contribute to creating an empowered and inclusive workplace, inspiring staff members to actively participate in the company's growth and innovation.

Enhancing communication and decision-making.

Improved communication and streamlined decision-making processes are central benefits of integrating I4.0 technologies and Lean practices. Tools such as VSM and simulation technologies enhance communication channels across departments, organizations, and workers. For instance, simulation techniques generate diverse scenarios and provide alternative solutions, aiding decision-making processes and reducing organizational hierarchy (Citybabu and Yamini, 2024). Additionally, the VSM tool enables the visualization of information flows, material flows, and communication pathways, further strengthening interdepartmental and intradepartmental coordination (Ishak *et al*., 2018). I4.0 technologies complement these tools by establishing robust communication networks across horizontal and vertical value streams, resulting in a more transparent, efficient, and collaborative organizational environment. This integrated approach promotes both social and operational sustainability.

Enhancing employee morale and motivation.

The implementation of Lean Six Sigma (LSS) and I4.0 technologies has been shown to significantly enhance employee morale and well-being. These technologies create opportunities for workers to achieve personal and professional growth by enabling access to competitive jobs, fair pay, and meaningful work. Employees feel more accomplished and motivated to contribute to long-term organizational success (Citybabu and Yamini, 2024). By offering relevant education, skills training, and knowledge development, LSS 4.0 technologies enhance employee capabilities while simultaneously increasing social protection. Ergonomics-based principles further improve work performance, while virtual environments facilitated by I4.0 technologies enable accident-free training, better skill development, and enhanced worker safety. This approach cultivates a culture of safety and well-being, reducing absenteeism and workplace illnesses (Kumar *et al*., 2024). Kamble *et al*. (2018) highlight how I4.0 technologies help create more satisfying work conditions, improving both employee motivation and morale. Ultimately, these advancements promote a healthier, more empowered, and more productive workforce.

4. SYNERGISTIC EFFECTS OF I4.0 TOOLS AND LM PRACTICES ON SOCIAL SUSTAINABILITY FUNCTIONS

The integration of I4.0 technologies and LM practices significantly contributes to social sustainability by improving workplace safety, employee empowerment, well-being, and communication. Table 2 summarizes the key social functions impacted, alongside the related technologies and tools.

I4.0 technologies play a crucial role in promoting worker health, safety, and overall well-being. Big BDA supports ethical conduct (Bag *et al*., 2023), while simulation tools assess risks to design safer environments (Citybabu and Yamini, 2024). Augmented Reality (AR) enhances safety and quality in processes (Mukhuty *et al*., 2022), and IoT improves working conditions. Robotic Systems and AI automate hazardous tasks, thereby enhancing decision-making, safety, and satisfaction (Makridis and Han, 2021). Digital Twins (DT) enable continuous monitoring, reinforcing safe operations (Hallioui *et al*., 2023). These technologies create safer, more modern workplaces, boosting morale and motivation (Herrmann *et al*., 2014). In addition, the learning curve associated with I4.0 increases employee engagement, skills, and sense of purpose (Mukhuty *et al*., 2022; Kamble *et al*., 2018).

LM practices similarly strengthen social sustainability by creating safer and more empowering work environments. Beyond eliminating waste, they promote worker participation and responsibility in continuous improvement (Beraldin *et al*., 2019; Hao *et al*., 2021). Tools like Kanban, Value Stream Mapping (VSM), and Total Productive Maintenance (TPM) reduce risks and improve process flow. Kaizen and 5S enhance safety and efficiency (Abdullah *et al*., 2023), while JIT and 5Whys improve problem-solving and well-being (Shaharudin *et al*., 2022). Green Lean Six Sigma (Green LSS) introduces long-term environmental and safety benefits (Kaswan *et al*., 2022), and VSM further facilitates communication (Ishak *et al*., 2018). Kaizen, 5Whys, and VSM jointly contribute to risk identification, workflow refinement, and continuous improvement (Mirghafoori *et al*., 2018), consolidating LM's impact on worker protection.

The synergy between I4.0 and LM tools further amplifies their effects. For example, combining simulation tools with VSM enhances collaboration, decision-making, and communication (Citybabu and Yamini, 2024; Dotoli *et al*., 2014). LSS paired with AR and VR strengthens training and safety protocols, while I4.0 tools improve LM implementation, raising job satisfaction and work quality (Kamble *et al*., 2020). BDA and IoT enhance LM's performance in health and safety management (Ghaithan *et al*., 2021). AR-supported Kaizen improves precision and fault reduction (Kaswan *et al*., 2022), and IoT or Robotic Systems integrated with tools like SMED streamline processes while prioritizing well-being (Fonda and Meneghetti, 2022).

Ultimately, integrating LM and I4.0 optimizes operations and elevates key social functions such as safety, empowerment, and communication. This convergence boosts organizational agility, reduces ambiguity, and nurtures a motivated, resilient workforce. The literature confirms that LM's emphasis on training, incentives, and safety, combined with I4.0 innovation, lowers injury rates, absenteeism, and dissatisfaction (Eskandari *et al*., 2022; Wadood *et al*., 2022). These outcomes extend beyond the organization, advancing societal sustainability through improved health, reduced waste, and employment stability (Camuffo *et al*., 2017; Hao *et al*., 2021). The combined approach creates a human-centered vision of innovation, where technology and continuous improvement jointly enhance social sustainability.

Table 2. Sustainability functions integrated with I4.0 technologies and LM practices.

REFERENCE[10]	**SOCIAL SUSTAINABILITY FUNCTION**					**I4.0 TECHNOLOGY**	**LM PRACTICE**	**RESULTS**
	EHS	**QWL**	**EIE**	**CDM**	**EMM**			
Dotoli *et al.* (2014)	x	x				/	VSM	The use of VSM with simulation improves work quality and reduces accidents
Hermann *et al.* (2014)					x	CPS	/	I4.0 enhances learning opportunities, boosting employee motivation.
Ng *et al.* (2015)	x	x				/	5S; OEE; VSM; KAIZEN	Companies benefit from safer conditions, better skills, higher employability, stronger team spirit, trust, and a sense of accomplishment.
Camuffo *et al.* (2017)	x	x				/	JIT; SMED; TPM; SPC; OEE	LM minimizes waste and enhances occupational health and safety, improving workers' living conditions.
Kiel *et al.* (2017)	x	x	x			IoT	/	Optimized human-machine interaction and advanced safety features improve work quality and employee involvement.
Ishak *et al.* (2018)				x		/	VSM; 5S; KAIZEN	VSM improves communication by mapping information, material, and workflow.
Kamble *et al.* (2018)	x				x	IoT; RS; CPS; RFID	/	I4.0 enhances work conditions, provides safety, and boosts motivation.
Mirghafoori *et al.* (2018)	x						5Whys	5Whys helps implement solutions that improve employee well-being and safety.
Souza *et al.* (2018)	x						JIT; VSM	LM minimizes waste reduction, better health, and improved societal living conditions.
Beraldin *et al.* (2019)			x			/	JIT	Worker engagement, training, and continuous improvement in LM boost well-being, job satisfaction, and empowerment.
Ciano *et al.* (2019)		x	x					Total quality management improves workers' quality of life at work.
Varela *et al.* (2019		x				RS		Autonomous Robots significantly enhance working conditions.
Bai *et al.* (2020)	x					AM; AI; AR; RS; BDA; Blockchain; CC; CSS; IoT; RFID; Sensors; Simulation		I4.0 improves workplace conditions, well-being, and safety.
Brozzi *et al.* (2020)			x					I4.0 technologies support LM processes, enhancing social sustainability.

[10] Entries are sorted chronologically and then by first author.

Kamble *et al.* (2020)	x	x			x	BDA; CC; IoT; Sensors; Simulation; AM; VR; AR; IoT; RS; CPS; CSS	SF; JIT; SD; CI; PS; CF; STR; TPM; SPC; EI	I4.0 technologies facilitate LM processes, and finally improve the social dimension of sustainability.
Ramirez-Peña *et al.* (2020)	x					BDA; IoT; AI; RS; AR		Factories become safer and more efficient when robots handle hazardous tasks; AR enhances safety, quality, and process management.
Ganjavi and Fazlollahtabar (2021)	x		x	x			5S; KAIZEN; LSS; POKA-YOKE; TPM; KANBAN; VSM	Practices improve worker and community safety.
Ghaithan *et al.* (2021)	x				x	IoT; BDA; AM; RS; AR; CC	SF; JIT; SD; CUSTOMER INVOLVEMENT; PS; CF; STR; TPM; SPC; EI	LM amplifies I4.0's impact on social sustainability.
Hao *et al.* (2021)	x							Reducing waste and improving workplace safety enhances societal living conditions.
Makridis and Han (2021)	x				x	AUTOMATION; AI		Automation and AI reduce tedious tasks, improving job satisfaction and well-being.
Eskandari *et al.* (2022)	x	x						LM enhances social sustainability by improving safety, training, and incentives.
Fonda and Meneghetti (2022)	x						SMED	SMED improves worker safety, productivity, and engagement by fostering well-being initiatives.
Kaswan *et al.* (2022)	x					BDA; AR; Sensors; AM	POKA-YOKE; JIDOKA; GREEN LSS; KAIZEN; VSM 4.0	Kaizen, Poka-yoke, and Jidoka ensure long-term safety and process reliability.
Mukhuty *et al.* (2022)	x					RS; IoT; BDA; Blockchain		I4.0 enhances well-being and job security, improving social performance.
Shaharudin *et al.* (2022)	x						KAIZEN; Gemba; 5Whys	KAIZEN, Gemba, and 5Whys foster a culture of continuous improvement, enhancing worker safety, well-being, and social responsibility.
Yilmaz *et al.* (2022)	x		x	x		Simulation; RS; IoT; RFID; CPS	JIT; KANBAN; ANDON; VSM; HEIJUNKA	Improving employee welfare reduces workplace accidents.
Abdullah *et al.* (2023)	x					BDA; AM; RS; IoT; AI; ML; CC	Kanban; VSM; SMED; SW; LSS; KAIZEN; TPM; 5S	SMEs enhance social sustainability using I4.0 and LM methodologies.

Bag *et al.* (2023)		x				BDA		BDA improves ethical behavior and improves workforce conduct.
Benkhati *et al.* (2023)	x		x			BDA; AM; IoT; ML	JIT; VSM	LM reduces hazards, improving social performance.
Fiorello *et al.* (2023)		x				IoT; RS; AR; VR; DT; CC; AI; ML	JIT; KANBAN; SMED; TPM; KAIZEN; TQM; VSM; SW; POKA-YOKE; JIDOKA	Smart-Lean methods show minimal impact on work quality improvement.
Hallioui *et al.* (2023)	x			x	x	DT; AI	5S; SUSTAINABLE TPM	DT and AI contribute to sustainability and operator safety.
Maware and Parsley (2023)	x	x			x	CC; BDA; IOT; AM; RS; AR.	SPC; TPM; EI; PS; STR	I4.0 indirectly boosts social sustainability through LM mediation.
Saha *et al.* (2023)	x	x				BDA; IoT	JIT	LM, through safety, training, and incentives, strengthens social sustainability, with I4.0 reinforcing the effect.
Wadood *et al.* (2023)	x						KAIZEN	LM practices like KAIZEN and equipment management reduce injuries, enhancing health and safety.
Aljuaid *et al.* (2024)	x					RS; AM; AI; IoT		Localized production integrated with I4.0 increases safety and protection.
Citybabu and Yamini (2024)	x		x	x		Simulation; BDA; IoT; CPS; RFID; AR; VR; RS	VSM; Kanban; LSS; JIT; TPM	VSM and I4.0 improve communication, reduce hierarchy, and support decision-making. LSS 4.0 enhances motivation, skills, and accident-free training while reducing absenteeism.
Citybabu and Yamini (2024)		x				Simulation; AR; VR	KAIZEN	VSM 4.0 and KAIZEN encourage employee responsibility in workplace improvements.
Díaz-Reza *et al.* (2024)	x	x	x				KAIZEN; Gemba; 5Whys	KAIZEN creates a safe, healthy, and equitable work environment.
de Mattos Nascimento *et al.* (2024)	x					BDA		BDA reduces waste and fosters employee empowerment and flexibility.
Kumar *et al.* (2024)	x				x	BDA; IoT; CC; CPS.	LSS	BDA reduces waste and fosters employee empowerment and flexibility.
Sahoo and Upadhyay (2024)	x	x					LSS	In terms of social performance, the impact of LSS appears to be not very significant on the employee well-being dimension
Sharma *et al.* (2024)		x						The relationship between LM and the social dimension is significant.
Skalli *et al.* (2024)	x					BDA; CPS; Simulation; CC; AR; AM; CSS; RS;	LSS	LSS and I4.0 have a positive effect on social dimension

						horizonal/vertical integration		

Source: Author's own elaboration.

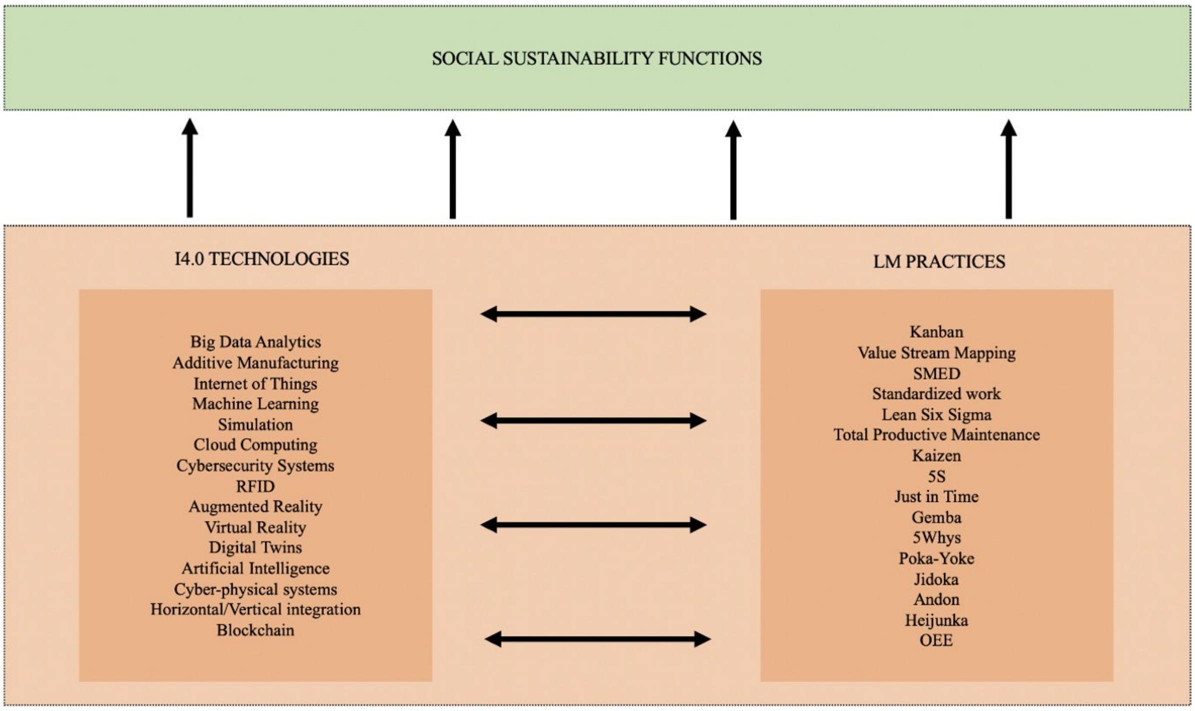
*__Industry 4.0 technologies:__ BDA= Big Data Analytics; AM= Additive Manufacturing; RS= Robotic Systems; IoT= Internet of Things; ML= Machine Learning; CC= Cloud Computing; AR= Augmented Reality; RFID= Radio Frequency Identification; VR= Virtual Reality; CPS= Cyber-physical systems; DT= Digital Twin; CSS= cyber-security systems; IIoT= Industrial Internet of Things. **LM practices**: VSM= Value-Stream Mapping; SMED=Single Minute Exchange of Die; SW= Standardized Work; LSS= Lean Six Sigma; TPM= Total Productive Maintenance; JIT= Just-in-Time; TQM= Total Quality Management; VPM= Visual Performance Measures; SF= Supplier Feedback; SD= Supplier Development; PS= Pull System; CF= Continuous Flow; EI= Employee Involvement; CI= Customer Involvement; STR= Setup Time; Reduction; SPC= Statistical Process Control; OEE Overall Equipment Effectiveness. **Social Sustainability Functions:** EHS= Enhancing health, safety, and protection at work while creating risk-free environments; QWL= Enhancing employee quality of work life; EIE= Enhancing employee involvement and creating an empowering work environment; CDM= Enhancing communication and decision-making; EMM= Enhancing employee morale and motivation.

The analysis confirms that the social dimension of sustainability, often overshadowed by economic and environmental priorities, is a key factor for long-term organizational resilience. As noted by Machado *et al*. (2020), increasing inclusivity, equity, and employee satisfaction is not only ethically imperative but also essential for navigating the challenges of technological transformation. Despite the potential, many “hidden synergies” between LM and I4.0 remain underexploited. While digitalization can enhance collaboration within Lean-oriented firms, it may simultaneously exacerbate skill gaps and workforce polarization where integration is lacking (Kamble *et al*., 2020). This underlines the need for a coordinated approach that treats LM and I4.0 as complementary, rather than parallel, strategies. Without such alignment, organizations risk over-relying on technology while neglecting the human dimension vital for sustainable performance (Bai *et al*., 2022).

Successfully integrating LM and I4.0 to advance social sustainability involves navigating both opportunities and challenges. Real benefits are achievable only through deliberate efforts that elevate social goals alongside economic and environmental ones. This demands a paradigm shift: positioning social sustainability as a core strategic driver, guiding innovation in both technology and management. Only with this holistic mindset can the full value of LM and I4.0 be unlocked in service of broader societal well-being.

Figure 7 visually synthesizes this reasoning, outlining how I4.0 technologies and LM practices jointly support key social sustainability functions. The framework highlights the enabling tools and practices that allow firms to generate effective and lasting social outcomes.

Figure 7. Framework for I4.0 and LM practices affecting social sustainability functions.



Source: Author's own elaboration.

5. FUTURE RESEARCH DIRECTIONS

The integration of I4.0 technologies and LM practices holds great potential for advancing social sustainability, yet several critical research gaps remain. This section proposes a future research agenda focused on contextual differences, socio-psychological dimensions, ethics, regulation, and long-term impact evaluation.

Exploring sector-specific applications of I4.0 and LM

Most existing studies generalize the effects of tools like IoT, AR, and VSM, overlooking how their impact varies by industry. For instance, IoT's contribution to workplace safety differs in pharmaceutical versus automotive contexts. Comparative studies across sectors such as healthcare, agriculture, and electronics could clarify how technologies influence communication, morale, and safety in distinct environments.

Human-machine collaboration and workforce adaptation

The increasing automation and data-centricity of work raise psychological concerns such as job insecurity, skill redundancy, and demotivation (Yang *et al*., 2023). While these tools improve efficiency, their impact on engagement and adaptation needs deeper exploration. Longitudinal research should investigate how workers respond to automation, identifying strategies to mitigate displacement and increase acceptance. Real-time engagement tracking could offer insights into enhancing human-machine collaboration.

Balancing empirical and qualitative insights

Current literature favors quantitative indicators (e.g., productivity, safety) over qualitative elements like satisfaction, ethics, or cultural compatibility. Mixed-method designs, combining ethnographies, interviews, and focus groups with data-driven analysis, could uncover latent barriers to adoption, such as resistance or job security concerns. This approach would enrich performance metrics with human-centered understanding.

Evaluating long-term social sustainability outcomes

Research often emphasizes immediate benefits, neglecting the enduring effects of I4.0 and LM on inclusivity, morale, and well-being. Future work should build evaluation models that assess long-term organizational and societal outcomes. Longitudinal studies tracking these variables over time would offer valuable insights into the sustained social impacts of these integrated strategies.

CONCLUSIONS, IMPLICATIONS, AND LIMITATIONS

This research systematically explores the intersection of I4.0 technologies, LM practices, and social sustainability within the TBL framework. Using an SLR, it highlights how these paradigms synergize to enhance workplace safety, well-being, communication, and empowerment. The study makes key contributions by addressing a critical gap in literature, prioritizing the social dimension of sustainability often overshadowed by economic and environmental concerns. Synthesizing findings from 43 articles, it provides a holistic perspective on how I4.0 and LM jointly improve social sustainability outcomes. Unlike previous research, this study places social sustainability at its core, directly addressing its specific functions. Second, the study establishes a comprehensive framework mapping the synergistic effects of I4.0 technologies (e.g., IoT, BDA, AR) and LM practices (e.g., Kaizen, VSM, LSS) on social sustainability. It categorizes their contributions into dimensions such as safety, quality of work life, employee involvement, and communication, serving as a structured reference for research and industry. Another key contribution is highlighting the human role in LM and its interaction with I4.0 tools. The study emphasizes integrating technological advancements with employee-centered practices, showing how I4.0 reduces hazardous tasks while LM enhances involvement and empowerment. It also reveals the complementary nature of these paradigms. This integration not only enhances efficiency but also improves social outcomes, reducing workplace stress, increasing job satisfaction, and enhancing employee empowerment. Finally, the outlined research directions aim to establish social sustainability as a core pillar of industrial transformation. Addressing sector-specific dynamics, workforce adaptation, ethics, and long-term evaluation can bridge critical knowledge gaps. Future studies should integrate I4.0 and LM not just for efficiency but as drivers of inclusive, equitable, and socially sustainable workplaces. This paradigm shift would redefine technology and management's role in shaping the future of work, ensuring industrial progress aligns with societal well-being and sustainability.

5.1 Theoretical and managerial implications

This study makes significant theoretical contributions to the literature on organizational sustainability and the integration of I4.0 technologies with LM practices. It demonstrates how these paradigms enhance social sustainability, expanding the sustainable development debate within the TBL framework (Elkington, 1999; Geissdoerfer *et al*., 2017). While Cherrafi *et al*. (2017) discuss Lean-green integration, our findings offer further evidence on the social dimension's value. Contrary to traditional views that treat social sustainability as secondary to economic and environmental pillars (Ghaithan *et al*., 2021; Kamble *et al*., 2020), this study reframes it as a core driver of long-term success, echoing Sousa-Zomer *et al*. (2020), who highlight the strategic importance of social factors in leveraging I4.0 for sustainability.

Moreover, the study advances social exchange theory by incorporating the role of employee empowerment and involvement as mediators. Prior literature often assumes a linear relationship between technology adoption and employee well-being; however, our results indicate a contingent effect, shaped by workers' engagement levels. This aligns with De Treville and Antonakis (2006), who emphasize how Lean job design can boost intrinsic motivation. The study also identifies a methodological gap: the dominance of quantitative approaches limits the depth of understanding regarding LM and I4.0's social impacts. While empirical analyses are valuable, the lack of case studies and conceptual contributions constrains theoretical development. By employing a systematic literature review (SLR), this research responds to calls for comprehensive analytical frameworks (Ghobakhloo *et al*., 2021), offering a more robust structure for assessing social sustainability functions, such as health, safety, quality of work life, and employee empowerment.

However, it is important to notice that while I4.0 technologies hold remarkable potential for promoting social sustainability through safer workplaces and higher engagement, their rapid diffusion also introduces a set of ethical and psychosocial challenges that require critical scrutiny. Advanced systems such as AI, machine learning, and predictive analytics can inadvertently generate new forms of inequality and stress within the workforce. Potential drawbacks include job displacement due to automation, loss of autonomy, increased algorithmic monitoring, and data privacy concerns. These issues may undermine trust, affect employee morale, and blur the boundaries between professional and personal life, particularly in digitally interconnected environments. Moreover, the substitution of human judgment with algorithmic decision-making raises questions about accountability, bias, and transparency in industrial operations. Beyond workforce implications, AI-driven management systems may reinforce hierarchical control rather than empowerment if not ethically designed. The social sustainability discourse should therefore move beyond a purely functionalist view and engage with critical perspectives on digital labor, ethics of automation, and human–machine interdependence.

Practically, the findings highlight gaps in organizational readiness for implementing integrated LM-I4.0 strategies. Many companies invest in technological solutions while neglecting training, inclusive job design, and employee development (Kumar *et al*., 2022). This disconnect underscores the importance of a holistic perspective in which technological and managerial innovations reinforce each other. Combining I4.0 tools like IoT, RS, and AR with LM practices such as Kaizen and VSM can create safer, more inclusive, and efficient workplaces. For example, delegating dangerous tasks to robots, using ergonomic principles, and enhancing process visualization can reduce physical risks and boost well-being. At the same time, workforce upskilling is essential to mitigate displacement and increase morale.

This study also emphasizes the role of policymakers and industry leaders in ensuring that I4.0-driven Lean implementations are matched with inclusive, human-centered policies, especially to protect vulnerable populations. The proposed framework serves as a practical tool for organizations seeking to align technological investments with social goals, creating a culture of empowerment and continuous improvement. Due to the complex interdependencies between human and technological systems, cross-sector collaboration among firms, governments, and academia is critical for developing shared standards. Public policies should incentivize innovation that promotes social sustainability, balancing capital investment with human development to ensure equitable industrial transitions.

Ultimately, the findings suggest that embedding social sustainability in strategic planning is not only a matter of compliance but a key source of long-term competitive advantage. Firms that integrate inclusive practices and employee empowerment tend to perform better financially and retain talent more effectively, as evidenced by recent case studies (Buer *et al*., 2022).

5.2 Limitations of the study

Despite its contributions, this study presents several limitations. The reliance on an SLR confines the analysis to published literature, potentially excluding emerging trends and recent advancements in I4.0 and LM. This may limit its ability to reflect real-time technological developments. Future research could incorporate empirical approaches, such as case studies or longitudinal studies, to better capture the evolving dynamics between digital tools and managerial practices.

While the literature search was designed to ensure breadth and methodological rigor, certain limitations arise from the selection of search terms. The Boolean string privileged general terms such as “Industry 4.0”, “Lean manufacturing”, and “social sustainability”, rather than the inclusion of specific technological proxies such as “big data analytics”, “artificial intelligence”, “additive manufacturing”, or “Internet of Things”. This deliberate choice aimed to maintain conceptual focus and avoid excessive fragmentation of the search field. However, it may have led to the exclusion of studies primarily framed around individual technologies that nonetheless contribute to the understanding of social sustainability within Industry 4.0.

Another limitation concerns the thematic scope of the review. The decision to exclude papers not explicitly addressing social sustainability, despite their potential indirect relevance, may have reduced the breadth of analysis. Some contributions might have discussed social outcomes implicitly, but without explicitly framing them under the “social sustainability” terminology. Consequently, the boundary set by the inclusion criteria ensured conceptual precision but possibly at the expense of thematic inclusiveness.

Additionally, the exclusion of grey literature (e.g., industry reports, conference papers, book chapters) narrows the scope, overlooking practical applications and innovative solutions. Including these sources would enhance the connection between theory and practice.

The study also lacks a detailed examination of regional and sectoral differences, which can shape how I4.0 and LM affect social sustainability. Comparative research across sectors like automotive, healthcare, and electronics could identify specific challenges and improve generalizability.

Moreover, the dominance of quantitative methods in the reviewed literature limits insights into socio-psychological aspects, such as employee perceptions, ethical dilemmas, and cultural dynamics. Mixed-methods approaches combining interviews or ethnographies with quantitative data could offer more holistic understanding.

Lastly, the qualitative interpretation of results may be affected by subjective judgment. While this is necessary for thematic analysis, future studies could adopt bibliometric tools (e.g., VOSviewer) for citation mapping and main path analysis, to ensure greater transparency and rigor (Zhu *et al*., 2021; Shah *et al*., 2020).

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CHAPTER III: EXPLORING AI-DRIVEN TRAINING FOR LEAN MANUFACTURING: A CASE STUDY ON SOCIAL SUSTAINABILITY IN AN SME*

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ABSTRACT

This study explores the integration of Artificial Intelligence (AI)-driven training within Lean Manufacturing (LM) practices in an SME, focusing on knowledge dissemination, employee engagement, and social sustainability. Through a qualitative case study involving semi-structured interviews and thematic analysis, the work highlights how AI training democratizes Lean knowledge, enhances employee autonomy and proactive problem-solving. However, it also reveals challenges, including digital skill disparities, performance-related stress, and concerns over job security. The findings emphasize the importance of hybrid training approaches, structured digital onboarding, and clear communication about AI's role as a support rather than a replacement. Building on these insights, the study also introduces the AI-driven Lean learning equilibrium framework, which conceptualizes AI-driven training as a socio-technical mediation system balancing empowerment and control, efficiency and empathy. By offering practical insights into the human-centered implementation of AI in LM, the study contributes to ongoing discussions on technology-enabled workforce development.

Keywords: Lean Manufacturing; AI-driven training; social sustainability; SMEs

1. INTRODUCTION

Lean Manufacturing (LM) is a management philosophy originating from the Toyota Production System (TPS) that aims at reducing waste, optimizing processes, and creating value (Womack and Jones, 1996). Recognized as a multi-dimensional concept (Shah and Ward, 2003; Valente *et al*., 2020), its core objectives include achieving the highest levels of profitability, quality, and customer service while minimizing costs and ensuring timely delivery through the continuous elimination of waste (Tasdemir *et al.,* 2018).

The existing literature identifies LM as a combination of both philosophical and practical dimensions. The philosophical aspects encompass core principles and overarching goals, while the practical elements consist of management strategies, tools, and techniques that enable implementation (Basu and Dan, 2020; Bhamu and Sangwan, 2014; Bhasin and Burcher, 2006). Additionally, the philosophical dimension integrates human-related factors, highlighting the critical role of individuals in the LM framework (Bento and Tontini, 2018; Psomas and Antony, 2019; Koemtyzi *et al*., 2023). Indeed, several studies emphasize that people play a central role in LM (Sawhney and Chason, 2005; de Treville and Antonakis, 2006), underscoring the need for adjustments in human resources (HR) practices and policies to align with LM's objectives (Biazzo and Panizzolo, 2000).

In this regard, LM is considered a radical techno-organizational innovation requiring an integrated focus on both technical and HR elements. While LM tools and principles have demonstrated effectiveness, successful implementation also depends significantly on "soft" factors such as training, teamwork, and employee engagement (Bortolotti *et al*., 2015).

In this context, the social dimension of sustainability is increasingly acknowledged, playing a crucial role in enhancing workplace inclusivity, employee well-being, and equitable access to professional development. Social sustainability closely aligns with LM's human-centered principles, emphasizing continuous learning, employee engagement, and fair opportunities for skill development (Ciannella *et al*., 2022). It represents an ethical framework for human survival and progress in a mutually inclusive and responsible manner. It prioritizes welfare, equity, and labor rights (Olawumi and Chan, 2018), with workplace processes that enhance human health and safety as critical determinants (Husgafvel *et al*., 2015). Furthermore, lean management techniques contribute significantly to sustainability by enhancing governance, environmental, and social outcomes. In particular, employee performance, particularly in waste management, directly impacts sustainability by improving both operational effectiveness and sustainable practices (Thawornsujaritkul and Boonnual, 2024). Thus, the interconnection between LM and social sustainability is increasingly recognized in the literature, highlighting the role of human and social dimensions in operational success.

For small and medium-sized enterprises (SMEs), LM offers significant benefits, including waste reduction, quality improvement, and competitive parity with larger firms (Shah and Ward, 2007). However, SMEs frequently struggle with LM implementation due to resource constraints, such as limited financial capacity and human resources (Hu *et al*., 2015). These limitations often prevent SMEs from providing the continuous, high-quality training necessary for successful LM adoption, posing challenges in sustaining LM initiatives. Consequently, SMEs adopt lean practices far less frequently than large corporations (Shah and Ward, 2003; Bhamu *et al*., 2014; Belhadi *et al*., 2018).

In this scenario, Industry 4.0 (I4.0) emerges as a transformative concept, integrating automation, digital innovation, and data-driven intelligence to revolutionize manufacturing (Vashishth *et al*., 2024). Developed under a German government initiative, it is driven by cyber-physical systems, the Internet of Things (IoT), and artificial intelligence (AI) (Kagermann *et al*., 2013). Among these technologies, artificial intelligence (AI) has proven particularly impactful in the realm of human resources, supporting administrative tasks and personnel searches while addressing challenges related to employment and education (Weber, 2023). Several studies have indeed highlighted AI's essential role in HR-related functions, including recruitment, data collection, analysis, and employee satisfaction (Orosoo *et al*., 2023). Additionally, AI-driven tools such as robotic technologies, visual monitoring, facial recognition, and natural language processing are increasingly being integrated into training and selection processes to enhance skill acquisition, demonstrating AI's growing importance in improving HR management practices (Orosoo *et al*., 2023). The involvement of top management in AI initiatives further facilitates strategic action plans, such as HR training and communication (Baabdullah *et al*., 2021). AI also assists employees in identifying areas for personal and professional growth, helping them optimize their contributions to the workplace (Vrontis *et al*., 2021). Given these advantages, AI emerges as a promising solution for SMEs, offering scalable and adaptive training platforms tailored to individual learning needs (Murtaza *et al*., 2022). Furthermore, AI-based HR management systems facilitate data-driven decision-making in personnel development, ensuring employees receive personalized learning experiences based on their progress and needs (Verma, 2023).

This approach enhances job satisfaction while aligning with LM's social sustainability objectives by enhancing inclusivity, lifelong learning, and equitable skill development (Akter *et al*., 2024). In this context, by enabling continuous learning, AI-driven platforms contribute to both LM implementation and social sustainability, promoting employee development and creating a culture of engagement and continuous improvement. Additionally, this approach aligns with LM's emphasis on employee empowerment and engagement, as it provides equal access to training and professional growth opportunities, especially for SMEs.

Despite the growing recognition of the relationship between LM and social sustainability as a fertile research area (Bhattacharya *et al*., 2019; Henao *et al*., 2019) and the acknowledgment of workers as a critical component in LM environments (Wong and Wong, 2014), studies examining this relationship remain scarce. Moreover, there is limited consensus on HR's role in supporting LM (Conti *et al*., 2006; de Treville and Antonakis, 2006), and there is a significant gap in the literature regarding AI's potential to enhance the social dimensions of LM, particularly within SMEs, where resource constraints hinder extensive HR training initiatives. Addressing this research gap is essential, as AI-driven training has the potential to bridge inequalities, empower underrepresented groups, and enhance LM organizations' long-term social sustainability. Furthermore, only a limited number of studies examine how LM practices influence social sustainability (Bhattacharya *et al*., 2019; Cherrafi *et al*., 2016). Consequently, research on how these practices impact employees' social outcomes remains limited and often inconclusive (Camuffo *et al*., 2017; Salentijn *et al*., 2021). Finally, to the best of the authors' knowledge, no study has explored how AI-driven training platforms can enhance LM knowledge and practices while improving social sustainability outcomes.

Considering these gaps and observations, the present study addresses the following research questions:

RQ1: How can AI-driven training effectively support LM adoption in SMEs?

RQ2: What's the impact of AI-driven training on social sustainability outcomes in an LM environment?

The primary objectives of this study are to analyze the capacity of AI-driven training platforms in accelerating LM knowledge dissemination and to examine the impact of AI-enabled learning on workplace dynamics and social sustainability. By focusing on SMEs, this research seeks to explore how AI and HR strategies can work synergistically to enhance Lean practices while creating an inclusive, employee-centered work environment.

The remainder of this paper is structured as follows: Section 2 presents the theoretical background, examining LM in SMEs, HR practices, and the role of AI in these contexts. Section 3 outlines the study methodology. Section 4 presents and discusses the findings, while Section 5 provides concluding remarks, implications, and future research directions.

2. THEORETICAL BACKGROUND

2.1 Lean Manufacturing in SMEs

LM was first introduced and developed in the 1950s on the Japanese manufacturing shop floor. The main goal of this philosophy is to improve business performance (Ghobadian *et al.,* 2020; Nawanir *et al.,* 2013) and operations (Zhu and Lin, 2018) by methodically and continuously identifying and removing wastes (overproduction, waiting, unnecessary transportation, inappropriate processing, defects, unnecessary inventory and motions). According to Green (1999, p. 23) Lean manufacturing "comprises complex cocktail of ideas including continuous improvements, flattened organization structures, teamwork, elimination of waste, efficient use of resources and cooperative supply chain management".

Since they greatly contribute to economic growth through job creation, innovation, and industrial production, and account for 99.8% of enterprises in Europe, SMEs play a crucial role in European job creation and economic development[11], and have long been seen as the backbone of developing economies worldwide (Sajan *et al.*, 2017).

SMEs are commonly praised for their simple organizational structure and flexible production methods, all of which contribute to an environment that is conducive to lean initiatives (Yadav *et al.,* 2019). Thus, lean is particularly critical in SMEs where resources are limited (Shah and Ward, 2007; Bhamu and Sangwan, 2014). Psomas *et al.* (2018) claim that SMEs are more equipped to implement the lean mentality than larger companies since they are thought to be more flexible in modifying their operations and quick to respond to the constantly shifting needs of their clients. Sahoo and Yadav (2018) further found that LM is competitive for SMEs since it shortens the engineering process and reduces manufacturing costs with higher-quality process flows, and manufacturers have implemented a variety of LM techniques to maximize potential values and minimize non-value-added tasks (Qureshi *et al*., 2022).

Despite the potential benefits, many SMEs struggle in implementing and maintaining in a successful way LM practices within their organizations. The barriers include fragmented knowledge transfer, resistance to cultural shifts, and resource scarcity (Bhamu and Sangwan, 2014). This knowledge gap is exacerbated by SMEs' reliance on informal, on-the-job training, which lack structure to teach LM's analytical tools (Bortolotti *et al*., 2015). LM requires indeed decentralized decision-making and employee empowerment, which clashes with the hierarchical structures prevalent in SMEs (Hu *et al*., 2023). SMEs struggle to implement lean packages and improve upgrading processes (Subramanian, 2024) and to provide the ongoing, high-quality training required to support lean processes. They find it challenging to invest in the regular, specialized training that LM demands due to a lack of resources, time restrictions, and smaller HR infrastructures (Eswaramoorthi *et al*., 2011). The long-term viability and performance of LM projects may be hampered as a result of employees' potential lack of the abilities and knowledge required to participate in lean processes.

In order to address the difficulties that these manufacturing SMEs face, lean HR methods are essential. Manufacturing SMEs may increase their competitiveness, sustainability, and agility in today's dynamic environment by implementing strong HR strategies (Subramanian, 2024). Applying

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[11] https://www.statista.com/chart/32960/small-but-mighty_-european-smes-lead-in-jobs-and-value-added/.

lean principles to HR seeks to improve staff efficiency, streamline HR procedures, and promote a continuous improvement culture (Anwar *et al*., 2022; Ta'Amnha *et al*., 2023). This can contribute to the organization's sustainable growth in the competitive and dynamic business environment by improving overall performance, employee satisfaction, and competitiveness (Bonavia and Marin-Garcia, 2011; Martínez-Jurado *et al*., 2014; Ta'Amnha *et al*., 2023).

Indeed, despite these challenges, research highlights that the success of LM is strongly linked to the human component. Employee involvement, problem-solving capabilities, and continuous training are critical elements in effective LM adoption (Biazzo and Panizzolo, 2000). The engagement of workers at all levels further ensures that LM practices are not only successfully implemented but also sustained over time. Thus, enhancing a human-centric approach to LM through training and workforce development can enhance both operational efficiency and social sustainability outcomes.

2.2 The human-centered approach and social sustainability

Although some firms have made successful advances in LM implementation, others have not achieved the results that were expected and failed transitions to LM are common (Scherrer-Rathke *et al*., 2009). Indeed, LM adoption is a complex task and there are obstacles that can stand in the way of its success (Womack and Jones, 1996). These obstacles are often linked to the key role played by HR rather than to technical aspects (Bateman, 2005; de Treville and Antonakis, 2006). LM requires significant changes in HR policies and practices (Olivella *et al*., 2008) that affect the role played by employees (Hiltrop, 1992; de Treville and Antonakis, 2006). Literature demonstrates that employee participation and organizational changes are necessary for the implementation of lean policies and practices (Furlan *et al*., 2011; Tortorella *et al*., 2018; Vidyadhar *et al*., 2016).

Bortolotti *et al*. (2015) pointed out that successful lean plants use "soft" LM practices more extensively than unsuccessful lean plants. Indeed, while LM improves operational efficiency, its success depends significantly on addressing human factors (Dal Pont *et al*., 2008; Sparrow and Otaye-Ebede, 2014). Research also describes the LM approach as a socio-technical system that embraces various HR features like teamwork, empowerment, motivation, and respect for others, all of which have an impact on its success (Bhasin and Burcher, 2006; Hines *et al*., 2004; Cullinane *et al*., 2014; Taylor *et al*., 2013).

In this regard, numerous empirical studies have been conducted globally in a variety of settings, including manufacturing and service sectors, governmental and private organizations (Agus and Hajinoor, 2012; Burawat, 2019; Grigg *et al*., 2020; Maarse and Janssen, 2012). Despite this, scholars' attention was focused on the instruments, approaches, protocols, and strategies used to enhance businesses' operations by cutting waste (Larteb *et al*., 2015). But in order for LM to be implemented successfully, soft techniques must also be analyzed in addition to the hard LM components (Mamat *et al*., 2015; Solaimani *et al.,* 2019).

In this sense, few studies focus on HR's role in LM's successful implementation at the operational or company level because interest in the human factor components has only recently grown (Bonavia and Marin-Garcia, 2011; Martínez-Jurado *et al*., 2014).

According to Bonavia and Marin-Garcia (2011), lean production combined with HR techniques lowers inventory while increasing productivity and stock reduction. Bortolotti *et al*. (2015) identified that organizational culture, leadership, and employee participation are equally vital to long-term lean success. In this stream of line, through their systematic literature review, Bouranta *et al*. (2022) identified the following: the implementation of LM requires attention to "soft" factors such as employee training, leadership, national culture, and participation. These factors help shape the organizational environment that supports lean practices. In particular, training programs as also emphasized by Shah and Ward (2007), tailored to LM can help employees understand lean tools, thus improving the success of LM projects. Practical training (e.g., hands-on simulation of lean activities) enhances workers' problem-solving capabilities and enables them to participate in lean initiatives more effectively. This dimension has been defined by Bouranta *et al*., (2021) as "vital", highlighting that it should be adopted in order to properly adjust and improve LM implementations.

Training also enhances social sustainability by promoting employee empowerment, job satisfaction, professional growth, workforce well-being and inclusivity (Ciannella and Santos, 2022). When employees receive proper training and skill development opportunities, they actively contribute to LM initiatives, creating a positive work environment and boosting productivity (Subramanian *et al*., 2024).

However, traditional training requires significant investment, making it challenging for SMEs with limited resources (Hu *et al*., 2015). This highlights the need for cost-effective, scalable training solutions that support both LM implementation and social sustainability.

To address these challenges, digital tools and technological innovations emerge, particularly AI-driven training solutions. AI personalizes learning, provides real-time feedback, and enhances knowledge retention (Weber, 2023). By bridging training gaps in SMEs, AI ensures employees at all levels receive structured, tailored learning experiences, strengthening LM adoption and workplace sustainability.

2.3 Social sustainability in LM environments

The majority of research on LM focuses on operational and financial aspects; however, there aren't many studies that link it to social sustainability (Abdul-Rashid *et al*., 2017), since environmental concerns are often prioritized over social sustainability, and a company must balance its social, economic, and environmental performance in order to be considered sustainable (Iranmanesh *et al.,* 2019). This necessitates incorporating environmental and economic sustainability as well as social sustainability standards into organizational procedures.

According to studies, supply chain agility and LM can have a positive effect on social sustainability (Agrawal and Nath, 2020), LM practices can prevent accidents and occupational hazards, and LM, social sustainability, and green competitiveness of businesses are linked to the adoption of eco-friendly technology and innovation (Afum *et al*., 2021).

The social dimension stresses workplace well-being, equity, and ethical practices, which are aligned with HR's role in lean implementation (Elkington, 1997; Jamali, 2008). Lean manufacturing inherently relies on empowered, skilled, and engaged employees, but these outcomes require deliberate HR interventions (Martínez-Jurado *et al*., 2014). Social sustainability in manufacturing thus aligns with HR practices that prioritize employee health, job satisfaction, and professional development, and a socially sustainable approach to lean requires leadership commitment to employee welfare and active involvement in organizational culture transformation (Amrutha *et al*., 2020). Social sustainability has become a crucial focus within lean environments, where the stress of continuous improvement can sometimes lead to negative outcomes, such as increased workload and employee burnout (Ghobadian *et al*., 2020). Properly aligned HR practices can mitigate these risks and promote social sustainability. For instance, well-structured training programs and safety initiatives can enhance both operational efficiency and workplace well-being.

So, since social sustainability is very connected to human resources management, the present paper also focuses on this aspect. In particular, social sustainability refers to practices that ensure the well-being, safety, and job satisfaction of employees while maintaining equitable treatment (Jabbour and Jabbour, 2016) and among such dimensions, the present work focuses on the training indicator recognized as a measure of social sustainability (Afshari *et al*., 2022). Particularly in operations like machining, low worker training can result in unskilled labor and high defect rates.

As pointed out by Bouranta *et al*. (2022) a little number of studies addresses the ways in which HR practices and LM are integrated to create the necessary conditions for successful implementation. As a result, there is a conceptual and technical lack of knowledge regarding the human components involved in LM (Antony *et al*., 2020). Gaiardelli *et al*. (2019) claimed that the discussion surrounding LM implantation and human factor components is still ongoing and that further research is needed to fully understand this relationship. Moreover, Lean's emphasis on employee-driven improvements and waste reduction is complemented by a need for regular training and upskilling, which AI can potentially support by offering scalable, accessible training solutions (Galeazzo *et al*., 2017).

While LM constitutes an established and mature managerial philosophy, the integration of AI-driven training systems introduces a new learning paradigm that redefines how Lean knowledge is transferred, internalized, and updated within organizations. AI enables dynamic and data-informed learning pathways that contrast with the static, top-down models traditionally used in LM training. AI-driven training differs from traditional e-learning by incorporating adaptive feedback, pattern recognition, and performance analytics, creating continuous learning ecosystems aligned with Lean's principles of kaizen and continuous improvement. This convergence creates what can be defined as "AI-empowered Lean training", where technology supports, not substitutes, human expertise and collective learning.

The present research therefore conceptualizes LM not as the main variable but as the content domain of AI-enabled training. In this sense, the study's novelty lies in the educational function of AI systems, how they shape knowledge democratization, employee inclusion, and social sustainability outcomes.

2.4 The role of AI-driven training

In recent years, the digital transformation process has become fundamental to the management debate (Zoppelletto *et al*., 2023). This phenomenon arises from integrating modern technologies that enhance data gathering, archiving, and analysis. Such technologies encompass numerous innovations and state-of-the-art instruments, including robotic automation, additive manufacturing, AI, and the Internet of Things (IoT) (Strange *et al*., 2022). Among these, AI has emerged as a critical facilitator, offering essential opportunities for innovation and growth across various industries by helping to overcome computational, logical, and even creative limitations that have long-constrained human activities (Dwivedi *et al*., 2021; Kumar *et al*., 2022). The distinctive characteristics of AI, such as its capacity to learn, build connections, and adapt, set it apart from other technologies. These attributes enable AI systems to continuously improve, evolve, and leverage the data and experiences they encounter (Brock and Von Wangenheim, 2019).

The OECD (2022, p. 4) described AI as "*a machine-based system that can, for a given set of human-defined objectives, make predictions, recommendations, or decisions influencing real or virtual environments with varying levels of autonomy*". The term "AI adoption" refers to its acceptance and utilization by society and its integration within an organization. Technologies made possible by AI can be employed to improve operations, products and services, and other aspects of the business, such as corporate performance. AI enables continuous operational refinement through data analysis and insight generation, providing organizations with improved decision-making, increased productivity, and competitive advantage (Magistretti *et al*., 2019; Denicolai *et al*., 2021).

Numerous scholars have investigated the evolution of human capital in the era of AI. The consequences of AI on human capital, encompassing labor management, education, and skill development, have been widely discussed. For instance, Chen and Wang (2020) examined the potential uses of AI in human resources, focusing on hiring, training, performance evaluation, and talent retention. Similarly, Lee and Kim (2020) explored both the opportunities and ethical challenges associated with integrating AI into HR programs, particularly its implications for learning enhancement and skill development. Complementarily, Wang and Liu (2020) analyzed how organizations can leverage human capital to maximize the benefits of AI while reducing associated risks, whereas Gupta and Singh (2020) reviewed recent advancements in AI-based HR and proposed directions for future research in this rapidly evolving field. Collectively, these studies illustrate a growing recognition of AI's transformative role in reshaping workforce management and continuous learning processes.

Building on this foundation, AI-driven training platforms have emerged as a pivotal mechanism for workforce development. Such systems offer adaptive learning paths, real-time feedback, and high scalability, making them particularly effective for dynamic manufacturing environments. Previous research (Chan *et al.,* 2015; Herrmann *et al.,* 2015) has highlighted AI's potential to enhance employee competencies and support knowledge management beyond traditional machine-based problem-solving.

By improving accessibility and personalization, AI training helps SMEs overcome conventional barriers to skill development, ensuring more effective LM adoption and implementation. Moreover, by mitigating learning inequalities, AI empowers employees with the tools and flexibility needed to thrive in technology-enabled LM environments. Beyond its operational advantages, AI-driven training also contributes to social sustainability. It enhances workplace inclusivity, reduces skill gaps, and nurtures continuous learning cultures (Galeazzo *et al.,* 2017), while simultaneously promoting greater employee engagement and participation in Lean initiatives (Baabdullah *et al.,* 2021). Hence, AI in training does not merely serve as a digital tool for efficiency, it represents a socio-technical enabler that bridges technological innovation with human development, reinforcing both organizational performance and social well-being.

3. METHODOLOGY

3.1 Research design and data collection

This study adopts an exploratory case study approach to investigate the impact of AI-driven training on LM adoption within an Italian metalworking SME. This method enables an in-depth exploration of complex, under-researched phenomena (Yin, 2009), especially focusing on AI's role in workforce training, LM implementation, and social sustainability. Specifically, the training program employed Notebook LM, Google's Natural Language Processing (NLP)-based tool, designed to synthesize information, extract key insights, and generate structured summaries. The system was integrated into existing production and training workflows to enhance employees' comprehension of Lean principles and facilitate the translation of procedural knowledge into practice.

Data were collected over a six-month period through semi-structured interviews lasting between 45 and 60 minutes, involving participants across different organizational levels. Supplementary data were obtained from internal reports, training records, and digital logs generated by the AI platform to enable triangulation. The implementation unfolded across four progressive phases each representing a distinct step in the design and deployment of the AI-driven training system, as summarized in Table 1.

Table 1. Implementation phases

Implementation Phase	Description
P1: Assessment and programming	In the first phase, a thorough assessment of the organization's current lean practices, employee skill levels, and specific training needs was conducted. This stage involved evaluating existing knowledge gaps, understanding employee learning preferences, and setting training objectives aligned with both lean manufacturing goals and social sustainability principles. The programming aspect included designing the structure and content of the AI-driven training modules, ensuring they were customized to the workforce's needs and the SME's operational requirements.
P2: Launch of training modules	During this phase, the pre-designed AI training modules were officially launched and made accessible to employees. The modules were tailored to the skill levels and progress of individual learners, providing personalized, interactive, and adaptive learning experiences. The AI platform introduced employees to essential lean tools and principles, facilitating engagement through a user-friendly interface. The goal was to encourage active participation and ensure employees were well-equipped to support lean practices in their roles.
P3: Continuous monitoring	Continuous monitoring was critical to track progress and make adjustments as needed. Participant observation was in this phase required and fundamental. Continuous feedback loops allowed for real-time adjustments to the training content, ensuring it remained relevant and effective in meeting both lean and social sustainability objectives.
P4: Post-intervention evaluation	The final phase assessed the overall impact of the AI-driven training intervention through semi-structured interviews. Post-intervention evaluation included measuring changes in employee understanding of the lean principles, of their competencies, and social sustainability indicators, such as job satisfaction and engagement. This phase provided valuable insights into the effectiveness of the training program, highlighting successes and areas for improvement. The results of this evaluation informed future strategies for sustaining lean practices and aligning them with organizational goals.

Source: Author's own elaboration.

Data collection occurred over six months, when interviews with the Production Operator, Production Flow Manager, Lean Manager, and Team Leader captured different organizational perspectives and alignment with LM goals (Kallio *et al*., 2016). These profiles represent the hierarchical layers directly involved in Lean implementation and training activities. Since the literature highlights various HR practices that contribute to successful LM, including training, teamwork, and communication (Bortolotti *et al*., 2015), interview questions were crafted based on these dimensions and aimed to identify shifts in perceptions, engagement, and overall satisfaction resulting from AI-driven training interventions. These questions aligned with existing literature on LM's social dimensions, including employee participation and continuous improvement (Bonavia and Marin-Garcia, 2011; Bouranta *et al*., 2022). The concept of social sustainability in this study was operationalized through qualitative and perceptual indicators derived from the literature on human-centered Lean transformation. Specifically, four main dimensions were considered: i) employee participation and autonomy (Angelis *et al.,* 2011); ii) inclusivity and access to learning opportunities (Vinodh *et al.,* 2020); iii) psychological well-being and perceived fairness (Conti *et al.,* 2006); and iv) skill development and empowerment (Tortorella *et al.,* 2020). These indicators guided both the interview protocol and the thematic analysis, allowing a structured interpretation of social sustainability outcomes within the case organization.Although few studies specifically examine interview frameworks for AI in LM training, this study draws from prior research on HR factors critical to lean success and on theories of adaptive learning in AI-enhanced training (Murtaza *et al*., 2022).

The selected case company is a family-owned Italian SME operating in the metalworking industry, employing approximately 110 workers. The company was chosen using a purposive sampling strategy (Yin, 2009), based on three criteria: i) active implementation of LM principles for at least five years; ii) recent integration of AI-based tools for employee training and process monitoring; and iii) explicit managerial commitment to social sustainability goals (e.g., participation in regional upskilling initiatives). The characteristics are represented on Table 2.

Table 2. Overview of the selected case company.

Dimension	Description
Company profile	Family-owned Italian SME operating in the metalworking industry, employing approximately 110 employees.
Lean Manufacturing maturity	LM principles have been actively implemented for over five years, supported by continuous improvement programs and internal standardization of production processes. The firm has institutionalized Lean routines such as daily stand-up meetings, 5S practices, and visual management tools.
Adoption of AI-based training	The company recently introduced AI-driven training modules based on natural language processing (NLP) and machine learning algorithms. These tools assist employees in understanding Lean procedures, simulate operational scenarios, and provide automated feedback during process monitoring activities.
Purpose of AI-training	The main goal is to enhance learning efficiency, ensure inclusive access to knowledge across job roles, and strengthen employees' understanding of Lean principles through personalized, on-demand learning sessions. The AI system acts as a facilitator for skill development and digital literacy.
Organization of training activities	Training is conducted through a blended learning format, combining in-person sessions with AI-supported digital modules. Sessions occur monthly (60 minutes each), supplemented by microlearning activities available on tablets and shop-floor terminals. The system tracks progress and adapts content to workers' performance levels.
Commitment to social sustainability	The company demonstrates a strong social responsibility orientation, investment in workplace safety, and participation in regional upskilling programs. Management explicitly links AI-training to its broader goals of employee empowerment and social well-being.

Source: Author's own elaboration.

3.2 Data analysis

Since thematic analysis is well-suited to investigating new and understudied subjects, it has been selected as the main technique for examining qualitative data in this study. Given the novelty and intricacy of the research topic, where there are currently few theoretical frameworks, this method is especially pertinent, since it offers a strong framework for finding and analyzing patterns in qualitative data.

The procedure for data analysis adhered to the guidelines provided by Clarke and Braun (2021): i) data familiarization, in which transcripts were read several times to guarantee a thorough comprehension of the information; ii) initial coding, which involved methodically coding the data using both deductive and inductive approaches; iii) identifying themes, which involved grouping codes into themes that mirrored the goals of the study; iv) reviewing and refining the themes to make sure they were coherent and in line with the data; v) defining and contextualizing the themes, highlighting their importance within the larger research narrative; and vi) writing the analysis, which involved integrating the themes into a cohesive narrative that served as the foundation for the findings reported in the results section.

By combining these methods, this methodology enables a balanced examination of AI-driven training's impact on lean processes and social sustainability, addressing a significant research gap in understanding the human and technical dimensions of lean within resource-constrained SME settings.

4. RESULTS ANALYSIS AND DISCUSSION

This section presents findings from the interviews, offering insights into the experiences, perceptions, and outcomes of the AI-driven training platform.

4.1 Effectiveness of AI training in a LM context

AI-driven Lean training significantly improved employees' understanding and confidence in LM practices. Initially met with skepticism, particularly by those less familiar with digital tools, it ultimately deepened comprehension by explaining not only what to do but also why LM matters. This was especially beneficial for the Production Operator who had previously followed procedures without grasping their rationale. As he noted, *"At first, I was skeptical, but the platform helped me understand why Lean matters, not just how to follow procedures"*. Employees also became more proactive in identifying inefficiencies, with AI modules on workflow management and waste reduction making productivity gains more tangible.

The most valued module was on the Seven Wastes of Lean, as it translated abstract concepts into practical applications through simulations and exercises. The integration of AI-driven training on LM has reshaped employees' perceptions of Lean principles. While it enhanced awareness and structured understanding of Lean methodologies, its effects on motivation, workload balance, and engagement. A key shift was in how Lean was perceived, moving from a rigid framework to an efficiency-driven approach. The Production Operator initially saw Lean as *"just extra rules to follow,"* but AI training clarified its practical benefits. Similarly, the Team Leader noted, *"Before, Lean was based on experience. Now, it feels like a structured way of thinking"*. Despite these benefits, challenges emerged. Digital literacy gaps, particularly among senior employees, required additional support. The Production Flow Manager noted, *"For younger workers, this system is great, but senior employees struggle with digital training"*.

4.2 Social sustainability and job satisfaction

A deeper understanding of Lean principles did not universally translate into greater job satisfaction and workplace fulfillment. While the Lean Manager acknowledged that AI training reinforced Lean values, it also intensified pressure: "*Lean is about efficiency, but sometimes it feels like we're never doing enough*". The Production Flow Manager similarly noted that greater visibility into inefficiencies increased scrutiny and stress: "*Before, we worked based on instinct; now, everything is measured*". Motivation and engagement also differed across roles. Employees with decision-making authority, like the Team Leader, felt empowered: "*Seeing real-time process improvements makes me feel more involved*". In contrast, the Production Operator, despite gaining Lean knowledge, felt unable to implement changes: "*We all get the same training, but not everyone has the power to apply it*". In terms of work-life balance, AI training helped with time management but also introduced pressure to continuously improve. The Lean Manager appreciated its role in prioritization, while the Team Leader remarked, "*There's always another module to complete, another improvement to track*". Overall, AI made Lean principles more structured and accessible, but its impact on job satisfaction was mixed, empowering some while heightening pressure for others.

From a social sustainability perspective, AI-driven training improved inclusivity, employee well-being, and access to structured development. Previously limited to managers, Lean knowledge became available to all employees. As the Production Flow Manager noted, "*Before, training opportunities were inconsistent. Now, everyone receives the same structured content*," echoed by the Lean Manager: "*With AI, we can ensure standardized learning for all employees*". However, broader access raised concerns about job security and recognition. Some saw AI training as a path to growth, while others feared automation could undermine their roles. The Team Leader reflected, "*Training helps develop skills, but career growth requires a clearer path forward*". AI also supported well-being by clarifying expectations and reducing uncertainty. "*Now, AI explains the reasoning behind processes, so we're not just blindly following orders*," said the Production Operator. Yet performance tracking introduced new pressures. The Lean Manager noted, "*AI tracking makes optimization feel never-ending*," and the Team Leader added, "*Sometimes it feels like we're never doing enough*". Collaboration improved through a shared Lean foundation, which facilitated coordination. "*Now that everyone has the same Lean knowledge, it's easier to coordinate tasks,*" said the Production Flow Manager. Still, gaps remained between theory and practice. As the Production Operator put it, "*The training is helpful, but real-world execution doesn't always match the theory*". Autonomy also generated differing views. The Lean Manager saw AI as enabling: "*It gives us confidence to make data-driven decisions*," while the Production Operator felt constrained: "*There are more rules now,* *and sometimes I feel like I have less flexibility*". This highlights the need to balance improved problem-solving with operational autonomy.

Ultimately, AI-driven Lean training has improved inclusivity and standardized knowledge sharing, but its effects on career advancement and autonomy remain uneven. While it enhances efficiency and collaboration, it also brings new performance pressures. For AI training to enhance social sustainability, it must support workflows and promote equitable opportunities for all employees.

4.3 Future plans for AI-driven training in LM contexts

The future of AI-driven training in LM presents both opportunities and challenges. AI enhances flexibility, personalized learning, and data-driven decision-making, but concerns remain about its detachment from hands-on experience, over-reliance on digital tools, and potential depersonalization of learning. A key advantage is AI's adaptability to individual learning speeds. The Lean Manager noted, *"The AI system adjusts based on interaction, allowing tailored support,"* while the Production Flow Manager emphasized, *"Before, training was rigid. Now, employees engage at their own pace, improving learning outcomes"*. AI also strengthens real-time problem-solving by integrating data into Lean practices, as the Team Leader highlighted: *"AI helps connect training with actual floor activities, allowing immediate application of Lean principles"*. However, employees stressed AI's limitations in replicating real-world problem-solving. The Production Operator remarked, *"The platform is useful, but it can't replace hands-on learning from experienced colleagues,"* while the Production Flow Manager added, *"Lean is about context. AI provides information, but it can't replicate shop-floor complexity"*. This highlights the need for AI to complement, not replace, experiential learning. Concerns also arose about over-reliance on AI at the expense of human mentoring. The Team Leader cautioned, *"AI is great for technical knowledge, but it can't teach leadership or handling unexpected challenges"*. Additionally, the Production Flow Manager warned that AI-driven metrics risk reducing performance evaluations to numbers: *"If everything is measured by AI, we might lose sight of the bigger picture"*. To enhance AI-driven training, the Lean Manager proposed, *"Combining AI with AR/VR would make training more effective"*. Customizing training content to real shop-floor challenges was another recommendation, with the Production Flow Manager stating, *"The platform should reflect actual workplace problems"*.

4.4 Thematic analysis

The thematic analysis was refined to focus exclusively on the AI-driven training component as the central analytical construct. While LM remains the application domain, the emphasis here is on how AI as an educational enabler transforms learning dynamics, social relations, and knowledge equity within the organization.

It specifically revealed the multifaceted and sometimes contradictory impact of AI-driven training on LM implementation in an SME, identifying three emerging themes.

AI-driven LM training as an equalizer and a disruptor emerged as a central theme, illustrating how the training platform democratized access to Lean knowledge. Historically, formal Lean education had been the domain of managers and continuous improvement specialists, leaving operators to learn through informal, experience-based methods. With the introduction of AI-driven training, this asymmetry began to shift. As the Production Operator explained, "*Now I don't just do my job; I actively think about how to make it better*," illustrating a new sense of agency and reflective practice. The Team Leader similarly reported increased confidence in cross-functional decision-making, noting that AI-supported training helped create a common language around Lean across departments. Nonetheless, this inclusivity exposed new barriers. Senior and less digitally literate employees found it difficult to adapt to the platform's technology. The Production Flow Manager observed, "*Some of our senior employees struggle with digital training*," pointing to a generational digital divide that could reinforce new forms of exclusion. At the same time, the Lean Manager emphasized AI's ability to reduce subjectivity in evaluation: "*It evaluates based on progress rather than perception*." This duality framed AI as both an equalizing force and a disruptive one, showing that its success depends not only on accessibility but also on the ability to accommodate different digital competencies. Blended learning strategies and structured onboarding emerged as key enablers for inclusive adoption.

The paradox of continuous improvement: empowerment vs. burnout, is the second emerging theme that underscored the tension between empowerment and strain. AI training bolstered employee autonomy and critical engagement with Lean processes. Interviewees described a cultural shift from reactive compliance to proactive improvement, with employees increasingly using data and training insights to suggest process enhancements. According to the Lean Manager, operators began contributing more meaningfully to meetings, while the Team Leader noted an uptick in critical thinking among the workforce. However, the same digital tools that enabled this engagement, performance dashboards, real-time feedback, and KPI tracking, also increased a sense of constant scrutiny. "*You always feel like there's more to improve, and that can be exhausting*," the Team Leader admitted, reflecting a growing psychological burden. As AI systems made inefficiencies more visible, employees experienced mounting pressure to optimize continuously. This was especially pronounced in roles with higher responsibility, where visibility translated into implicit accountability. The analysis suggests that organizations need to actively manage this paradox by balancing performance incentives with psychological safety, clear limits to optimization expectations, and recovery time, especially in resource-constrained environments.

The digital divide in LM adoption: access, equity, and resistance theme revealed the socio-cultural frictions provoked by AI training implementation. While the platform's flexibility and personalized modules were praised by digitally fluent employees, those with extensive tacit knowledge often questioned its real-world applicability. "*AI gives me the theory, but it doesn't replace experience*," stated the Production Operator, highlighting the disconnection between abstract training and situational problem-solving. This skepticism was not solely about usability but also reflected deeper concerns about professional identity and relevance in an increasingly data-centric environment. Senior employees expressed doubts about AI's ability to replicate the nuanced judgments required on the shop floor. "*Lean isn't just about following procedures. It's about adjusting to situations*," noted the Production Flow Manager. These sentiments point to a broader resistance rooted in perceived erosion of experiential expertise and fear of job displacement. As the Lean Manager emphasized, "*If people feel that automation is a threat rather than a tool, we risk resistance rather than engagement"*. To address these challenges, participants recommended hybrid learning solutions that merged digital tools with hands-on mentoring and collaborative group exercises. The Lean Manager proposed integrating AI into structured mentorship programs, while the Team Leader suggested embedding it into team discussions to preserve a collective learning environment. These proposals reflect a need to contextualize AI within existing social dynamics and value systems, rather than treating it as a purely technical solution.

To provide a clearer overview of the thematic analysis, Table 3 summarizes the main themes and sub-themes that emerged from the data.

Table 3. Overview of the thematic analysis' results.

Theme	Sub-Theme	Description	Key Findings
AI-Driven LM training as an equalizer and a disruptor	**Equalizing knowledge across hierarchical divides**	AI training has democratized Lean knowledge, allowing all employees to access structured learning materials, breaking hierarchical barriers in knowledge acquisition.	Lean training is now accessible to all levels, fostering inclusivity. Employees feel more competent in Lean concepts and decision-making.
	A disruptor to traditional learning pathways	While AI improves accessibility, it also disrupts traditional learning methods, creating challenges for employees who struggle with digital tools.	Some employees find it difficult to transition to digital learning, highlighting the need for better onboarding and blended learning approaches.
The paradox of continuous improvement: empowerment vs. burnout	**Increased engagement and decision-making authority**	The AI-driven training has led to greater employee participation in Lean initiatives, empowering workers to take ownership of process improvements.	Operators now use data to justify process improvements rather than relying on intuition. Engagement in Lean initiatives has increased significantly.
	The dark side of optimization: psychological pressure and burnout	Continuous optimization pressure from AI training has increased workplace stress, particularly for leadership roles, leading to concerns about burnout.	Leaders feel pressured to continuously improve, leading to stress. Some employees perceive Lean as a never-ending pursuit of efficiency.
	The need for balance: sustainable Lean practices	A need for a balanced approach where AI supports Lean improvements without creating an overwhelming expectation of constant optimization.	Organizations should set realistic performance targets and frame AI as a supportive tool rather than a performance metric.
The digital divide in Lean adoption:	**The generational digital divide**	Senior employees with lower digital proficiency face barriers in engaging with AI training, risking	Digital literacy gaps create unequal participation in AI-driven training. Addressing this

access, equity, and resistance		exclusion from Lean upskilling initiatives.	requires tailored training and onboarding support.
	AI as a double-edged sword for job security	While AI is perceived as a tool for upskilling, some employees worry that automation may replace certain manual roles, raising concerns about job security.	Clear communication is needed to position AI as an enabler rather than a replacement to ensure workforce engagement and prevent resistance.

Source: Author's own elaboration.

To synthesize the above findings and provide a theoretical interpretation of the empowerment-anxiety tension, this section develops a conceptual model, the AI-driven Lean learning equilibrium, which explains how AI training simultaneously enables and constrains social sustainability in Lean contexts.

4.5 The AI-driven Lean learning equilibrium: balancing empowerment and anxiety

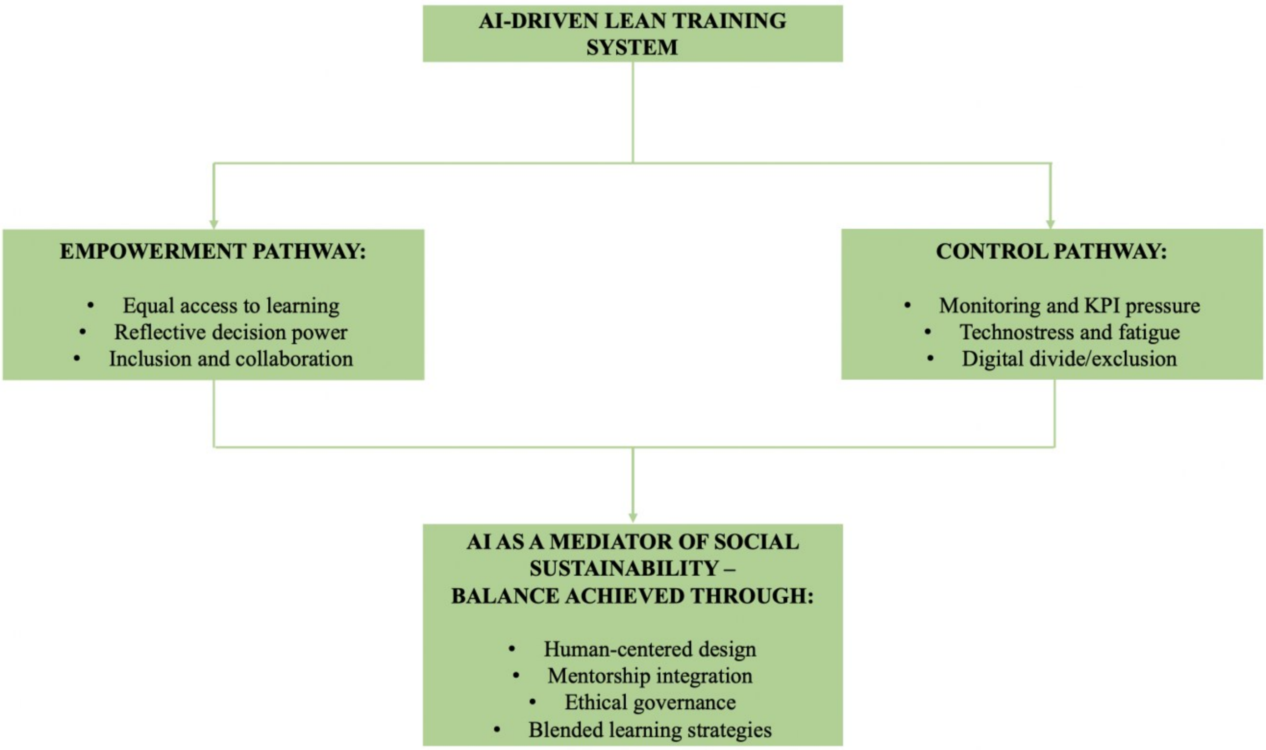
The case analysis highlights that AI-driven training introduces a multifaceted transformation in Lean-based organizations, one that cannot be reduced to a simple narrative of technological progress or human resistance. Instead, the empirical findings suggest that the adoption of AI training systems creates a dynamic social paradox characterized by simultaneous empowerment and anxiety. Employees experience unprecedented access to structured Lean knowledge and the capacity to engage more autonomously in process improvement. Yet, this empowerment coexists with new psychological burdens: stress linked to continuous digital monitoring, cognitive overload, and the fear of professional obsolescence. These ambivalent outcomes reveal that AI-driven learning operates not as a unidirectional enabler but as a socio-technical tension field in which empowerment and anxiety coexist and co-evolve.

To conceptualize this duality, the study advances the AI-driven Lean learning equilibrium model (Figure 1). The model theorizes AI training as a system shaped by two parallel and interacting mechanisms. The first, the *Empowerment Mechanism*, arises when AI functions as a knowledge democratizer facilitating equitable access to Lean education, enhancing employees' self-efficacy, and reinforcing participatory decision-making. This mechanism enhances inclusivity and reflective practice, particularly by flattening traditional hierarchies in learning access. The second, the *Control Mechanism*, emerges when AI systems act as psychological stressors, amplifying feelings of surveillance, fatigue, and continuous self-optimization. Here, the same feedback and monitoring tools that enhance efficiency may simultaneously intensify pressure, reducing employees' perceived autonomy and sense of psychological safety.

These mechanisms coexist within a continuum rather than a binary opposition. Their interaction determines whether AI-based Lean training contributes to social empowerment or to digital strain. In organizations with supportive cultures, transparent AI systems, and effective mentoring, the empowerment mechanism tends to dominate, resulting in higher motivation, collaboration, and organizational learning. Conversely, in contexts with rigid performance evaluation systems or limited digital literacy, the control mechanism prevails, manifesting in stress, exclusion, and resistance. Thus, the social sustainability of AI-driven Lean training depends not on the technology itself but on how its design, implementation, and governance mediate between these two forces.

The mediating role of AI becomes central in achieving this equilibrium. Rather than functioning merely as a neutral instructional tool, AI operates as a social mediator: a system that shapes, filters, and redistributes organizational knowledge and emotional energy. When governed ethically and integrated into human-centered learning architectures, AI can bridge cognitive and generational divides, transforming the workplace into a participatory learning ecosystem. This aligns with recent calls in sustainability and organizational behavior literature to frame digitalization as both a technological and moral project, requiring intentional governance mechanisms that balance innovation with human dignity.

Figure 1. AI-driven Lean learning equilibrium model



Source: Author's own elaboration.

From a theoretical perspective, the model offers a conceptual advancement by reframing AI-driven training as a socio-technical learning ecology rather than a purely functional tool. It integrates perspectives from digital sociology, organizational psychology, and sustainability studies to illustrate how digital transformation produces both cognitive empowerment and emotional vulnerability. This duality enriches the understanding of social sustainability in manufacturing, demonstrating that human-centered digitalization requires not only technological adoption but also the cultivation of ethical, inclusive, and psychologically supportive learning environments.

5. CONCLUSIVE REMARKS, IMPLICATIONS, AND FUTURE RESEARCH DIRECTIONS

5.1 The dual impact of AI-driven training on Lean adoption and social sustainability in SMEs

Addressing RQ1, the findings demonstrate that AI-driven training significantly facilitates the adoption of LM in SMEs by enhancing the accessibility, structure, and personalization of learning processes. The case study revealed that AI platforms democratize Lean knowledge, traditionally confined to managerial or specialized roles, by equalizing learning opportunities across hierarchical levels. Operators, team leaders, and managers now share a common conceptual framework of Lean principles, which promotes greater consistency in implementation and enhances cross-functional collaboration. This democratization process represents a shift from tacit, experience-based learning to a standardized and data-supported educational model, aligning with Lean's emphasis on transparency and continuous improvement. Furthermore, AI-driven training provides adaptive and personalized learning pathways, allowing employees to progress according to their skill levels and learning speeds. This flexibility enhances engagement and retention, addressing one of the most critical barriers for SMEs: limited time and resources for continuous training. The inclusion of real-time feedback mechanisms and performance analytics has reinforced employee confidence and autonomy in applying Lean tools to their daily operations, leading to a transition from reactive compliance to proactive problem-solving.

However, the results also highlight several challenges. The introduction of AI accentuates digital literacy gaps, particularly among senior employees, thereby creating a new form of inequality in learning access. While younger or more digitally fluent workers benefit from the adaptive interface, others require targeted onboarding and mentoring. Consequently, the findings emphasize the importance of hybrid training models that combine AI-assisted modules with experiential learning, peer mentoring, and human facilitation. Such blended approaches preserve the experiential wisdom and contextual understanding that remain vital for effective Lean implementation.

Overall, AI acts not merely as a technological instrument but as a transformational learning mediator, reconfiguring how knowledge is created, shared, and applied. Its potential lies in balancing automation with human-centered pedagogy, ensuring that digital systems support, rather than replace, the experiential and collaborative dimensions of Lean learning.

Concerning the RQ2 which explored how AI-driven training influences social sustainability within a LM context, the empirical findings indicate that AI-driven learning systems contribute positively to several social sustainability dimensions, namely inclusivity, equity, and participatory engagement, but also introduce new psychosocial challenges related to stress, surveillance, and digital overload. From an inclusivity perspective, the AI platform has equalized access to professional development across the workforce, allowing all employees to receive the same structured and transparent learning content. This shift aligns with social sustainability principles emphasizing fairness, continuous learning, and equitable access to skills development. Employees who previously lacked formal training opportunities now perceive themselves as legitimate contributors to Lean improvement initiatives, thereby enhancing their sense of agency and belonging.

At the same time, the findings reveal that this empowerment coexists with psychological strain and perceived loss of autonomy. The continuous monitoring of performance through AI dashboards and feedback loops fosters an "always-on" culture of optimization. While Lean traditionally promotes continuous improvement, the introduction of AI magnifies this pressure by quantifying efficiency in real time. Participants reported feelings of increased scrutiny, performance anxiety, and fatigue—particularly among team leaders and supervisors responsible for maintaining performance metrics. This phenomenon reflects the paradox of empowerment versus burnout, where the same digital tools that enable learning and self-efficacy can also generate cognitive overload and emotional stress.

For clarity reasons, Table 4 provides an overview of the results and the implications of the RQs addressed.

Table 4. Results and the key implications of the RQs.

Research Question	Key Empirical Findings	Theoretical Implications	Practical Implications
RQ1: How can AI-driven training effectively support LM adoption in SMEs?	• AI democratizes Lean knowledge, enhancing cross-level accessibility. • Adaptive learning paths increase engagement and comprehension. • Encourages proactive problem-solving and reflective practice. • Digital divide among employees limits inclusivity. • Hybrid (AI + experiential) learning models are essential.	• Positions AI as a socio-technical enabler of Lean learning. • Expands the concept of Lean education beyond managerial hierarchies. • Highlights need for human–AI complementarity in training.	• Implement blended learning strategies. • Invest in digital onboarding and mentoring. • Use AI to support, not substitute, human expertise.
RQ2: What is the impact of AI-driven training on social sustainability outcomes in an LM environment?	• Improved inclusivity and equal access to training. • Enhanced collaboration and shared understanding. • Psychological strain due to performance tracking. • Tension between empowerment and burnout. • Perceived risks to autonomy and job security.	• Introduces the concept of the *AI-driven Lean learning equilibrium*. • Frames social sustainability as a balance between empowerment and control. • Extends sustainability theory to include psychosocial dimensions of digitalization.	• Ensure transparent communication about AI's supportive role. • Integrate human mentoring and psychological safety mechanisms. • Develop inclusive and ethical digital governance policies.

Source: Author's own elaboration.

5.2 Toward a framework for socially sustainable AI-driven Lean transformation

This study examined the integration of AI-driven training within LM in an SME, focusing on how digital learning systems reshape knowledge dissemination, employee engagement, and social sustainability. The findings reveal that AI-based training played a transformative role in democratizing Lean knowledge, shifting learning from informal, hierarchical models, traditionally dominated by managers and Lean specialists, toward standardized, inclusive, and accessible formats. This transformation enabled employees across all organizational levels, particularly shop-floor operators, to move from passive task execution to reflective, autonomous engagement with Lean principles.

As such, AI functioned not merely as a training instrument but as a catalyst for cultural and structural change, enhancing shared understanding, communication transparency, and wider participation in continuous improvement efforts. It reconfigured internal learning hierarchies and expanded opportunities for collaborative problem-solving, signaling a shift toward a more participatory and human-centered form of Lean implementation.

Building upon the thematic synthesis, this research advances a conceptual framework (Figure 1) that links AI-driven training mechanisms to social sustainability outcomes in SMEs, emphasizing the balance between technological efficiency and human-centered design. This framework underscores that the social sustainability potential of AI-driven training depends on the equilibrium between empowerment and control, efficiency and empathy. Human-centered learning design, grounded in transparency, inclusivity, and psychological safety, acts as the critical balancing force ensuring that digital transformation contributes to both operational performance and social well-being.

However, the case also uncovered significant challenges that temper these positive dynamics. Digital literacy gaps, particularly among senior employees, created asymmetries in training accessibility, requiring targeted onboarding and mentoring interventions. Algorithmic monitoring and performance analytics, while improving objectivity and visibility of process inefficiencies, were also perceived as intrusive, producing psychological strain and a sense of constant evaluation, especially among team leaders and supervisors. This empowerment–anxiety tension revealed that while AI facilitates knowledge democratization and autonomy, it may simultaneously heighten cognitive and emotional stress if not accompanied by safeguards.

The findings thus highlight the importance of organizational mediation mechanisms that buffer digital stress while maintaining engagement. Hybrid training models, combining AI-driven modules with experiential learning, peer mentoring, and team-based reflection, emerge as essential to balance efficiency with well-being. Such an approach allows organizations to harness AI's analytical and adaptive potential without eroding the human dimension of Lean. Structured onboarding programs can bridge generational digital divides, while ethical performance tracking and clear communication about AI's supportive rather than punitive role can mitigate anxiety and resistance. Reinforcing collaborative learning rituals, such as cross-functional improvement meetings and mentoring loops, further grounds AI training in shared experience rather than individual performance metrics.

From a broader theoretical point of view, this study contributes to sustainability and organizational learning literature by framing AI-driven training as both a technological and social mediator. The proposed framework advances three central insights:

1. AI as an enabler of social inclusion by democratizing access to structured Lean knowledge and enhancing participatory decision-making;
2. AI as a generator of psychosocial tension when digital monitoring, performance feedback, and cognitive overload surpass human adaptability; and

3. AI as a mediator of equilibrium capable of reconciling technological and human needs when embedded within ethical, transparent, and supportive learning environments.

This dual nature positions AI as both a knowledge equalizer and a psychological disruptor, emphasizing that the path to socially sustainable Lean transformation lies not in the elimination of tension but in its governance. The sustainability of AI integration therefore depends on the organization's capacity to transform digital tension into productive learning energy, supported by empathetic leadership, participatory design, and collective sensemaking.

Moreover, this study contributes to the growing discourse on AI in Lean Manufacturing and HR by providing a nuanced understanding of how AI-based learning influences workplace engagement, social sustainability, and organizational learning dynamics. While previous research has largely focused on the technical and operational benefits of Lean, this study extends the literature by examining its intersection with digital transformation and human factors.

For practitioners, these findings provide essential insights into strategically implementing AI-driven training in Lean environments. Organizations must address the digital divide by incorporating structured onboarding programs that accommodate employees with varying levels of digital proficiency. Training should be designed to cater to different learning styles, blending digital modules with hands-on workshops to ensure inclusivity. While Lean methodologies emphasize continuous improvement, it is crucial to maintain a balance between efficiency and employee well-being. Excessive pressure to optimize processes can lead to workplace stress, making it necessary for managers to set realistic performance targets and incorporate psychological safety measures into Lean initiatives. Another key aspect is the perception of AI within the workforce. Concerns about automation and job security emerged in this study, emphasizing the importance of clear communication about AI's role as a support tool rather than a replacement for human expertise. Organizations should foster transparent dialogue between leadership and employees to build trust in AI-driven learning and ensure its acceptance. Additionally, while AI training was considered useful, some employees found it overly theoretical. To enhance its practical value, training should be integrated with real-time shop-floor data, enabling employees to apply Lean principles in real-world scenarios as they learn.

Given the evolving nature of AI-driven training in LM, several research avenues remain open. Future studies should explore the long-term retention of AI-driven learning, assessing how knowledge application evolves over time and whether engagement declines as employees become accustomed to the system. Comparative studies across different industries, such as automotive, aerospace, or service sectors, would provide further insights into the adaptability of AI training in various Lean environments. Additionally, as stress and burnout were recurring concerns, further research should examine the cognitive load, job satisfaction, and overall well-being of employees engaged in AI-driven training. Interdisciplinary approaches combining organizational psychology, human–AI interaction, and sustainability science would enrich understanding of the mechanisms through which digital learning ecosystems contribute, or fail to contribute, to social sustainability.

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CHAPTER IV: THE ROLE OF ARTIFICIAL INTELLIGENCE IN INTERNATIONAL STRATEGIC DECISION-MAKING FOR SMES*

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ABSTRACT

Purpose. The study investigates the integration of artificial intelligence (AI) into the international strategic decision-making processes (ISDMPs) of small and medium-sized enterprises (SMEs), assessing its potential to improve quality, speed, and accuracy of decisions, while also identifying key barriers to adoption.

Design/ methodology/ approach. The research employs a qualitative thematic analysis within a multiple case study design involving six Italian manufacturing SMEs. Data were collected through semi-structured interviews with key international decision-makers. Guided by the Strategic Decision-Making Process (SDMP) theory, the analysis explores the role of AI in shaping decision-making dynamics, including quality, decentralization, communication, and formalization.

Findings. While AI demonstrates significant potential to democratize decision-making, accelerate operations, and support international expansion, its adoption by SMEs remains cautious and incremental. Challenges and major barriers to full integration include financial constraints, limited technical expertise, and cultural resistance to change. The development of a conceptual framework illustrating how AI reshapes the dimensions of SDMP within SMEs further reveals how firms with greater AI awareness tend to demonstrate higher decision-making speed and formalization, while constraints such as resource scarcity hinder decentralization and cross-functional collaboration. Moreover, human-centric values and organizational culture mediate the strategic impact of AI.

Originality/ value. The paper extends the SDMP theory to the underexplored context of AI adoption in SMEs, offering a theoretically grounded and empirically informed framework. Not only it highlights AI’s dual role as both a structuring and enabling force in ISDMPs, but also provides actionable insights for SMEs and policymakers to strategically implement AI technologies, enhance international competitiveness, and manage the challenges of digital transformation with greater efficiency.

Keywords: Artificial Intelligence; International Strategic Decisions; Strategic Decision Making; SMEs; Thematic Analysis; Multiple case study

1. INTRODUCTION

The digital transformation has emerged as a central theme in the management debate (Zoppelletto *et al*., 2023). Far from being a simple information technology evolution, this transformation greatly affects firms' activities, business models, decision-making processes, boundaries, cultures, and value chains (Iscaro *et al.,* 2022). This process integrates modern technologies that enhance data gathering, storage and analysis, encompassing numerous innovations such as robotic automation, additive manufacturing, artificial intelligence (AI), and the Internet of Things (IoT) (Strange *et al.,* 2022). Among these, AI offers essential opportunities for innovation and growth across various industries by extending the cognitive, analytical, and even creative capacities traditionally associated with human decision-making (Dwivedi *et al*., 2021; Kumar *et al.,* 2022). The managerial relevance of AI is accentuated by both the disruptive nature of its applications and the centrality of data as a strategic asset in contemporary business environments (Biloslavo *et al.,* 2024).

The OECD (2022, p. 4) defines AI as "*a machine-based system that can, for a given set of human-defined objectives, make predictions, recommendations, or decisions influencing real or virtual environments with varying levels of autonomy*". Core features such as adaptive learning, relational inference, and dynamic evolution enable AI systems to continuously refine their performance by leveraging data and experiential inputs (Brock and Von Wangenheim, 2019). Its transformative potential lies in its ability to address complex problems traditionally managed by human intelligence (Ahn *et al*., 2022). Through work automation, data-driven insights, and robust predictive analytics, AI integration helps manage complex global situations (Bag *et al.,* 2021; Wamba-Taguimdje *et al*., 2020) and enables continuous operational refinement, leading organizations to improved decision-making, increased productivity, and competitive advantage (Magistretti *et al.,* 2019; Denicolai *et al.,* 2021). The incorporation of AI into organizational processes offers strategic benefits including enhanced demand forecasting and risk management, optimized supply chain coordination, improved logistical performance, and greater support for international operations (Li *et al*., 2021). Additionally, AI enhances customer engagement through increased efficiency and personalized support, particularly via intelligent chatbot systems (Wu and Zheng, 2025; Cheng *et al.,* 2021). From a production perspective, firms with extensive AI experience report higher innovation results (Rammer *et al*., 2022). Moreover, AI's ability to automate content summarization facilitates the simplification and dissemination of complex information, thereby improving organizational knowledge management (Garcia-Mendez *et al*., 2023; Rezaei *et al*., (2024).

These advantages can significantly enhance the effectiveness of international business (IB) activities, where managing complexity, ensuring agility, and driving innovation are critical to success. Within this context, analyzing the impact of different types of knowledge on international strategic decision-making becomes particularly relevant, as it describes how organizations and policymakers face complex global environments (Ding *et al.,* 2024). Consequently, interdisciplinary research at the intersection of AI and IB is gaining increasing attention. The OECD Trade Policy Paper (2022) emphasizes AI's capacity to refine market selection processes and manufacturing location strategies. Complementary research highlights its influence on firm-level competitiveness (Feliciano-Cestero *et al.,* 2023; Baabdullah *et al.,* 2021; Bag *et al.,* 2021), as well as its contribution to strengthening international connectivity through partnerships, stakeholder engagement, and optimization of entry modes (Benito *et al.,* 2022). Recent contributions further reinforce the transformative role of AI in shaping strategic decision-making within international business, especially for small and medium-sized enterprises (SMEs). Notably, AI tools are increasingly employed to support real-time scenario planning, predictive analytics, and data-driven international strategy development, assisting firms in responding to volatile global markets (Rivero, 2025). Additionally, empirical evidence confirms that AI is capable of generating internationalization strategies with a degree of sophistication comparable to that of experienced entrepreneurs, thereby redefining the sources of competitive advantage in IB contexts (Csaszar *et al.*, 2024).

However, while multinational enterprises (MNEs) are leveraging AI, especially to identify foreign market opportunities and streamline international operations (Dillon *et al*., 2020), SMEs encounter more significant difficulties in managing digital transformation due to limitations in size and resources *(*Saleem *et al.*, 2024). This is particularly noteworthy, given that AI can offer SMEs more sustainable and cost-effective business solutions (Castillo and Taherdoost, 2023), contributing to the development of new business models and enhancing both customer and entrepreneurial experiences (Enshassi *et al*., 2024; Peretz-Andersson *et al.*, 2024). Furthermore, AI's adaptability enables small businesses to maintain technological relevance while avoiding the substantial recurring costs of full infrastructure replacements. As such, AI is recognized as a driver of economic growth, productivity, and opportunity creation, also for SMEs' international activities (Meltzer, 2018), and its growing accessibility has generated interest in both the workplace and the commercial environment (Menzies *et al*., 2024). Recent studies confirm that AI adoption accelerates SMEs' digital competitiveness and enables them to adapt internationalization strategies more proactively by simulating market scenarios and customizing offerings to global audiences (Aizenberh, 2024). Accordingly, the European Economic and Social Committee (2021) emphasizes the importance of promoting AI adoption among SMEs to reinforce innovation capacities, facilitate global expansion, and improve competitiveness in international arenas.

Within the realm of international strategic decisions (ISDs), AI has emerged as a valuable tool for managerial support, particularly in tasks such as international market selection (IMS). This growing line of inquiry has attracted considerable scholarly interest, highlighting the need for advanced AI-driven models that can enhance market analysis, accurately forecast foreign market trends, and support the development of data-informed entry strategies (Menzies *et al*., 2024). In addition to IMS, other critical ISDs include entry mode choice (Francioni *et al*., 2015) and the identification of suitable foreign partners, such as prospective clients, agents, and distributors. Consequently, the global success of SMEs may be significantly impacted by using AI in key ISDs (Denicolai *et al.,* 2021; Kumar *et al.,* 2022).

Such capabilities are particularly beneficial for SMEs, which frequently lack thorough internationalization plans and methodical strategies for market selection (Vissak and Francioni, 2013; Musso and Francioni, 2014), as they can use AI to accelerate their expansion. Following the footsteps of Fish (2006), who addressed the issue of IMS using AI computing and Kohonen Self-Organizing Maps, a contemporary example may be the successful application of Large Language Models to identify an appropriate foreign market for a recently developed product. Similarly, AI can assist in finding potential clusters of cross-national segments.

Despite the potential benefits, many SMEs remain hesitant to adopt AI technologies. This reluctance is largely attributed to structural limitations related to firm size, including restricted financial capacity and insufficient technical expertise (Silva and Gonçalves, 2022). The effective integration of AI into SMEs necessitates the resolution of important concerns, including trust, data security, cost-effectiveness, managerial dedication, and technological expertise (Enshassi *et al.,* 2024). Consequently, further empirical research and actionable guidance are required to assist them in recognizing the strategic value of AI and to facilitate its practical adoption in alignment with their business models and operational contexts (Prem, 2019).

In response to this gap, this research is grounded in the Strategic Decision-Making Process (SDMP) theory (Dean and Sharfman, 1996; Dimitratos *et al.*, 2011; Esch *et al.*, 2019; Dwivedi *et al.*, 2021), which conceptualizes decision-making as a structured process which involves key dimensions such as decision quality and speed, hierarchical decentralization, lateral communication, and formalization. Specifically, we propose that AI tools introduce new mechanisms that reshape these SDMP dimensions within the context of resource-constrained firms operating globally. This constitutes a novel theoretical contribution, as we illustrate how AI integration may enhance or constrain each SDMP dimension in real-world SME settings. In doing so, the present study extends the application of SDMP theory to the relatively understudied context of AI-driven international strategic decisions in SMEs and advances the theoretical scope of the theory by positioning AI as a mediating mechanism that shapes the structure, speed, and decentralization of decision-making under resource constraints.

By focusing on how AI technologies influence managerial cognition and strategic processes, the paper bridges the operational and systemic insights emerging from prior research on digital transformation with a strategic perspective. This approach allows for a more comprehensive understanding of how AI acts not only as a technological enabler, but also as a cognitive and organizational infrastructure shaping the way SMEs interpret and navigate international opportunities.

To achieve these objectives, a multiple case study approach involving six small manufacturing companies located in central Italy has been adopted. Specifically, following the suggestion of Ratten *et al*. (2024), interviews with main decision-makers in international activities have been conducted to understand their perceptions and experiences on AI adoption processes. By adopting the SDMP lens as a focus and thematic analysis to identify and examine key themes and sub-themes (Braun and Clarke, 2021), the study captures the complexity and richness of SMEs' experiences with AI. This provides insights that are both contextually grounded and theoretically meaningful and ensures a clear understanding of how technological innovation intersects with organizational strategy in the context of IB.

From a theoretical perspective, the study contributes by extending the SDMP framework to the AI-internationalization nexus in SMEs. It shows how AI can function both as a structuring and enabling mechanism across core dimensions of strategic decision-making, offering valuable insights into the interplay between emerging technologies and established decision-making approaches in the context of small firms. Further, it provides a comprehensive analysis of how AI can enhance SMEs' international strategic decision-making, identifying the key benefits and challenges associated with AI adoption. In addition, it presents practical recommendations to support successful implementation of AI adoption in SMEs.

The paper is structured as follows: the next section provides an overview of the relevant literature; section 3 describes the adopted methodology, while Section 4 presents the analysis of the main results; section 5 discusses the themes emerged in the analysis while also presenting a final framework that encompasses the dimensions of strategic decision-making process explored. Finally, the last section presents the conclusive remarks, discussing the theoretical and managerial implications, acknowledging the limitations of the study, and suggesting directions for future research.

2. LITERATURE REVIEW

2.1 Strategic Decision-Making Process and Artificial Intelligence

Strategic decision-making processes are essential for the success of firms, particularly those operating in international markets. They represent an established construct in strategic management research (Dean and Sharfman, 1996; Eisenhardt and Zbaracki, 1992), referring to the patterns, structures, and practices through which organizations develop and implement strategic decisions. These processes are shaped by cognitive, contextual, and structural factors, including information use, decision speed, communication flows, formalization, and decentralization (Elbanna, 2006; Schwenk, 1995). A critical component of SDMPs lies in the effective configuration and deployment of organizational resources and capabilities, activities closely tied to the pursuit of sustained competitive advantage and long-term performance optimization (Dean and Sharfman, 1996; Mintzberg *et al.*, 1976). Within the international context, the international strategic decision-making process (ISDMP) extends these principles to the global arena, encompassing decisions that directly influence firms' international positioning and strategic direction.

In this scenario, AI technologies are indispensable tools for improving the dimensions that characterize and compose SDMPs, including decision-making quality and speed, hierarchical decentralization, lateral communication, and formalization. Indeed, AI's ability to process vast amounts of data, identify patterns, and generate insights, offers new opportunities for improving *decision-making quality and speed* (Dwivedi *et al.,* 2021; Kumar *et al*., 2022; Kaggwa *et al.,* 2024). Notably, AI-powered predictive models have demonstrated strong potential in replicating complex international business scenarios and forecasting strategic outcomes, making them particularly valuable in turbulent and uncertain global environments (Vudugula and Rozony, 2023).
Additionally, within the framework of SDMP, *hierarchical decentralization* refers to the vertical dimension of decision-making, characterized by the extent to which different hierarchical levels within an organization are involved in strategic choices (Dimitratos *et al.*, 2011). This multilevel involvement enhances inclusivity, organizational learning, and responsiveness, qualities that are particularly critical for companies facing the complexities of internationalization. In this context, AI can facilitate the hierarchical decentralization dimension by providing decision-makers at different levels of the organization with access to real-time data and insights, enabling more informed and autonomous decision-making (Bag *et al*., 2021).

Regarding *lateral communication,* AI can enhance collaboration and information sharing across departments and international subsidiaries by integrating data from various sources and providing a unified platform for analysis and decision-making (Cheng *et al*., 2021). AI-powered tools such as machine learning algorithms can help identify trends and correlations that might not be evident through traditional analysis, encouraging a more collaborative and informed approach to strategic decision-making.

Furthermore, the integration of AI has been demonstrated to facilitate the *formalization* of decision-making processes. AI can standardize data collection and analysis procedures, ensuring consistency and accuracy in decision-making (Denicolai *et al*., 2021). AI algorithms can automate routine tasks, reduce human errors, and provide decision-makers with structured insights, enabling more systematic and reliable decision-making processes. This is particularly valuable in the international context, where consistency and accuracy in data interpretation are crucial for making strategic decisions across different foreign markets.

2.2 Key International Strategic Decisions and AI applications

ISDMPs play a central role in shaping the global expansion strategies of firms. They encompass key decisions like IMS (Francioni *et al*., 2013; Francioni *et al*., 2015), entry mode selection (EMS) (Agarwal and Ramaswami, 1992), and the selection of the appropriate foreign partners, such as international clients, agents, and distributors. Among these, IMS is particularly complex, as it involves managing heterogeneous market environments while facing the inherent uncertainty and risk associated with international expansion. The academic literature has extensively investigated the challenges of identifying and evaluating new foreign markets (Francioni and Martín Martín, 2024). Given the variety of international markets and the difficulties businesses encounter when locating, assessing, choosing, and seizing opportunities overseas, IMS demonstrates its strategic role in firm performance (Brouthers *et al*., 2009; Martín Martín *et al*., 2022; He *et al*., 2016). Moreover, research has highlighted the significant strategic and financial risks associated with poor market selection. As noted by Papadopoulos and Martín Martín (2011), entering inappropriate markets may incur higher costs and lead to substantial missed opportunities, while more informed market choices can yield considerable strategic benefits.

EMS constitutes another critical strategic decision, involving the selection of governance forms such as exporting, contractual modes, joint ventures, or wholly owned subsidiaries (Ji and Dimitratos, 2013). Research has established a positive link between optimal entry mode selection and export performance (Brouthers, 2002). Alongside IMS, EMS involves identifying target segments and suitable international partners, such as clients, agents, and distributors (Francioni *et al*., 2015; Francioni and Martín Martín, 2024).

In the specific domain of ISDMPs, several AI tools have been analyzed to understand their specific impact on IMS or EMS because they have proven to be increasingly relevant. AI algorithms, such as Kohonen Self-Organizing Maps (SOMs), have been shown to assist in low-cost market screening, offering companies an accessible way to assess foreign markets systematically (Fish, 2006). Moreover, AI facilitates the analysis of network structures and country-specific externalities, which can lead to more strategically grounded business engagements and more effective connections with international suppliers, intermediaries, and clients. Notably, Menzies *et al*. (2024), using a narrative literature review, investigate how AI can be incorporated into the various strategies, practices, and activities of IB, including an examination of both IMS and EMS. Their study demonstrates that AI enhances IMS by improving international prospect identification, market trend forecasting, and reducing psychic distance. It also facilitates informed decision-making by evaluating country-specific externalities and streamlining the identification of suppliers, partners, and clients, strengthening global networks. In EMS, AI mainly contributes to IB ecosystems by enhancing the selection process. Additionally, it supports the development of digital platforms, facilitates crowdsourcing and freelance networks, and ensures compliance with export regulations through the analysis of product descriptions about legal standards. Extending these insights, Dillon *et al.* (2020) introduce digital infrastructure models that incorporate cloud computing, crowdfunding, and machine learning to examine how entrepreneurs gain international experience and how this, in turn, influences opportunity recognition and exploitation. The evolution of AI applications is further exemplified by tools such as Google's Gemini, which reflect the expanding capabilities of AI in IB contexts. Similarly, large language models like ChatGPT have demonstrated substantial usefulness in analyzing customer feedbacks, unstructured data, and audience profiles, offering firms insights into target markets that directly inform both IMS and EMS processes (Haleem *et al.,* 2022). In this regard, generative AI is increasingly recognized not merely as a tool for operational enhancement, but also as a transformative force within the cognitive and creative dimensions of international strategy formulation (Sadaf *et al.,* 2023; Cimino *et al.,* 2024). Similarly, AI-powered segmentation technologies have proven effective in identifying and targeting specific consumer segments with customized marketing approaches, thereby streamlining market entry strategies, and enhancing the overall efficiency of internationalization efforts (Saleem *et al.,* 2024). Moreover, the integration of generative AI tools facilitates the evaluation of international strategic alternatives by simulating competitive positioning and entry mode implications in real time (Doshi *et al.*, 2024).

Despite these advancements, research on the use of AI in ISDMPs remains scarce, particularly for SMEs. Most studies focus on large enterprises or theoretical applications without detailing the specific needs and challenges of smaller firms. To the best of authors' knowledge, only a few contributions, such as Fish (2006) and Saleem *et al.* (2024), explicitly address SMEs. The former emphasizes the use of low-cost AI approaches for market screening, while the latter highlights the need to integrate AI with business model innovation to achieve meaningful internationalization results. However, both studies require updates to reflect the latest developments in AI technology and its applications.

2.3 AI adoption in Small and Medium-Sized Enterprises and its impact on International Strategic Decisions

While AI enhances SDMPs, SMEs face unique challenges in adoption, including financial constraints, lack of technical expertise, and concerns about data security and privacy (Silva and Gonçalves, 2022). They struggle with foreign market expansion due to limited resources and uncertainty about where to start, frequently resulting in early disengagement from cross-border initiatives (Fish, 2006). These barriers can hinder the effective integration of AI technologies in their SDMPs.

Despite these challenges, AI can significantly improve SMEs' international competitiveness by offering advanced data analysis, market prediction, and customer engagement tools (Enshassi *et al*., 2024). Predictive analytics enables SMEs to anticipate market trends and customer preferences in international markets, allowing more informed decisions. Additionally, AI assists SMEs in optimizing resource allocation by automating repetitive tasks, thus enabling decision-makers to reallocate focus toward higher-value strategic activities, and ultimately increasing their operational efficiency (Denicolai *et al*., 2021).

Concerning IMS, previous studies highlight the potential of AI for SMEs. For instance, Fish and Ruby (2009) developed an AI-based model tailored for SMEs, offering a cost-effective approach to guide IMS choices. Similarly, Neubert (2018) found that Lean global startups can use AI algorithms to help estimate the potential of future international markets. However, to the best of the authors' knowledge, no studies have examined the perceived benefits, barriers, and concerns that influence decision-makers' decisions to adopt AI in their firms and during ISDs. Moreover, as Menzies *et al*. (2024) stressed, studies should look at how AI can help with IB data collection, decision-making, and market selection.

For this reason, this paper aims to answer the following research questions (RQs):

RQ1. How do SMEs' decision-makers adopt AI digital technologies in their International Strategic Decisions?

RQ2. How does AI integration reshape Strategic Decision-Making Process dimensions in firms operating in international markets?

3. METHODOLOGY

3.1 Research design

To address the research questions, the study adopts a multiple case study approach, highly relevant in international research (Eisenhardt, 1989; Ghauri, 2004; Yin, 2009; Yin 2018). Multiple case studies allow comparisons across different contexts, providing a comprehensive understanding of both unique and shared experiences. The approach is particularly appropriate for this research because it facilitates an in-depth exploration of how contextual factors influence AI adoption in ISDs. Six interviews were conducted, one with a key informant from each participating firm. This approach is consistent with established precedents in qualitative IB research (Hultman *et al.,* 2021; Sousa *et al*., 2008). Several scholars have demonstrated that conducting a single interview per case can be methodologically robust, particularly when the study adopts an exploratory aim and combines interview data with additional sources for triangulation. For instance, Käss *et al.* (2024) introduce the concept of "multiple mini case studies" in which one informant per case provides focused insights on specific phenomena, enabling cross-case comparisons while maintaining theoretical rigor.

Piekkari *et al.* (2009) provide further support for this approach, showing that IB case studies based on a single respondent per firm are widely accepted when methodological transparency and data triangulation are ensured. Following Eisenhardt (1989), the range between 4 and 10 companies is suitable for the multiple case studies. Also, Pauwels and Mathyssens (2004) point out that the number of cases is not the criteria for evaluating the quality of the research, as the critical point is that the selected cases should reveal the research problem and fit the research objectives (Ghauri, 2004).

3.2 Case selection and data collection

Cases were selected through purposive sampling, a non-probability sampling technique in which participants are selected based on specific characteristics and their relevance to the research objectives (Palinkas *et al.*, 2015). This approach ensures that selected cases offer meaningful insights into the phenomenon under investigation by capturing variation across relevant dimensions. The selection criteria included: i) less than 250 employees and an annual turnover of at least €50 million[12]; ii) active involvement in international operations, generating at least 25% of total sales abroad (Knight *et al.*, 2004), conducted for at least two consecutive years; iii) evidence of either existing or exploratory AI adoption efforts.

The decision to target SMEs is due to their dominance in the Italian economy, particularly well known for their proactive adoption of digital innovations (Matarazzo *et al.*, 2021). The relevance of this sample stems from the significance of Italian SMEs in both the national and European industrial landscape. SMEs form the backbone of Italy's economy and are integral to European supply chains. However, they often encounter structural limitations when integrating advanced technologies like AI, including resource constraints and workforce digital skill gaps (Kapustina *et al.*, 2017). Specifically, the sample for this study comprises six SMEs located in the Marche region of central Italy, a historically industrialized territory known for its dense network of manufacturing districts and strong export-oriented tradition. The region is particularly active in sectors such as mechanical engineering, furniture, and specialized production (Potter *et al.*, 2010; Mucelli *et al.*, 2015), and SMEs based in this area often emerge from artisanal traditions but have demonstrated a growing openness to internationalization and innovation (Testi, 2023; Cainelli and Zoboli, 2004), particularly through the adoption of emerging digital technologies. This dual orientation, rooted in tradition yet seeking technological modernization, makes them an especially insightful sample for investigating the dynamics of AI adoption within the ISDMP. The selected SMEs reflect this regional specialization, operating in industries such as mechanical components, security doors, safety equipment, wood-

[12] According to the European Union's SMEs definition, their annual turnover is equal to or below €50 million and a balance sheet total is equal to or below €43 million (https://ec.europa.eu/growth/smes/business-friendlyenvironment/sme-definition_en, accessed February 13, 2025).

processing machinery, and high-end furniture production. By focusing on this regional and industrial context, the study provides a deep and contextually rich understanding of how SMEs face digital transformation and internationalization. The selected companies are introduced in Table 1 with fictional labels for confidentiality reasons.

Table 1. Firms' and respondents' overview.

FIRM	INTERNATIONAL SITUATION	EMPLOYEES	SECTOR/PRODUCT	RESPONDENT'S ROLE	TYPE OF AI TECHNOLOGY USED	DEGREE AND USE OF AI IN IB ACTIVITIES
FIRM A	8 years in international markets, passive approach relying on referrals and platforms.	102	Mechanical Processing	Managing Director	Exploratory interest in predictive and analytical AI tools for data-driven market and logistics insights (Salesforce Einstein; IBM Watson).	Currently not using AI, but considering it for strategic decision-making, especially in logistics and international sales. Evaluating Salesforce Einstein and IBM Watson.
FIRM B	30+ years in international markets, active approach with trade fairs and regional teams.	103	Devices for working at height and safety	Marketing and export manager	Use of generative AI (ChatGPT) and creative AI (Adobe Sensei) for text, translation, and visual content; supports NLP-based market analysis.	Moderate to high use of AI. ChatGPT and Adobe tools are used for market analysis, multilingual content, and communication adaptation. Enhances speed and coherence of international strategies.
FIRM C	Founded in 1970s, exports >50% to diverse markets, strong export focus.	73	Furniture	Export manager	Generative AI (NLP) for translation, technical text generation, and multilingual communication (ChatGPT).	Basic and emerging use of ChatGPT for multilingual content, technical documentation, and product naming. Mostly applied in technical and sales departments.
FIRM D	Emerging international focus, exploring e-commerce for France, limited international reach.	44	Security doors	Sales manager	Exploratory adoption of conversational AI (chatbot) planned for customer-service automation.	Minimal use. Considering chatbot for FAQs in e-commerce. AI has not yet applied to international strategic decisions. Cultural and resource barriers present.
FIRM E	Manufacturing expertise with growing focus on export opportunities.	67	Wood processing machinery	Export manager	Generative AI and large-language models (ChatGPT, Gemini) for market scanning and text-based predictive insight generation.	Exploratory use of ChatGPT and Gemini for analyzing new markets, prioritizing international targets, and identifying trade barriers and opportunities.
FIRM F	Started exporting around 2010, mostly in Europe and Canada, with passive, project-driven expansion.	17	Furniture	Back-office export	Generative AI (Large Language Models) for market analysis and cultural adaptation; early experimentation with predictive text analytics for scenario evaluation.	Light but effective use of ChatGPT and Gemini for market trend analysis, communication adaptation, and cultural localization. Supports decision-making and speeds up response to foreign inquiries.

Source: Authors' own elaboration.

Consistent with established methodological frameworks (Rashid *et al*., 2019; Yin, 2009), the study carried out the following steps: planning, design, preparation, data collection, analysis, and development of findings. Data was collected via semi-structured interviews, balancing structured responses with exploratory insights (Kallio *et al.,* 2016). The interviews were conducted in a structured format, lasting between 45 and 60 minutes, with the participants' consent for recording. The goal was to explore six key areas to gather insights: company background, AI adoption strategies, the role of AI in international markets, integration into decision-making, challenges encountered, and future plans. In line with methodological triangulation principles (Eisenhardt, 1989), interview data was supplemented by a range of secondary sources, including internal company documents, official websites, white papers, publicly available reports (e.g., annual reports, EU policy documents), and sector-specific databases (such as Archiproducts, chamber of commerce portals, and trade associations). Internal documents offered insights into the firm's strategic orientation, digital transformation initiatives, and historical decision-making patterns. Company websites allowed the research team to assess communication strategies, international engagement, and the presence of AI-related initiatives in publicly presented narratives. Public reports and sector analyses provided essential contextual grounding, enabling the interpretation of firm-level behaviors within broader industry and policy dynamics. These materials were consulted prior to the interviews to inform the design of the interview protocol, ensuring contextual relevance, and to cross-validate the information provided by respondents during data collection.

3.3 Data analysis

Thematic analysis was chosen due to its flexibility and suitability for exploring emerging topics like AI adoption in ISDs. Given the novelty and complexity of the subject, this method allows for a systematic yet adaptable approach to uncover key and novel insights. While underutilized in business studies, thematic analysis effectively identifies latent themes, making it ideal for examining how SMEs perceive, adopt, and implement AI. This ensures an iterative, grounded interpretation, contributing to the growing but still nascent literature on AI in IB. For data analysis, the process followed the steps outlined by Braun and Clarke (2021): i) familiarization with data through repeated reading of transcripts for deep understanding; ii) initial coding using both deductive and inductive approaches; iii) themes identification through grouping into themes aligned with the research objectives; iv) theme refinement to ensure coherence and alignment with the data; v) definition and contextualization of themes; vi) writing of the analysis where themes were integrated into a coherent findings section.

The SDMP theory (Dean and Sharfman, 1996; Eisenhardt and Zbaracki, 1992; Elbanna, 2006; Schwenk, 1995) guided the thematic analysis of this study, informing the coding framework and interpretation of how AI influences each decision-making dimension. In investigating the adoption of AI in ISDs among SMEs, the SDMP lens was applied, focusing on decision-making quality and speed, hierarchical decentralization, lateral communication, and formalization as key dimensions. These dimensions were incorporated into the interview framework to capture AI's role in shaping SMEs' adaptability and competitiveness in international markets. To enhance rigor and credibility, a reflexive approach was maintained to minimize bias (Braun *et al*., 2023). Triangulation of multiple data sources and member checking with respondents further validated findings. For confidentiality, the six Italian manufacturing firms remain anonymous using fictional labels (A, B, C, D, E, F) instead of company names.

4. RESULTS ANALYSIS

In response to RQ1, the following sections explore how decision-makers in SMEs use AI technologies in the context of ISDs, based on their reported experiences, strategic intent, perceptions, and applications of AI in IB operations. To support the analysis across the various investigated topics, all key quotations emerging from the interviews are presented in Table 2, with the aim of enhancing clarity and transparency of the findings.

4.1 AI adoption and strategic vision

The adoption and strategic vision of AI among the SMEs reflect a spectrum of engagement, showing variations in implementation and intent. Firm A is in the early exploratory stage, with its managing director independently researching AI tools for logistics and market analysis. However, progress is limited by a lack of expertise and a clear roadmap. Firm B, by contrast, demonstrates a more integrated AI approach, using tools like ChatGPT for content creation and Adobe's AI-enhanced applications for image processing. Their AI usage enhances workflow efficiency and decision-making, though it remains operational rather than transformative. Firm C focuses on internal efficiencies, using AI-driven translation tools to overcome linguistic and communication barriers in international operations affirming: *"We experimented with AI for content generation and translation. We are now exploring further automation possibilities" (…) "AI ensures culturally and linguistically appropriate content, minimizing misinterpretation*". Similarly, firm D explores AI-driven chatbots to improve customer service on its e-commerce platforms. However, economic and infrastructure constraints hinder full implementation. Firm E is cautiously testing AI in data-driven manufacturing and considering predictive analytics. Their approach prioritizes incremental modernization while assessing AI's feasibility within traditional workflows, reflecting an intent to modernize operations incrementally while assessing the feasibility of AI integration within their traditional manufacturing workflows. Finally, firm F presents a pragmatic and proactive engagement with AI. Initially unfamiliar with the potential of AI, the firm became aware of its utility through external webinars and began experimenting with tools like ChatGPT and Gemini. AI is now used to support a variety of international strategic tasks such as market analysis, client profiling, translation, and communication adaptation. Across the spectrum, the adoption of AI within the SMEs reveals an evolving landscape where operational efficiency often precedes strategic innovation.

4.2 The role of AI in international market strategy

The role of AI in shaping international market strategies among SMEs is characterized by cautious optimism, with significant room for growth. Firms A and D see AI's potential in customer behavior analysis and market segmentation but face expertise and financial barriers, limiting the adoption. In this sense, firm A reports that they are exploring tools such as Salesforce Einstein and IBM Watson for market data analysis but note that they still need to assess their potential usefulness for the company. By contrast, Firm B actively uses AI in market research, leveraging ChatGPT for regional analysis and consumer preference insights to adapt marketing strategies. However, strategic decisions like market entry and partner selection remain human-led, reflecting a hybrid AI-human approach, affirming *"AI helps us in market analysis and adapting our marketing to different markets, but it is not yet fully integrated"*. Firm C focuses on AI's role in global communication, using AI-driven translations to ensure culturally and linguistically appropriate marketing materials. This highlights AI's value in cross-border engagement, though broader strategic applications remain limited. Firm E has not yet integrated AI into international strategies, prioritizing operational efficiency over market-oriented AI applications. Finally, firm F offers a compelling case of how AI can enhance international market strategies. Although AI adoption is still informal and non-systematic, the company uses tools like ChatGPT and Gemini to perform exploratory market analyses, evaluate entry scenarios, and assess cultural preferences in new target countries. These tools have supported the company in avoiding market missteps, identifying opportunities, and aligning the company material (i.e., brochures) with the new country's expectations.

Collectively, SMEs recognize AI's strategic potential, yet practical constraints and hesitations slow down broader adoption.

4.3 AI integration and Decision-Making Process

The integration of AI into decision-making processes among the SMEs demonstrates different degrees of skill and commitment. Firms A and C acknowledge AI's potential to analyze data and forecast trends but emphasize the importance of aligning these tools with their specific operational contexts to prevent generic or misaligned applications. They note that they are still in the early stages of integrating AI into their decision-making processes and are considering involving more staff in exploring AI solutions, especially in sales and logistics. Firm B adopts AI, particularly ChatGPT, to speed up decision-making and improve the creation of marketing content. While AI improves efficiency, human oversight remains essential for complex strategic decisions: *"We use AI mainly in content creation and preliminary market research, but it has not yet been applied to strategic decision-making"*. Firm D is in early exploratory stages, facing financial and infrastructural challenges, limiting AI integration into decision-making. Firm E is experimenting with AI in production planning and logistics, focusing on internal efficiencies rather than strategic transformation. Finally, firm F, despite lacking a formal IT department or predictive analytics systems, uses AI tools regularly to simulate international scenarios, evaluate market conditions, and support strategic assessments, such as choosing between direct or indirect export modes. The respondent reports that AI reduces the time required to gather and interpret data from platforms like Archiproducts and social media, accelerating early-stage decisions. The firm also applies AI to filter foreign market opportunities more rationally, shifting from intuition-based decisions to a more data-informed process. Across the cases, AI is integrated incrementally, prioritizing applications with immediate and measurable benefits. The gradual adoption reflects resource constraints and organizational inertia, demonstrating a pragmatic approach to AI-driven decision-making.

4.4 AI adoption challenges

There are many obstacles to SMEs' adoption of AI, including financial, cultural, and technical ones. Financial constraints are common, particularly for smaller firms like firm D, where the cost of advanced AI tools often exceeds budgetary allowances. This financial barrier limits access to transformative technologies, compelling SMEs to prioritize incremental and cost-effective solutions. Moreover, the manager expresses significant hesitation toward AI tools, admitting a strong sense of fear and describing herself as still very much a "pen-and-paper" person as highlighted by firms A and E. In the case of Firm A, knowledge gaps emerge as a significant challenge, with the lack of familiarity with AI tools cited as a key barrier to adoption. This deficiency limits the firm's ability to identify appropriate technologies, and weakens confidence in their practical implementation, as they point out that the main difficulty has been the absence of internal knowledge regarding available tools and the investments they entail.

Addressing this challenge requires targeted training programs and accessible resources that help demystify AI for smaller enterprises. Cultural resistance also plays a role, as exemplified by firm C affirming: *"We are still trying to understand how AI can be useful for us. The main challenge is cultural adaptation rather than financial or technical constraints"*. Employee skepticism, fueled by fears of job displacement and doubts about AI's reliability, has slowed the pace of adoption. Overcoming such resistance necessitates a concerted effort to demonstrate AI's benefits through pilot projects and success stories. Additionally, firm B noted operational challenges, especially in integrating AI into existing workflows without causing disruptions. Firm F reinforces many of these barriers, particularly the lack of technical infrastructure and internal expertise. The export back office admits that more advanced implementations, such as predictive analytics or CRM-integrated AI modules, remain out of reach due to time constraints, limited resources, and the absence of IT personnel. Moreover, the artisanal nature of the company reinforces a preference for intuitive, human-centric decision-making, which may slow full-scale adoption of more autonomous AI systems. These challenges highlight the need for tailored implementation strategies that align with organizational structures and capabilities.

4.5 Future plans

Despite various challenges, SMEs expressed optimism regarding the transformative potential of AI. Firm A indicated intentions to explore AI applications in logistics optimization and advanced market analysis, while Firm B reported plans to expand its use of predictive analytics and to enhance e-commerce platforms, particularly by focusing on personalized customer experiences. Moreover, the firm also referred to translation capabilities as a noteworthy application area, which it described as "very reliable." Firm B further suggested that AI could soon become central to business decision-making processes. These initiatives are consistent with the proactive international strategies adopted by these firms. Firm C plans to leverage AI for deriving customer insights and evaluating international partners, all while preserving a human-centric approach to decision-making. Firm D reported its intention to develop AI-driven customer service tools and to enhance e-commerce capabilities through chatbot implementation. Firm E conveyed a cautiously optimistic stance toward the integration of AI into production and logistics operations. It emphasized a gradual modernization process to prevent disruption of core functions and highlighted ongoing considerations around AI-based automation in production lines and AI-driven analytics for sales and customer behavior. Firm F sees AI as a long-term strategic partner rather than a temporary trend. In the short term, it plans to integrate AI into its CRM to enhance analysis of international customer behavior, response times, and purchasing preferences. Additionally, the firm is exploring generative AI solutions for rapid 3D rendering and customized product previews. Looking ahead, Firm F envisions developing an AI assistant embedded in daily decision-making processes: "*The goal, for us, is not to digitalize everything blindly, but to understand which tools can truly add value and save time. AI is a powerful lever, but it must be used with balance and adapted to our real context, made of relationships, artisanal care, and experience*."

This reflects a grounded yet ambitious approach, where AI is seen as a capacity multiplier, especially for SMEs operating internationally, while maintaining a strong human and craftsmanship-centered identity. Collectively, SMEs view AI as a driver of innovation and competitive advantage but stress the need for alignment with organizational goals, continuous learning, and ethical considerations. Their pragmatic step-by-step approach reflects AI’s potential, tempered by real-world SMEs’ constraints.

Table 2. Main quotations emerged for the topics discussed.

FIRM	AI ADOPTION AND STRATEGIC VISION	THE ROLE OF AI IN INTERNATIONAL MARKET STRATEGY	AI INTEGRATION AND DECISION-MAKING PROCESS	AI ADOPTION CHALLENGES	FUTURE PLANS
FIRM A	*"We are evaluating AI as a future opportunity. I am starting to gather information and study which tools might be useful".*	*"I am reading many articles and success stories related to the metalworking sector that use artificial intelligence... I realize there is potential".* *"I am reading about tools like Salesforce Einstein and IBM Watson that can analyze market data, but I still need to understand if they would be useful for us".*	*"I'm starting to gather information... with an external consultant we're applying for funding calls... with the aim of improving critical processes like logistics".* *"We are still at the early stages of integrating AI into our decision-making process".* *"We are considering involving more staff in exploring AI solutions, especially for sales and logistics".*	*"I don't know them well... I definitely need to study them better... I still don't fully trust them".* *"We still rely on traditional methods... we rely on word of mouth... our ability to analyze international markets is practically nonexistent".* *"The main challenge has been a lack of internal knowledge about the tools available and the investments required".*	*"I am starting to get informed and study which tools might be used… to exploit them. I am also thinking of involving other figures to implement AI-based solutions in our internal strategic departments".* *"As I said, I am open to using artificial intelligence tools to make internationalization strategy decisions".*
FIRM B	*"We have expanded the use of AI to several departments to improve operational efficiency and stay up to date with new technologies".*	*"AI was used for preliminary market analyses... it supports initial analyses by offering a clearer view of market dynamics".* *"AI has been useful for analyzing terminology and local preferences, improving the adaptation of communication materials to cultural specificities".*	*"It improved the speed of content creation... AI has standardized technical terminology to better adapt content to international markets".* *"We organize training courses and constantly evaluate new technologies... we anticipate that the use of AI could increase decision-making autonomy in the future".* *"We use AI mainly in content creation and preliminary market research, but it has not yet been applied to strategic decision-making".*	*"We don't yet use advanced predictive tools... AI only supports preliminary research".* *"We don't yet use advanced predictive tools... AI only supports preliminary research".*	*"We are gradually expanding the use of AI… we are evaluating integration with AI also in departments like administration and e-commerce".* *"ChatGPT has helped speed up the processing of market analysis and content… but we are not yet using advanced predictive tools".*
FIRM C	*"We started with AI gradually. The first concrete*	*"We have integrated ChatGPT into our workstations... when we need to write short editorials for*	*"ChatGPT... is definitely a great help... if before I had to rack my brain to make*	*"We're a bit old style... our sector is quite old style*	*"We are planning in 2025 to train ourselves more on this… every brochure we make is*

	use was ChatGPT to speed up translation processes". "We experimented with AI for content generation and translation. We are now exploring further automation possibilities". "AI ensures culturally and linguistically appropriate content, minimizing misinterpretation".	*different markets, I have used it quite a lot". "We're a bit old style... the human factor is what gets appreciated first... but we can't pretend the world isn't changing". "AI helps us in market analysis and adapting our marketing to different markets, but it is not yet fully integrated".*	*certain presentations, now... it's a big help".*	*anyway... the human factor is what's appreciated first". "We started with AI gradually... in an extremely superficial way... we were very busy with a large number of new developments". "We are still trying to understand how AI can be useful for us. The main challenge is cultural adaptation rather than financial or technical constraints".*	*always done in five languages, so we have always handled translation internally…". "We mainly use ChatGPT to support the sales and technical teams. It helps with translation and reviewing multilingual content…".*
FIRM D	*"Artificial intelligence scares me a lot. I'm still a pen-and-paper person".*	*"We'll definitely launch the chatbot in France... what we'll do in Italy might also be an option for more mature markets".*	*"I definitely also have personal resistance... I always prefer active, let's say bibliographic, research".*	*"I definitely have personal resistance... I'm not aware of the benefits... we haven't been encouraged to learn about it". "We considered virtual headsets... but it required a big effort, economically speaking". "I have a lot of fear about AI. I am still very much a pen-and-paper person".*	*"We have been evaluating chatbots for some time. We will definitely launch e-commerce in France, and the chatbot will be useful". "I think it can be a tool for informational and educational purposes… but I'm really still very much paper and pen".*
FIRM E	*"We have been using AI since 2024 mainly to collect initial data on new countries. It has allowed us to develop a much more precise entry strategy".*	*"Thanks to ChatGPT, we managed to get a preliminary analysis of local demand for our machinery... to develop a much more precise entry strategy".*	*"Currently, we use it mainly in the sales and marketing departments... it helps us identify priorities in international markets".*	*"The biggest difficulty was adapting our internal processes to this new way of thinking."; "The transition required a change in mindset and investments in new skills".*	*"We believe that in the future, AI can be used to optimize logistics and improve internal communication among our international teams". "Thanks to ChatGPT… we were able to obtain a preliminary analysis of local demand… identifying the main logistical and regulatory obstacles".*
FIRM F	*"ChatGPT has become for us a sort of 'digital colleague' that allows us to better*	*"We asked ChatGPT for an overview of the custom furniture market, it gave us information*	*"AI is present in our company, but it is not yet structurally integrated... it's*	*"AI is not yet structurally integrated... we still rely heavily on our experience... we don't have the internal*	*"We are starting to think about something more advanced for 2025, maybe a small predictive*

	understand the context before acting".	*such as trends, required certifications, and competitors". "We started rewriting our product sheets and brochures according to the destination culture... with the help of AI we are starting to speak the customer's language". "With ChatGPT or Gemini, we can get a clear and structured summary within an hour... it allows us to be much faster in the response and presentation phase".*	*more of an occasional, cross-functional support". "AI is helping us better distinguish markets and prepare with greater precision... it has helped us avoid at least a couple of missteps".*	*resources to manage projects of that scale". "We're not talking about a structural revolution... AI adoption is not yet systematic for us".*	*tool integrated into our ERP system…". "Now we can do a first analysis internally… we don't eliminate intuition, but we support it with data, synthesis, and insights that AI makes accessible in real time". "The goal, for us, is not to digitalize everything blindly, but to understand which tools can truly add value and save time. AI is a powerful lever, but it must be used with balance and adapted to our real context, made of relationships, artisanal care, and experience".*

Source: Authors' own elaboration.

5. DISCUSSIONS

The thematic analysis identifies five emerging themes that capture the multifaceted experiences of AI adoption among the SMEs interviewed. These themes not only highlight the dynamic interplay of challenges and opportunities but also provide valuable insights into the complexities of integrating AI technologies into ISDMP.

5.1 Awareness and understanding of AI

The first theme that emerges concerns the *awareness and understanding of AI*. Notably, the degree of AI awareness across the SMEs interviewed reflects a broad spectrum, ranging from basic recognition to active engagement with sophisticated tools. Firm C, for instance, exemplifies a practical and applied understanding of AI, employing tools such as translation software to facilitate global communication and create localized content that resonates with different markets. This proactive approach highlights the potential of AI to bridge linguistic and cultural divides, positioning the firm as a frontrunner in its adoption path. Conversely, firm E remains in a preliminary exploratory phase, where AI's relevance is acknowledged but limited to CRM platforms with basic capabilities. Their approach underscores the initial stages of understanding AI's potential and broader implications. Firms A and B occupy intermediate and advanced stages of AI awareness, respectively. Firm A demonstrates moderate awareness, focusing on specific tools, indicating a growing curiosity about how AI can enhance business processes. In contrast, firm B showcases an advanced adoption stage, where AI seamlessly integrates into operational workflows, including market analysis and streamlining business processes. Meanwhile, Firm D's understanding of AI remains nascent, with its perception shaped by accessible, consumer-facing tools such as ChatGPT. Finally, firm F demonstrates a high level of practical awareness of AI, actively employing tools like ChatGPT and Gemini for scenario simulation, cultural insight, and communication tailoring. Despite the absence of formal technical training, the firm has developed an intuitive and strategically grounded understanding of AI's potential. The firm's experience highlights how SMEs can leverage practical experimentation and adaptive learning to compensate for limited infrastructure, enhancing a culture of innovation driven by accessible AI tools. These variations emphasize the critical influence of exposure, organizational readiness, and the sectoral context in shaping SMEs' perceptions of AI. Research suggests that moving from basic awareness to practical application requires targeted interventions tailored to SMEs' unique needs (Hussain and Rizwan, 2024). Workshops, industry-specific case studies, and hands-on demonstrations can effectively showcase AI's strategic value. By creating a culture of learning and experimentation, SMEs can overcome initial hesitations and align their understanding of AI with tangible business opportunities.

5.2 Perceived benefits of AI in ISDMP

Across the interviews, the *perceived benefits of AI in ISDMP* emerged as a recurring theme, highlighting its potential to transform operational efficiency and enhance strategic decision-making processes. For example, firm C emphasizes AI's ability to bridge cultural and linguistic barriers, enabling seamless communication in international markets. This capability not only improves operational workflows but also strengthens relationships with global partners and customers. Similarly, firm E identifies the potential of AI-enabled CRM systems to enhance customer segmentation, enabling more targeted and effective marketing strategies. Firm B provides concrete examples of AI's tangible benefits, citing significant time savings and improved accuracy in tasks such as translations, content creation, and preliminary market research. These advancements demonstrate how AI can automate repetitive tasks, allowing employees to focus on high-value strategic activities. While still in the early stages of adoption, Firm A envisions AI as a critical tool for logistics optimization and identifying market opportunities, signaling a forward-looking perspective on its utility. Firm F identifies several concrete advantages stemming from AI adoption, particularly in the context of international strategic decision-making. AI enables faster decision cycles, more targeted communication with international clients, and efficient pre-evaluation of new markets. The use of AI to filter opportunities, identify trends, and simulate market scenarios has enhanced the firm's responsiveness and agility. These insights suggest AI's emerging role in supporting data-driven strategic planning and the automation of routine processes, as increasingly recognized in practitioner-oriented sources[13]. Specifically, AI's capabilities in international market selection, predictive analytics, and customer relationship management empower SMEs to allocate resources more effectively and achieve competitive advantages in global markets. However, underutilizing AI's advanced features, such as export mode optimization or strategic partner selection, points to significant untapped opportunities. By addressing these gaps, SMEs can unlock the full potential of AI and strengthen their strategic decision-making processes.

Notable differences also emerged among the various contexts of AI application. In operational areas such as logistics and production (Firms A and E), AI was primarily used for optimization and predictive purposes, focusing on efficiency and control. Conversely, in marketing and communication contexts (Firms B, C, and F), AI served more strategic and cognitive functions, supporting creativity, market sensing, and international brand positioning. This suggests that the perceived benefits of AI depend not only on adoption level but also on the function and purpose of its use, with marketing-oriented applications showing greater potential for strategic transformation.

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[13] https://www.thestrategyinstitute.org/insights/the-role-of-ai-in-transforming-strategic-planning-processes?utm_source=chatgpt.com

5.3 Barriers connected to AI adoption

Another emerging theme concerns the *barriers connected to AI adoption.* Financial constraints are particularly pronounced, with firms C and E identifying limited budgets as a significant impediment to adopting advanced AI solutions. This challenge is compounded by infrastructural limitations, which hinder firm E's ability to scale AI initiatives effectively. On the other hand, Firm D highlights a lack of technical expertise and cultural resistance within the organization as key obstacles to adoption, as further supported by firm F. Employee skepticism, cited by firm C, further underscores the need for trust-building initiatives and transparent communication to create a culture of innovation. Even firm B, an advanced adopter, emphasizes the importance of developing scalable and cost-effective AI solutions tailored to the unique needs of SMEs. These barriers reflect broader trends in SME digital transformation, where resource limitations and organizational inertia frequently emerge as significant challenges (Radhakrishna *et al.,* 2023). Recent evidence by Abuzaid (2024) confirms that SMEs often lack the foundational infrastructure and strategic AI frameworks necessary to translate interest into implementation, especially in cross-border operations. This is consistent with Yusuf *et al.* (2024), who highlight that technical and infrastructural barriers significantly impact AI adoption in SMEs. One major issue is the lack of accurate data. AI systems rely on high-quality data to make effective decisions, but incomplete or inaccurate data can hinder the generation of valuable insights.

Additionally, many SMEs lack the necessary technical infrastructure to implement and scale AI technologies, including hardware, software, and IT systems (Baez and Igbekele, 2021; Ochuba *et al.,* 2024). This absence of infrastructure limits their ability to deploy AI solutions effectively. The sophisticated nature of AI can be overwhelming for SMEs, particularly those without in-house technical expertise, making it difficult for them to understand and implement these technologies. Moreover, limited access to relevant data sources restricts SMEs' ability to train AI models, reducing the effectiveness and applicability of AI solutions for their specific needs (Lada *et al*., 2023). To address these issues, incremental adoption strategies, such as piloting affordable AI tools like ChatGPT, can provide a low-risk entry point for SMEs. Lastly, collaborative partnerships with technology providers, industry associations, and academic institutions can offer the technical expertise and financial support necessary to overcome adoption hurdles. By leveraging these partnerships, SMEs can build the capabilities required to face the complexities of AI integration.

5.4 Human-centric implications

A recurring theme across the interviews concerns the *human-centric implications* of AI adoption, highlighting widespread apprehensions about its impact on roles, relationships, and decision-making processes. Firm C underscores the importance of maintaining personalized customer interactions, cautioning against an over-reliance on AI that could erode trust and relational dynamics. Similarly, firm E highlights the need to balance human judgment with AI-driven decision-making, ensuring that the technology complements rather than replaces human expertise. Also, firm F places a strong emphasis on maintaining its artisanal identity and personalized client relationships. AI is seen as a complement rather than a substitute for human judgment. Firms A and B echo these concerns, emphasizing the importance of transparency and employee involvement in AI adoption processes. Talent shortage and skill gap are some of the primary strategic challenges of most SMEs in the AI environment (Dwivedi *et al.,*2021; Johnson *et al.,* 2021). At present, many practitioners do not have a clear understanding of the capabilities and basic procedures required by organizations to obtain the potential of AI, and they are unable to solve the problem of human resources required for the promotion of AI (Lu *et al.,* 2022). This framing aligns with the affect-enacted model proposed by Grego *et al.* (2024), which explains how strategic decisions in SMEs are not solely shaped by formal analysis, but by emotions, contextual cues, and personal interpretations of what is seen as strategically meaningful. Moreover, these perspectives align with literature advocating for a collaborative approach to AI integration, where the technology is designed to augment rather than replace human capabilities (Xu and Gao, 2024). By enhancing an inclusive and transparent adoption process, SMEs can address employee apprehensions, build trust, and ensure that AI is perceived as an enabler of strategic growth rather than a threat to job security.

5.5 Potential for strategic transformation

Finally, the *potential for strategic transformation* is an emerging theme. Firm C exemplifies the strategic use of AI to enhance global communication and envisions broader applications in areas such as strategic planning and market expansion. Firm E, while cautious, recognizes AI’s potential to revolutionize customer insights and market positioning, signaling a growing awareness of its strategic value. Firm F recognizes AI’s high potential to transform its internationalization strategy. It currently employs AI to simulate market entry, scout for potential partners, and adapt its offerings to culturally diverse audiences. Although complete transformation is still in progress, the firm sees clear pathways for strategic growth through continued AI integration. Firm B represents the most advanced stage of strategic transformation, integrating AI into marketing, operational workflows, and real-time decision-making processes. This comprehensive approach highlights AI’s ability to drive cross-departmental collaboration, enhance predictive analytics, and support data-driven decision-making. In contrast, firms A and D remain in exploratory phases, lacking clear roadmaps for comprehensive AI adoption. These findings underscore the need for tailored training, accessible funding mechanisms, and sector-specific AI solutions that align with SMEs’ operational contexts (Proietti and Magnani, 2025).

In this sense, Table 3 captures and summarizes the main results of the thematic analysis.

Table 3. Thematic analysis.

FIRM	AWARENESS AND UNDERSTANDING OF AI	PERCEIVED BENEFITS OF AI IN ISDMPS	BARRIERS TO AI ADOPTION	HUMAN-CENTRIC CONCERNS	POTENTIAL FOR STRATEGIC TRANSFORMATION
FIRM A	Moderate awareness; exploring AI tools like Salesforce Einstein for logistics and market insights.	Envisions AI for logistics optimization and identifying market opportunities, but in early stages.	Limited by moderate financial resources and lack of a clear roadmap for adoption.	Concerned about transparency and employee involvement in the adoption process.	Exploring possibilities but lacks a clear implementation roadmap.
FIRM B	High awareness; advanced adoption of AI for operational streamlining and market analysis.	Significant benefits include time savings, operational efficiency, and improved market research.	Resource constraints exist but offset by scalable AI solutions tailored to SME needs.	Emphasizes maintaining trust and balancing AI with human decision-making.	Advanced integration into marketing and operational workflows; leveraging cross-departmental AI.
FIRM C	Practical understanding; uses AI for translation tools and localized content for global communication.	AI bridges linguistic/cultural gaps and supports international communication.	Financial constraints, employee skepticism, and lack of technical expertise.	Fears over-reliance on AI could harm personalized customer interactions.	Uses AI for global communication; envisions broader applications in strategic planning.
FIRM D	Nascent understanding; associates AI with basic tools like ChatGPT.	Limited benefits recognized, focused on basic AI applications.	Financial and technical constraints; cultural resistance within the organization.	Minimal focus on human-centric concerns due to low AI adoption.	Lacks transformative use due to low understanding and implementation.
FIRM E	Basic awareness; exploring CRM platforms with limited AI functionality.	Sees potential for AI in CRM-enhanced customer segmentation but remains in the exploratory phase.	Financial and infrastructural barriers; limited budgets hinder broader adoption.	Stresses the need to balance human judgment with AI capabilities in decision-making.	Cautious exploration; recognizes AI's potential for customer insights and market positioning.
FIRM F	High practical awareness; uses tools like ChatGPT and Gemini for scenario simulation, cultural insights, and communication. Strong intuitive grasp of AI's potential despite limited formal training.	Enables quicker decision-making, customized communication, and pre-assessment of new markets. AI supports market filtering, trend identification, and more responsive client engagement.	Lack of internal technical expertise, limited time and resources, and no dedicated IT infrastructure.	Strong emphasis on preserving artisanal identity and personalized customer relationships; AI is used as a complement, not a replacement.	High potential recognized; AI used in market entry simulation, partner scouting, and cultural adaptation. Transformation is seen possible through further integration and external consulting.

Source: Authors' own elaboration.

5.6 Linking findings with SDMP dimensions

This section addresses RQ2, examining how the integration of AI influences the core dimensions of the SDMP within SMEs operating in international contexts. Interpreted through the SDMP dimensions identified by literature, these emerging themes allow us to explain how AI helps in this process, especially in the international context. For clarity reasons, Table 4 provides a comprehensive summary of the responses, highlighting how each firm engages in these dimensions within their strategic decision-making processes.

In particular, the first dimension analyzed is *decision-making quality and speed*. Firms like companies B and C demonstrate proactive approaches by integrating AI tools like ChatGPT for operational decisions. This enables them to enhance decision speed while maintaining high quality. In contrast, firms like A and D exhibit slower processes due to reliance on traditional methods. Firm E represents a transitional case, cautiously exploring AI technologies to improve decision-making quality. Firm F's decision-making processes have notably improved in both quality and speed due to the integration of AI tools. By using platforms like ChatGPT and Gemini, the firm can simulate various international market scenarios, adapt strategies quickly, and tailor communications based on cultural nuances. While decision-making remains largely centralized, AI-supported insights from non-management staff are increasingly shaping strategic inputs. The literature demonstrates that AI's capacity to analyze large datasets and generate actionable insights can significantly enhance this dimension by enabling faster, data-driven strategic decisions (Dwivedi *et al*., 2021). Grashof and Kopka (2023) also demonstrate that efficiently adopting AI technologies equips human resources with essential information and skills, such as computer literacy, critical thinking, and effective decision-making.

The second dimension analyzed is *hierarchical decentralization*, which is influenced by AI's ability to provide decision-makers at different organizational levels with real-time data and insights (Bag *et al*., 2021). Firms like B are taking initial steps toward decentralization by encouraging cross-departmental collaboration through AI tools. On the other hand, companies A and D remain centralized, limiting broader participation in strategic decision-making. Firm E sees potential in using AI to decentralize processes, particularly in logistics and market analysis, demonstrating that the ability of AI to democratize access to information can increase agility and responsiveness, which is crucial for adapting to dynamic international markets. Similarly, firm F has a growing openness toward decentralization, especially for tasks related to market selection and strategy. AI tools are beginning to empower staff at lower hierarchical levels by providing them with relevant insights and decision-support capabilities.

The third dimension is *lateral communication* that is vital for effective ISDMPs, facilitating collaboration and information sharing across departments and international subsidiaries. While Firm

B is exploring tools to enhance inter-departmental dialogue, other firms have yet to fully embrace AI for this purpose fully. Firm E is beginning to recognize the importance of leveraging AI to improve lateral communication, which could streamline workflows and decision-making. In firm F, while formal mechanisms are still evolving, the current AI-enabled practices lay a promising foundation for future horizontal integration and cross-departmental synergy. AI-powered platforms that integrate data from various sources can create unified frameworks for collaboration, encouraging a more cohesive and informed approach to strategic decisions (Cheng *et al.,* 2021), guaranteeing an opportunity for enhanced communication and collaboration between businesses (Oldemeyer *et al.,* 2024).

Finally, the *formalization* dimension ensures consistency and accuracy in strategic decision-making, which is particularly important in international contexts. Firms like C exhibit high formalization levels, leveraging structured processes for their international strategies. Firm E, with moderate formalization, is exploring AI tools to standardize workflows and improve data management. Companies A and D remain less formalized, relying on traditional and informal methods. In firm F, formalization is limited, reflecting the company's preference for adaptive processes that preserve creativity and craftsmanship. Nevertheless, the integration of AI has introduced some degree of consistency, particularly in strategic documentation and international client interactions, suggesting that further formalization may emerge organically as AI adoption matures. AI's role in automating routine tasks and standardizing data collection and analysis can enhance formalization, ensuring systematic and reliable decision-making processes (Denicolai *et al*., 2021).

Therefore, integrating AI technologies into SDMP dimensions offers transformative opportunities for firms operating in international markets. By leveraging AI's capabilities, organizations can improve their agility, collaboration, and consistency, thereby enhancing their overall strategic effectiveness in a global context.

Table 4. SDMP dimensions explored.

FIRM	DECISION-MAKING QUALITY AND SPEED	HIERARCHICAL DECENTRALIZATION	LATERAL COMMUNICATION	FORMALIZATION
FIRM A	The decision-making process is slow and traditional, primarily relying on client referrals and passive strategies. AI tools are not yet integrated but are recognized as a means to enhance data-driven decision-making in the future. The company focuses on strategic long-term considerations but lacks immediate action plans.	Decision-making is centralized, with key strategic moves decided by the AD and a small leadership team. Potential for decentralization exists with AI, as tools might empower broader organizational input.	Communication remains traditional, with limited integration of technology to enhance cross-departmental dialogue. AI's role in fostering collaboration is acknowledged but not yet implemented.	Low level of formalization. Processes are not standardized, and strategic decisions rely heavily on informal referrals and traditional methods.
FIRM B	Demonstrates moderate integration of AI for operational decisions (e.g., market analysis and content generation). Decision speed is enhanced by tools like ChatGPT but remains reliant on human oversight. High-quality decisions result from continuous team training and structured evaluation.	Emerging decentralization, with different departments gradually adopting AI tools. Collaboration between marketing, e-commerce, and administration demonstrates potential for broader horizontal integration.	Encourages lateral communication through tools like Power BI. The potential of AI for collaboration, particularly in international teams, is being evaluated.	Medium to high formalization. AI tools are integrated into operational tasks, streamlining content creation and enhancing consistency in international communication.
FIRM C	Employs a proactive decision-making approach focused on international markets. While AI is not yet core, the firm shows enthusiasm for future integration, particularly in market analysis and partner selection. Decision-making is relatively swift due to the company's emphasis on structured export strategies.	Hierarchically centralized but shows openness to exploring team autonomy with AI tools, particularly for operational tasks like translations and market outreach.	Operates with a functional level of lateral communication but plans to improve it using AI to streamline translation and international content development.	High formalization. The firm employs structured international strategies and is exploring AI to further enhance precision and efficiency in processes.
FIRM D	Decision-making is heavily influenced by cost and resource constraints. AI adoption, such as chatbots for customer interactions, is cautiously considered, reflecting a conservative approach. The speed of decision-making is constrained by limited exploration of advanced tools.	Strongly centralized with limited delegation. Decision-making authority remains with top management, influenced by resource limitations.	Minimal lateral communication. Departments operate independently with limited inter-departmental collaboration due to resource and technology constraints.	Moderate formalization. Limited AI adoption reflects structured but cautious approaches to change.

FIRM E	Decision-making is cautiously transitioning towards leveraging AI tools. The firm acknowledges the potential for AI in enhancing data analysis and operational decisions but remains in the exploratory phase. This slows the speed of strategic implementation, though quality is emphasized through careful evaluation.	While decision-making is primarily centralized, the firm recognizes the potential of AI tools to decentralize processes, especially in areas such as logistics and market analysis. Implementation plans are in the early stages.	Lateral communication is in a nascent stage, with AI tools being considered to improve collaboration across departments. The firm views this as essential for optimizing workflows and decision-making.	Moderate formalization with growing interest in standardizing processes through AI tools. The firm is in the process of evaluating technologies to streamline data management and operational workflows.
FIRM F	Gradual AI adoption has improved the speed and quality of decision-making through tools like ChatGPT and Gemini. The firm uses AI for scenario simulation, market trend analysis, and communication adaptation, enabling faster and more informed ISDs .	Decision-making remains largely centralized but is increasingly influenced by AI-supported insights from non-management staff. There is growing consideration to decentralize through digital tools, especially for marketing and market selection.	AI tools such as ChatGPT and Gemini facilitate informal but effective cross-functional communication, especially for content creation, cultural adaptation, and market research. There is increasing awareness of the need for more structured lateral integration.	Low to moderate formalization. While the company leverages AI for strategic planning and communication, process standardization remains limited due to artisanal nature and flexible structure.

Source: Authors' own elaboration.

5.7 Development of a final integrative framework

To further interpret these findings, a final integrative framework (Figure 1) was developed by linking the thematic insights emerged from the case studies with the four SDMP dimensions. This framework reflects the patterns and associations observed across cases, showing how the AI-related themes that emerged interact with decision-making structures in multifaceted ways. It highlights how SMEs' strategic responses to AI are shaped by internal perceptions and contextual constraints. These, in turn, shape changes in the quality, structure, and formalization of international strategic decision-making processes. The framework provides a practical tool for understanding the pathways through which AI enables or constrains strategic evolution.

Specifically, firms with greater awareness and understanding of AI tend to exhibit faster, more structured decision-making processes. This awareness often reflects a practical familiarity with AI tools, thereby enabling more data-driven and strategic choices. As a result, these firms begin shifting from intuition-based decision models to more evidence-based and AI-supported approaches.

Often firms that perceive clear benefits from AI adoption are the ones that initiate changes in their organizational dynamics. They begin to decentralize decision-making and promote cross-functional collaboration, supported by AI tools that democratize information access and reduce dependency on top-down control.

Conversely, firms facing barriers such as limited resources, technical gaps, or cultural resistance tend to retain centralized and static decision structures. These limitations restrict their ability to formalize processes or engage in collaborative decision-making, thereby slowing their capacity for innovation.

Human-centric concerns, such as maintaining artisanal identity, trust, or personalized relationships, do not block AI adoption, but introduce tensions to be carefully managed at the company level. These firms often integrate AI cautiously, positioning it as a support tool rather than a replacement, to preserve key human values in their strategic activities.

Lastly, the potential for strategic transformation is most evident in firms already experimenting with AI for internationalization, scenario planning, or operational optimization. In such cases, AI begins to influence not only execution, but also strategic direction, signaling a shift from tactical use to a more transformative role in decision-making.

Figure 1. Final framework encompassing the discussions emerged.

THEME	DECISION-MAKING QUALITY AND SPEED	HIERARCHICAL DECENTRALIZATION	LATERAL COMMUNICATION	FORMALIZATION
AWARENESS AND UNDERSTANDING OF AI	↑	↑	↑	↑
PERCEIVED BENEFITS OF AI IN ISDMPS	↑	↑	↑	↑
BARRIERS TO AI ADOPTION	↓	↓	↓	↓
HUMAN-CENTRIC CONCERNS	↔	↔	↔	↔
POTENTIAL FOR STRATEGIC TRANSFORMATION	↑	↑	↑	↑

Source: Authors' own elaboration.

6. CONCLUSIONS

6.1 Conclusive remarks and implications

This research adopts the SDMP framework to systematically examine how SMEs integrate AI into their international strategic decision-making. The SDMP dimensions explored - decision quality and speed, decentralization, lateral communication, and formalization - serve not only as analytical categories but also as organizational mechanisms that mediate the impact of AI on strategic orientation. The findings highlight AI's significant role in transforming SMEs' international strategic decision-making by facilitating IMS and EMS through market analysis, opportunity recognition, and operational efficiency. However, financial constraints, skill gaps, cultural resistance, and infrastructural challenges continue to limit AI's full impact. The study demonstrates that AI democratizes decision-making, helping SMEs bridge resource disparities with larger firms by enabling cost-effective data processing, pattern recognition, and insight generation. This supports existing research on AI's role in improving decision-making efficiency (Dwivedi *et al*., 2021; Kumar *et al*., 2022). However, SMEs face significant adoption barriers, reinforcing the need for tailored interventions (Silva and Gonçalves, 2022; Radhakrishna *et al*., 2023). This study aligns with research showing that AI enhances SME competitiveness through data-driven insights and efficiency gains (Denicolai *et al*., 2021; Baabdullah *et al*., 2021). However, challenges such as cost, and expertise limitations mirror concerns raised by Silva and Gonçalves (2022). Unlike prior research that focuses on large enterprises' aggressive AI adoption (Bag *et al.,* 2021; Dillon *et al*., 2020), this study emphasizes SMEs' cautious, incremental approach. This underscores the importance of context-specific AI strategies aligned with SMEs' capabilities and constraints.

From a theoretical perspective, this study contributes to SDMP theory by extending it to the context of AI adoption in internationally active SMEs, demonstrating how AI integration reshapes these dimensions by enhancing decision-making speed and quality, facilitating decentralization, improving lateral communication, and formalizing decision processes. These findings are particularly relevant for resource-constrained firms operating globally, highlighting AI's potential to transform strategic behavior and structure. It enriches the AI and IB literature by addressing SMEs' unique challenges and opportunities, which have been largely overlooked compared to large enterprises. It offers a contextualized framework that integrates resource limitations and adaptive strategies, extending research on AI-enabled decision-making (Dwivedi *et al*., 2021; Magistretti *et al*., 2019). Research demonstrates how AI contributes to strategic decision-making dimensions, such as decision quality and speed, hierarchical decentralization, lateral communication, and formalization of processes. These dimensions align with literature emphasizing AI's structural and procedural benefits in complex decision-making (Bag *et al.,* 2021; Cheng *et al*., 2021). Additionally, this study advances IB research by situating AI within IMS and EMS, building on prior works (Fish and Ruby, 2009;

Menzies *et al*., 2024). It highlights AI-driven tools such as generative models and advanced analytics that assist SMEs in identifying foreign markets and selecting optimal entry strategies, expanding frameworks on technology's role in internationalization (Lecerf and Omrani, 2020).

From a managerial perspective, findings emphasize the strategic and incremental adoption of AI. SMEs should begin using cost-effective AI tools (e.g., ChatGPT) to enhance market analysis, content creation, and customer segmentation. For example, as shown in Firm F, ChatGPT was used to simulate international scenarios and assess certification requirements in the foreign market enabling more informed pre-entry evaluations. Similarly, Firm C leveraged AI-driven translation tools to adapt technical product documentation, minimizing miscommunication in international sales. These cases illustrate how low-barrier tools can serve as a first step toward more structured AI use. Additionally, SMEs may apply AI tools to identify market clusters or conduct preliminary screening for entry mode selection, functions that previously required either external consultants or intuitive work.

Moreover, AI literacy should be cultivated through multi-level training strategies. While structured corporate training is essential, especially through pilot projects that demonstrate clear returns, the findings reveal that many SME's managers initiate their AI exploration autonomously, using publicly available tools like ChatGPT or Gemini without formal training. This suggests a strong case for promoting accessible self-help learning resources, such as online courses, video tutorials, or platform-integrated guidance, tailored to the specific needs and time constraints of SMEs. These decentralized forms of training lower the barriers to experimentation while empowering firms to proceed incrementally, as shown in cases like Firm F and Firm A. For instance, the export manager in Firm A began using AI tools to explore logistics optimization strategies before engaging in formal digital transformation processes. This highlights the importance of enabling early experimentation with lightweight, practical tools that can demonstrate immediate value.

Nonetheless, advancing from exploratory to transformative AI adoption requires structural investments in education. As several firms noted, one of the most persistent barriers lies in the lack of internal expertise and AI literacy. Therefore, embedding AI into university and high school curricula would enhance a broader societal readiness for AI and equip future generations of entrepreneurs and managers with the skills required to evaluate and leverage AI tools effectively. This kind of long-term capacity building is particularly crucial for SMEs, which often lack the resources to hire external consultants or build internal tech departments. Introducing case-based learning or industry simulations at the academic level, for example, scenario analysis for IMS using generative AI tools, could further reinforce applied competencies in real business contexts. These educational efforts should be complemented by public and institutional support systems, including AI competence centers, regional digital innovation hubs, or open repositories of validated use cases. These shared infrastructures would help SMEs mitigate uncertainty and accelerate the shift from isolated operational use (e.g., translation or marketing) to more strategic applications, such as international market analysis, entry mode assessment, or partner evaluation.

Lastly, a hybrid AI–human approach should be adopted, whereby AI complements rather than replaces expertise, particularly in high-stakes decisions such as market entry and partner selection. In this respect, the study recommends that policymakers and industry associations support SMEs through subsidies for AI adoption, accessible training programs, and partnerships with technology providers.

6.2 Limitations and avenues for future research

Despite the valuable insights provided by this study, several limitations highlight the need for further research. First, the geographic and industry focus on six Italian manufacturing SMEs limits the generalizability of the findings, as different sectors, such as services or retail, may present unique challenges and opportunities for AI adoption. Similarly, while rich in contextual detail, the qualitative methodology introduces potential biases inherent to subjective interpretations and self-reported data. This calls for future research employing mixed-method approaches to validate findings and enhance robustness. Additionally, the cross-sectional nature of this study offers a snapshot of AI adoption without capturing its longitudinal impacts on SME performance and internationalization, underscoring the need for long-term studies to track these dynamics over time.

The scope of the study, focused on IMS and EMS, further leaves other critical dimensions of ISDMPs underexplored, including areas like international risk assessment, network building, and supply chain optimization. Future research should expand its scope to investigate AI's role across these decision areas, providing a holistic understanding of its strategic implications. Broadening the research context to include diverse industries, geographic regions, and cultural settings would offer richer insights into how AI adoption varies and reveal patterns unique to SMEs compared to larger enterprises. Finally, as AI adoption scales, ethical and human-centric considerations become paramount. Future studies should examine the effects of AI on job roles, ethics in decision-making, and worker dynamics, with a focus on building inclusivity and trust. Future research can fill these gaps and offer practical advice to help SMEs manage the challenges of international markets while exploiting AI's potential.

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CHAPTER V – CONCLUDING REMARKS AND FUTURE RESEARCH AVENUES

1. DISCUSSIONS

This doctoral research project originates from the observation of three interrelated phenomena, namely Lean transformation, advanced digitalization, and social sustainability, as they manifest within SMEs. It aims to contribute to the consolidation of emerging knowledge at the intersection of these domains, by critically examining their interaction and identifying both opportunities and tensions that characterize innovation trajectories in manufacturing ecosystems. At the same time, this work positions itself as a resource for SMEs seeking to manage the complex socio-technical challenges posed by digital transformation and sustainability imperatives. Accordingly, the overarching research aim of this dissertation was:

To investigate how the integrated application of Lean methodologies, advanced digital technologies (particularly AI), and social sustainability principles can enhance innovation within SMEs, and how such integration reshapes organizational learning, operational practices, and strategic decision-making across multiple levels.

To achieve this goal, the thesis employed a multi-level qualitative methodology, structured as a collection of three studies, each addressing a different level of analysis: theoretical (Chapter II), operational (Chapter III), and strategic (Chapter IV). These studies combined a systematic literature review with both single and multiple case study designs, drawing on interviews and observations. The research approach followed the logic of systematic combining (Dubois and Gadde, 2002), allowing iterative matching between theory and data.

The study demonstrated that meaningful innovation in SMEs does not stem solely from technological acquisition but emerges from a systemic alignment between organizational culture, technological affordances, and inclusive sustainability principles. Several core insights emerged across the three scientific articles forming the backbone of this dissertation.

First, the systematic literature review (Chapter II) demonstrated a growing interest in the combined application of Lean and I4.0 technologies, but with a limited focus on their social sustainability implications. The review highlighted how Lean and I4.0 are often studied separately, and when integrated, most studies emphasize economic or environmental outcomes. However, the analysis showed that the synergy between Lean and I4.0 can be leveraged to reinforce human-centered values, especially when continuous improvement, employee involvement, and respect for people are aligned with digital tools. The article therefore proposed a conceptual framework suggesting a path from fragmentation to integration: while many studies explore Lean or digitalization in isolation, and some touch upon sustainability, very few explicitly connect all three, particularly at the intersection of innovation. The article thus, contributes by proposing a conceptual framework that identifies key social sustainability functions, such as employee empowerment, workplace participation, inclusivity, and safety, potentially enhanced by Lean-I4.0 integration. This paper does not merely synthesize existing knowledge. It rather lays the normative and analytical groundwork for the rest of the thesis, repositioning the innovation discourse around SMEs from one focused on efficiency and scale to one where technological transformation is evaluated through ethical and human lenses.

Second, the single-case study (Chapter III) explored the implementation of an AI-supported training platform within a Lean transformation journey in an Italian SME. Moving from concept to practice, the article examined the operational translation of Lean-AI integration within a real SME context. The study investigated how an AI-driven training platform is used to support Lean implementation, focusing on employee experience, knowledge transfer, inclusivity, and digital learning dynamics, capturing both the affordances and frictions that emerge in practice. The findings highlighted a dual dynamic. On the one hand, the platform democratizes Lean knowledge, enabling wider access to training and empowering frontline workers. The convergence of Lean and AI can generate significant process efficiencies. Results demonstrated that SMEs that embedded AI-enabled training systems within participatory frameworks saw improvements in knowledge accessibility, employee engagement, and organizational trust, highlighting the importance of social design in shaping the impacts of digital tools (Rana *et al*., 2021). Yet, when implemented in isolation or through technocentric logics, such approaches often fail to address social risks like deskilling, exclusion, and psychological strain (Hussain *et al*., 2024). Therefore, on the other hand, it introduced new socio-psychological tensions, such as digital anxiety, perceived monitoring, and concerns about job security.

These dynamics underscore the importance of hybrid learning strategies, transparent communication, and inclusive governance in ensuring that digital transformation enhances rather than undermines social sustainability. Digital skills gaps, managerial resistance, and contextual misalignments frequently undermine AI’s transformative potential, particularly where Lean principles are treated as mechanistic rather than humanistic systems. Furthermore, the research exposed a paradox at the heart of Lean-AI integration: while Lean emphasizes respect for people and continuous improvement, AI can create conditions that depersonalize learning, standardize autonomy, and obscure accountability. The case thus evidenced both opportunities and risks, suggesting that AI alone cannot democratize learning without appropriate managerial support, psychological safety, and participatory implementation.

Third, translating from execution to vision, the third article (Chapter IV) expanded the analytical scope to the strategic and international level, exploring how AI technologies support international strategic decision-making processes (ISDMPs) in SMEs. Through a multiple case study of six Italian SMEs, the article revealed that AI tools are being increasingly used to inform key strategic activities such as market selection, partner evaluation, and entry mode choice. The results indicated that AI is being used to support operational monitoring, strategic forecasting, and data analysis, particularly in SMEs facing dynamic and uncertain international markets. However, the findings further highlighted that the use of AI in these contexts is still emergent and informal, often limited to supporting intuition-based decisions rather than replacing them. Moreover, AI was framed as a complementary tool, used selectively for improving information quality and risk awareness, rather than as a driver of organizational transformation. So, at the strategic level, the findings suggested that AI is not only a productivity enhancer but also a cognitive asset for international decision-making, helping SMEs manage uncertainty, analyze global trends, and simulate strategic scenarios. Yet, such benefits were contingent on a foundation of organizational readiness, data literacy, and participatory leadership. The emphasis on real-world SMEs foregrounded the role of informality, tacit routines, and adaptive learning loops, reinforcing the need for bottom-up, scalable design principles tailored to the lived realities of small firms (Yadav and Gahlot, 2022). This paper thus situated the transformative framework within a globalized competitive context, stressing that strategic innovation in SMEs requires more than digital tools; it demands organizational learning, adaptive foresight, and a deliberate alignment between strategic goals and operational capabilities.

Collectively, these three studies form a coherent analytical trajectory that moves from conceptual foundations to operational practice and strategic vision. The cross-level dialogue among them enabled the development of a comprehensive multi-level synthesis, connecting micro-level manufacturing practices with macro-level strategy and governance. This integrative perspective constitutes one of the thesis' most original contributions, emphasizing that innovation in SMEs must be understood as a context-sensitive and socially embedded process, one in which Lean methodologies and digital tools such as AI are aligned with human, cultural, and strategic dimensions to generate sustainable impact.

This dissertation contributed to the literature by highlighting the conditions under which AI and Lean can be integrated meaningfully in SMEs, focusing on real-world practices rather than idealized technological promises. A key insight across this dissertation was the recognition that social sustainability is not merely an ethical aspiration but a strategic enabler of innovation and organizational resilience, particularly within the context of manufacturing SMEs. The research demonstrated that inclusive practices, such as participatory training, equitable access to knowledge, and employee engagement, are not peripheral initiatives but foundational levers for building adaptive capabilities and enhancing long-term competitiveness. This aligned with recent evidence highlighting how social sustainability orientation can moderate and enhance the translation of innovation capabilities into organizational resilience (Do *et al*., 2024). Furthermore, social capital has been identified as essential for the implementation of sustainability strategies and the development of "resilient networks" in SMEs' ecosystems (Chiara, 2017). Such practices were particularly important for SMEs that operate under resource constraints and must rely on human-centered, capability-driven approaches to thrive in uncertain environments (Saman *et al*., 2025).

Considering the overall aim of the research and the research questions addressed along this work, Table 1 provides a synthetic recap of the main results emerged from the study.

Table 1. Main results of the research.

RESEARCH QUESTION(S)	MAIN RESULTS
RQ1. WHAT IS THE EFFECT OF INDUSTRY 4.0 TOOLS AND LEAN MANUFACTURING (LM) PRACTICES ON SOCIAL SUSTAINABILITY FUNCTIONS?	- Five key social sustainability functions identified are influenced by Lean-I4.0 integration: (i) Health and Safety, (ii) Quality of Work Life, (iii) Employee Involvement, (iv) Communication, and (v) Motivation. - The synergy between Lean and I4.0 promotes safer, more equitable, and participatory workplaces, strengthening learning and well-being. - Lean 4.0 acts as a human-centered innovation model, where Lean provides discipline and I4.0 adds flexibility and responsiveness. - Identified tensions between automation efficiency and human empowerment: AI and IoT improve process control but risk deskilling and surveillance if not balanced by participative governance. - The study introduces a conceptual framework mapping how technological and managerial integration contributes to socially sustainable industrial transformation. - Firms embedding social sustainability in Lean 4.0 strategies gain long-term competitive advantage through talent retention and employee trust.
RQ2. HOW CAN AI-DRIVEN TRAINING EFFECTIVELY SUPPORT LEAN MANUFACTURING ADOPTION IN SMES? **RQ3. WHAT IS THE IMPACT OF AI-DRIVEN TRAINING ON SOCIAL SUSTAINABILITY OUTCOMES IN AN LM ENVIRONMENT?**	- AI tools democratize access to Lean knowledge, standardizing learning and improving inclusivity across roles (especially shop-floor operators). - Enhanced autonomy, engagement, and reflective learning, shifting culture from top-down instruction to self-driven improvement. - Challenges: digital literacy gaps (notably among senior employees), techno-stress, and perceived surveillance due to data-driven monitoring. - Identified a tension between empowerment and pressure: AI can both motivate and overwhelm workers. - Recommended hybrid learning model combining AI modules with peer mentoring and experiential learning. - Responsible use requires ethical design, transparent communication, and well-being safeguards to ensure digital inclusion. - AI-enabled training is a transformative but complex lever for both operational and social sustainability in Lean-focused SMEs.
RQ4. HOW DO SMES' DECISION-MAKERS ADOPT AI DIGITAL TECHNOLOGIES IN THEIR INTERNATIONAL STRATEGIC DECISIONS? **RQ5. HOW DOES AI INTEGRATION RESHAPE STRATEGIC DECISION-MAKING PROCESS (SDMP) DIMENSIONS IN FIRMS OPERATING IN INTERNATIONAL MARKETS?**	- AI improves decision-making quality and speed, accuracy, and formalization, supporting market selection, partner evaluation, and risk assessment. - Identified dual role of AI: structuring (standardizing processes) and enabling (enhancing foresight and agility). - Barriers: financial constraints, lack of technical expertise, and cultural resistance limit decentralization and collaboration. - Firms with higher AI awareness show greater decision-making agility and formalized processes, while resource scarcity hinders cross-functional communication. - Developed a conceptual framework showing how AI reshapes SDMP dimensions (quality and speed, decentralization, communication, formalization). - The study extends SDMP theory to SMEs, emphasizing responsible AI adoption as a source of strategic resilience and global competitiveness.

Source: Author's own elaboration.

Overall, this dissertation argued that human-centered digital transformation in SMEs cannot be achieved through isolated interventions, but must be supported by systemic, value-driven frameworks that embed sustainability and inclusivity from the outset. The framework developed in this chapter responds to this imperative, offering evidence-based design principles and governance logics for responsible innovation.

1.1 The transformative framework: a progressive model of integrated innovation in SMEs

The final framework (see Figure 1) developed in this dissertation represents the culmination of a progressive synthesis between Lean methodologies, AI, and social sustainability as interdependent levers of transformation and innovation within SMEs. This integrative model conceptualizes innovation as a continuous, reflexive, and ethically anchored process in which operational efficiency, digital intelligence, and social inclusiveness coexist and reinforce one another.

Specifically, the framework is structured across interrelated layers. At the contextual layer, SME-specific factors, such as flexibility, resource constraints, and local embeddedness, shape the pathways through which Lean and AI practices are adopted and integrated. These contextual conditions influence the firm's absorptive capacity, learning potential, and overall innovation trajectory. Building on this basis, the foundational layer represents Lean methodologies and continuous improvement principles (value, flow, pull, and kaizen). This layer provides the structural discipline and human-centered logic that enable SMEs to operate efficiently and responsively despite limited resources. The enabling layer introduces advanced digitalization and AI as cognitive and adaptive catalysts. AI-driven learning systems, predictive analytics, and data-driven decision-making processes strengthen Lean operations by enhancing visibility, adaptability, and foresight, thereby supporting and accelerating transformation. Above this, the integrative layer embeds social sustainability as the normative and participatory dimension that moderates and guides the interaction between Lean and AI. It ensures that technological innovation remains human-centered, promoting inclusivity, equity, knowledge democratization, and employee well-being. Finally, the outcome layer represents the tangible and intangible results of this multi-level alignment, including product and process innovation, organizational learning, resilience, competitiveness, and social inclusion. These outcomes, in turn, feed back into the lower layers through continuous learning and reinforcement loops, strengthening the system's adaptive and sustainable capacity over time.

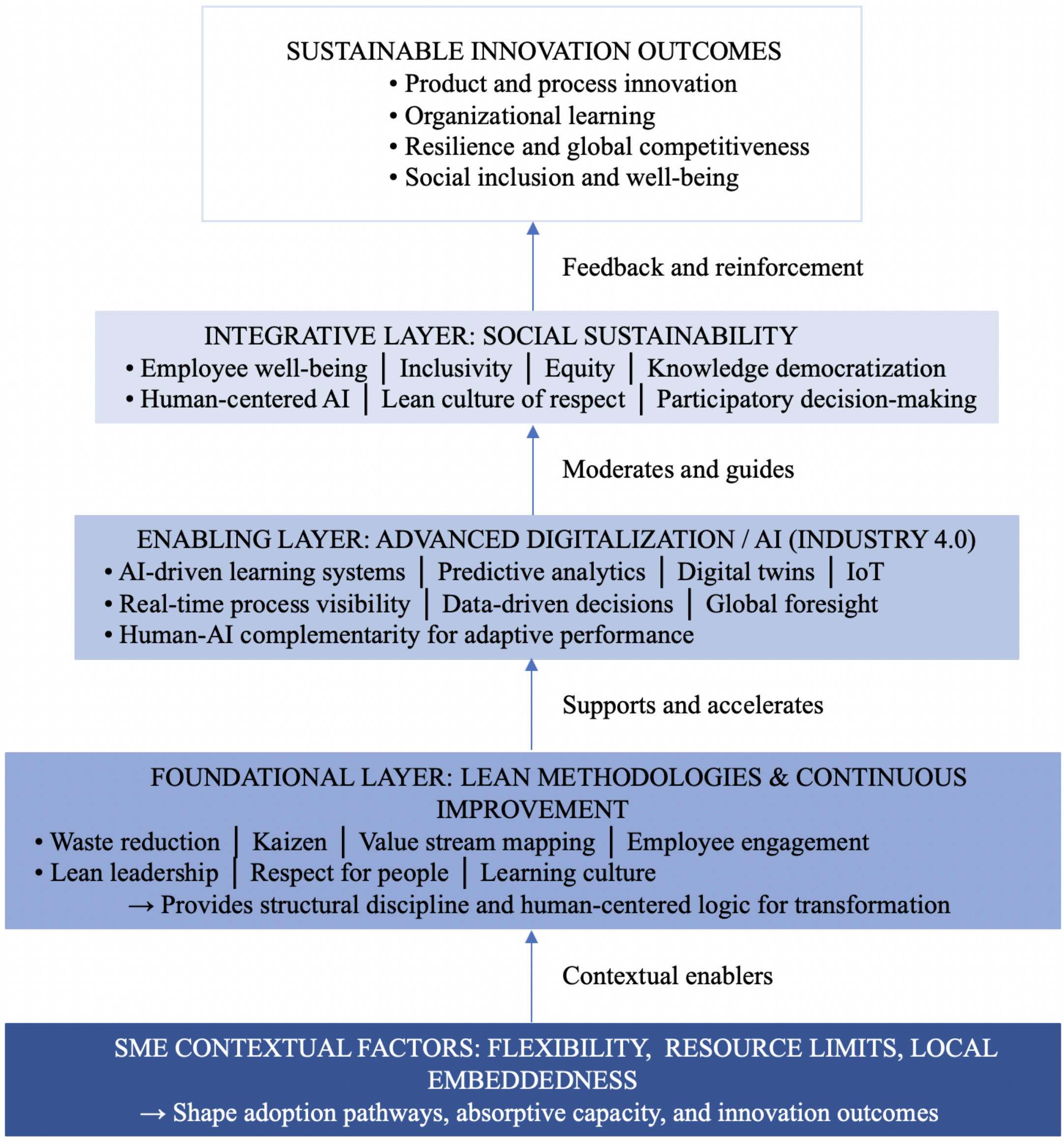
The empirical findings presented in Chapters III and IV offer concrete illustrations of how the three analytical levels proposed in this framework- systemic, operational, and strategic - manifest in practice across diverse SME contexts. At the operational level, the single case study described in Chapter III exemplifies how AI-based Lean training systems can operationalize the principles of social sustainability within everyday work practices. The integration of AI into Lean routines enhanced employees' capacity for problem-solving and learning autonomy, while simultaneously revealing tensions such as digital fatigue, perceived monitoring, and skill disparities. This case underscores how human-centered design, participatory learning, and transparent communication act as essential enablers for translating Lean and AI synergies into socially sustainable outcomes. At the strategic level, the multiple case study in Chapter IV demonstrates how AI adoption reshapes international strategic decision-making processes across six manufacturing SMEs. In these firms, AI-driven data infrastructures supported faster and more formalized decision-making, improved communication between managerial layers, and enhanced partner and market evaluation. Yet, these advantages were strongly mediated by organizational readiness, leadership style, and digital culture, revealing that AI's strategic value depends on the firm's ability to align technology with human and ethical governance.

Taken together, these cases concretely illustrate the multi-level synthesis discussed in this chapter. The operational case reveals how Lean and AI interact to shape inclusive, human-centered practices within daily operations, while the strategic cases highlight how digital intelligence and cultural adaptation inform higher-level strategic learning and decision quality. This cross-case reflection bridges the abstract framework with empirical reality, showing that the multi-level integration of Lean, AI, and social sustainability is not a theoretical construct but a set of interrelated processes observed across different organizational settings.

Overall, building on the empirical and theoretical insights of the research, the framework positions this triadic integration as both a strategic architecture and a moral compass for managing the complexity, uncertainty, and volatility that increasingly define contemporary industrial ecosystems.

Within this configuration, Lean serves as the methodological backbone, AI as the cognitive and adaptive catalyst, and social sustainability as the ethical and participatory foundation through which innovation becomes not only economically viable but socially meaningful and humanly sustainable.

Figure 1. A model for integrated innovation in SMEs.



Source: Author's own elaboration.

In this representation, the *foundational* layer demonstrates that LM acts as the cultural and operational foundation of innovation. Its principles, value, flow, pull, and continuous improvement (kaizen), create the internal infrastructure that allows SMEs to operate efficiently and responsively despite limited resources. Lean also establishes the human-centered philosophy of "respect for people," essential for social sustainability and for mitigating the dehumanizing potential of automation, finally providing the discipline, culture, and mindset needed to absorb digital technologies effectively.

The *enabling* layer positions advanced digitalization and I4.0 technologies at the center. Advanced digitalization in this scenario transforms Lean systems into smart socio-technical environments. AI, IoT, and Big Data Analytics function as enablers of real-time learning, predictive control, and global market agility. AI amplifies Lean's continuous improvement potential by introducing data-driven adaptability and enabling SMEs to move from reactive to anticipatory innovation. At the operational level AI-based training platforms democratize access to operational knowledge, while at the strategic level AI-enhanced decision-making for market intelligence and international expansion.

The *integrative* layer is defined by social sustainability which functions as the ethical compass of the framework. It ensures that digital and Lean transformations remain inclusive, participatory, and equitable. Rather than treating humans as peripheral to automation, this layer repositions them as co-creators of innovation. This dimension acts as a moderator that aligns technological and operational innovation with human values and social outcomes.

The *outcome* layer is given by the innovation outcomes. In this respect, when Lean, digitalization, and social sustainability interact in a coherent and integrated manner, SMEs enter a new paradigm of innovation that transcends traditional distinctions between efficiency, technology, and ethics. Within this configuration, product, process, organizational, and strategic forms of innovation emerge as interdependent outcomes of a single transformative system. Product innovation arises through the development of smart, eco-efficient, and user-responsive goods that combine technological sophistication with environmental consciousness and social inclusiveness, reflecting the firm's ability to design offerings that are both intelligent and responsible. Process innovation evolves through the implementation of data-driven workflows that incorporate circular and adaptive logics, enabling SMEs to optimize resources, minimize waste, and continuously adjust to environmental and market fluctuations. At this level, innovation manifests in the creation of learning-oriented and inclusive cultures, where employees become active participants in problem-solving, digital learning, and continuous improvement, embodying Lean's human-centered philosophy in a digital context.

This systemic integration culminates in strategic innovation, as the alignment of operational excellence, cognitive intelligence, and ethical purpose strengthens competitiveness, resilience, and agility in global markets. Through this holistic interplay, SMEs no longer innovate in fragmented ways but instead cultivate an integrated capacity for sustainable transformation, one in which economic performance, technological advancement, and social responsibility reinforce each other in a virtuous cycle of growth and renewal. The system is circular, meaning that innovation outcomes generate new learning and cultural feedback that reinforce Lean practices and digital maturity.

SMEs in this scenario operate within a distinctive *contextual* environment that profoundly shapes their capacity for transformation and innovation. Unlike large corporations, SMEs are not simply scaled-down versions of bigger organizations; rather, they possess unique structural and cultural characteristics that make them agile, adaptive, and locally embedded. Their flexibility, informal communication systems, and close relationships with stakeholders position them as ideal laboratories for experimenting with integrative innovation models that combine Lean methodologies, digitalization, and social sustainability. However, this potential can only be realized when the inherent constraints of limited resources, technical capabilities, and managerial capacity are explicitly acknowledged and strategically addressed.

Within this contextual layer, several moderating factors determine how effectively SMEs can adopt and internalize the principles of human-centered socio-technical transformation. The first and most critical of these is leadership commitment, the degree to which SME leaders embrace innovation as a holistic and human-centered journey rather than a purely technological or cost-driven process. Visionary leadership that values participation, learning, and ethical reflection provides the cultural anchor for sustainable transformation. A second determinant is the level of digital and Lean maturity, which refers to the organization's readiness to integrate data-driven tools, continuous improvement routines, and human-centered design into a coherent operational system. SMEs with higher maturity in these domains are better equipped to align digital innovation with Lean efficiency and social responsibility. Equally important are external collaborations, including partnerships with universities, innovation clusters, and digital innovation hubs. These networks compensate for SMEs' resource constraints by facilitating access to expertise, technology transfer, and shared infrastructures, thereby expanding their absorptive capacity and innovation potential.

The systemic dynamics of the framework reveal innovation in SMEs as an evolving, self-reinforcing, and multi-level process where culture, technology, and humanity are in constant dialogue. At its core, the system operates through a cyclical mechanism in which Lean, digitalization, and social sustainability interact to generate continuous improvement and adaptive renewal. Lean culture provides the initial foundation by embedding efficiency, discipline, and a mindset of perpetual learning into organizational routines. This Lean base creates a shared language of value creation, empowering employees to identify waste, experiment with improvements, and contribute actively to collective problem-solving. Building on this cultural infrastructure, AI and digitalization introduce a new dimension of data-driven adaptability, enabling real-time decision-making, predictive maintenance, and intelligent process optimization. These technologies extend Lean's potential by transforming static improvement cycles into dynamic, self-adjusting systems capable of responding swiftly to changing market conditions and environmental uncertainties.

Social sustainability functions as the moral and relational axis of this loop, ensuring that technological progress and operational efficiency remain aligned with inclusivity and long-term human well-being. It anchors innovation within values of participation and fairness, thus preventing the erosion of human agency in the face of digital acceleration.

When these three dimensions, Lean, digitalization, and social sustainability, operate coherently, they generate a set of outcomes that include heightened innovation capacity, organizational resilience, and enhanced competitiveness. Crucially, these outcomes do not represent an endpoint but rather feed back into the system itself, enriching Lean culture with new knowledge, reinforcing digital capabilities through experiential learning, and deepening social engagement through shared success. In this recursive dynamic, innovation ceases to be a linear sequence of technological upgrades and becomes instead a virtuous cycle of learning, reflection, and transformation. The SME thus evolves as a living socio-technical organism, where the balance between operational discipline, technological intelligence, and human values continuously regenerates its ability to innovate responsibly and sustainably.

In its essence, the final framework developed in this thesis consolidates the integration of Lean methodologies, AI, and social sustainability into a unified, human-centered socio-technical model that redefines how SMEs pursue innovation in a digital and sustainable era. Across theoretical, operational, and strategic levels, this configuration demonstrates that innovation emerges not from technological adoption alone, but from the deliberate alignment of cultural, technological, and ethical dimensions.

Within SMEs, these principles enable agility and responsiveness while embedding respect for people and participatory problem-solving as key organizational values. In these realities, where resources are scarce, and agility is critical, Lean enables streamlined operations and promotes a culture of experimentation. When implemented effectively, Lean drives SMEs toward systematic process optimization, reducing unnecessary steps and increasing responsiveness to market changes (Dey *et al*., 2019). Notably, Lean's influence extends to sustainable process design: several studies confirm that Lean practices help SMEs reduce their environmental impact by improving energy efficiency, minimizing raw material usage, and shortening production cycles, which often serve as steppingstones for broader green transformation initiatives (Flores *et al*., 2018).

When integrated with AI, particularly predictive analytics, machine learning, and real-time data systems, Lean evolves into an intelligent and adaptive architecture capable of supporting dynamic resource allocation, proactive decision-making, and autonomous process optimization (Ayoubi *et al*., 2023). This synergy transforms Lean into a digitally augmented system that combines operational discipline with cognitive agility, forming what the thesis conceptualizes as the operational core of sustainable transformation. AI further enhances process innovation by detecting bottlenecks, forecasting maintenance needs, and enabling predictive modelling and systemic adaptability, while also supporting product innovation through data-driven customer insights, automated product testing, and virtual prototyping. These capabilities empower SMEs to experiment rapidly with new solutions, iterate on feedback, and reduce time-to-market, even with limited R&D infrastructure, thus facilitating both incremental and radical forms of innovation. Importantly, this research underscores that SMEs do not need to choose between efficiency and sustainability, they can and should pursue both simultaneously.

For these reasons, this research provides original empirical and theoretical evidence on how the integration of Lean, AI, and social sustainability can jointly enhance innovation performance and organizational resilience in SMEs. While previous studies have shown that Lean and sustainability principles contribute to economic performance and long-term competitiveness (Rasheed and Saad, 2023), this thesis advances the field by demonstrating how and under what contextual conditions these synergies become truly transformative. Unlike previous research that described Lean-4.0 integration mainly in operational terms, this thesis identifies the critical mechanisms that determine its success. These include leadership commitment to ethical innovation, participatory design in AI applications, and organizational cultures that emphasize collaboration and trust. The findings highlight that SMEs must construct tailored integration pathways aligned with their specific resource base, workforce characteristics, and strategic orientation, rather than adopting one-size-fits-all digitalization models.

Moreover, the findings show that when AI is embedded within Lean-based systems guided by social sustainability principles, SMEs can achieve not only process efficiency but also human-centered innovation outcomes. The study reveals that the "Lean + AI + Social" configuration functions as a transformative architecture in which technological progress is ethically grounded and socially inclusive, ensuring that productivity gains do not come at the cost of human dignity or well-being. In this sense, the results clarify that technological and operational progress cannot be considered sustainable if detached from human and social implications. The research empirically substantiates social sustainability as a guiding principle that links innovation performance with inclusivity, equity, and long-term well-being. In the observed cases, socially oriented practices enhanced employee empowerment, psychological safety, and knowledge sharing, while mitigating risks of exclusion or digital anxiety. This demonstrates that when Lean and AI are implemented through a socially informed lens, they act as tools of inclusion rather than control, promoting access to learning and professional growth across different workforce groups. As highlighted throughout the empirical and theoretical analyses, technological and operational progress cannot be considered sustainable if detached from its human and social implications. For this reason, social sustainability emerges in the framework as a guiding principle that connects innovation performance with inclusivity, equity, and long-term well-being. By enhancing employee empowerment, psychological safety, and participatory governance, social sustainability ensures that Lean and AI act as tools of inclusion rather than exclusion, preserving tacit knowledge and promoting access to learning opportunities for different workforces (Yılmaz, 2024). In this sense, Lean's human-centric philosophy, anchored in respect for people and continuous learning, finds renewed significance when combined with AI systems designed to support human judgment instead of replacing it. The thesis thus emphasizes that digital transformation must remain grounded in ethical and participatory practices that protect human agency while enabling efficiency and innovation.

Operationally, the study finds that within SMEs, Lean practices streamline and stabilize workflows, while AI technologies enhance visibility, foresight, and adaptability, resulting in data-driven, circular, and self-correcting systems (Gomaa, 2025). These operational advances lay the groundwork for product innovation, enabling the creation of smart, eco-efficient, and user-responsive goods that incorporate sustainability principles from the earliest design stages (Sorli *et al.*, 2012; Afum *et al.*, 2021). However, the thesis extends this understanding by demonstrating that such outcomes are contingent on a social infrastructure that promotes transparency, participation, and shared accountability. The convergence of Lean, AI, and sustainability thus enhances a new organizational model-learning-oriented, inclusive, and ethically guided, where innovation becomes systemic rather than departmental.

Moreover, the convergence of Lean, AI, and sustainability enhances organizational innovation, as firms evolve into learning-oriented and inclusive environments characterized by participation, transparency, and shared accountability (Rahardjo *et al.*, 2023). One of the key findings across multiple studies is precisely this synergistic effect: when Lean, AI, and sustainability are pursued in tandem, innovation becomes systemic and continuous, driven by cross-functional learning, stakeholder input, and adaptive technologies, rather than being confined to single departments or product teams. Process innovation thus acts as the bridge between Lean's operational rigor, AI's intelligence, and sustainability's ethical imperatives, significantly enhancing supply chain performance and long-term resilience (Rasheed and Saad, 2023).

At the strategic level, the framework extends beyond internal operations to highlight how these synergies reinforce the external competitiveness and resilience of SMEs. AI provides the cognitive capacity to enhance foresight, improve the quality of decision-making, and reduce uncertainty in global and volatile markets (Ayoubi *et al.*, 2023). When combined with Lean's structural discipline and sustainability's social vision, SMEs develop an integrative capability that allows them to pursue efficiency and ethics simultaneously, achieving what this research defines as responsible and inclusive innovation.

The interaction among systemic, operational, and strategic levels unfolds as a recursive dynamic rather than a linear progression. Conceptual models developed at the systemic level (Chapter II) inform the operational practices explored in Chapter III, which in turn generate experiential learning feeding back into strategic decision-making processes analyzed in Chapter IV. For example, participatory AI training (operational level) enhanced data-driven awareness that later informed the firms' strategic evaluation of international partnerships (strategic level), confirming the presence of continuous feedback loops between organizational learning and strategic foresight. Overall, the findings demonstrate that the integration of Lean, AI, and social sustainability operates as an interconnected system of learning loops. Systemic frameworks provide cognitive scaffolding;

operational practices translate them into tangible routines; and strategic mechanisms consolidate them into long-term adaptive capabilities.

In synthesis, the framework depicts innovation in SMEs as a recursive and multi-level process driven by continuous interaction between Lean culture, digital intelligence, and social sustainability. Lean provides the structure and learning foundation; AI supplies the adaptive intelligence that enables data-driven transformation; and social sustainability ensures inclusivity and fairness. The outcomes, product and process innovation, organizational learning, resilience, and competitiveness, feed back into Lean systems, generating an iterative cycle of reflection and improvement (Hamburg, 2020). Through this interplay, innovation in SMEs is reframed as a human-centered and evolving process of co-creation, where technological advancement and social responsibility are not opposing forces but mutually reinforcing pillars of sustainable industrial renewal.

2. THEORETICAL IMPLICATIONS

The findings of this research project yield multiple layers of theoretical contributions that extend and reconfigure current paradigms within the domains of Lean management, digital transformation, and sustainability studies, particularly in the context of SMEs. Grounded in an exploratory, qualitative, and multi-level design, this dissertation advances theory by elucidating how organizational, technological, and social dimensions interact to shape innovation processes, therefore contributing to enriching the current literature in multiple ways.

First, the study reframes the convergence between Lean management and I4.0 not merely as a technical integration but as a socio-technical and human-centered system. While existing research has predominantly emphasized their operational compatibility (Rossini *et al.*, 2019; Buer *et al.*, 2018), this work demonstrates that Lean principles, especially those related to respect for people, standardized processes, and continuous improvement, act as organizational enablers for successful digitalization. Specifically, the systematic literature review conducted in Chapter II clarifies that Lean offers not only a cultural foundation but also a structural mechanism to align technological adoption with inclusive innovation processes, thereby contributing to the emerging view of Lean 4.0 as a socio-technical system grounded in cultural transformation (Vinodh *et al.*, 2020; Ghaithan *et al.*, 2023). In this sense, the research emphasizes that the often under-theorized "respect for people" pillar becomes increasingly relevant in the digital age, as the integration of Lean with I4.0 technologies requires careful social design to prevent the erosion of job security and autonomy, ensuring that digital tools empower rather than marginalize workers.

Second, the thesis extends the Lean-4.0 literature by explicitly foregrounding the social sustainability implications of integrating LM and I4.0 technologies. While much of the existing literature on Lean 4.0 focuses on its economic and environmental impacts, there has been relatively limited attention paid to its social dimension, particularly in the context of SMEs. This research fills this gap by proposing that Lean-4.0 should not only be evaluated in terms of its efficiency gains and technological adoption, but also through its impact on workplace well-being**,** employee autonomy, and organizational culture. However, when integrated with digital tools like AI and IoT, Lean practices must be carefully designed to avoid reinforcing inequalities or eroding job security, as digital tools can both democratize knowledge and exacerbate social divides. By foregrounding social sustainability as a strategic criterion for Lean-4.0 implementation, this dissertation calls for a broader understanding of Lean's potential impact. It proposes that sustainability cannot be fully achieved without considering how technology and organizational practices affect the human capital and social dynamics within firms. This insight extends existing frameworks on Lean by offering a socially conscious reimagining of Lean-4.0 that acknowledges its potential to empower workers rather than simply optimizing production systems for cost reduction. Therefore, the thesis provides a novel theoretical contribution to sustainability literature, particularly by highlighting the under-theorized role of social sustainability in digital innovation processes. While the environmental and economic pillars of sustainability have been widely addressed in connection with I4.0 (Bonilla *et al*., 2018; Gómez, 2021), the social dimension, encompassing employee well-being, inclusivity, autonomy, and participatory governance, remains less explored. This research addresses this gap by conceptualizing social sustainability not as a constraint, but as a strategic asset for enabling adaptive and resilient innovation models. The empirical findings in Chapter III, which examined AI-driven training platforms, substantiate this claim by illustrating how social sustainability-oriented practices enhance engagement, trust, and knowledge dissemination. This extends previous studies on human-centric digitalization (Dombrowski and Mielke, 2013; Rana *et al*., 2021) and aligns with calls to embed ethical and inclusive values into technological transformations (Sony and Naik, 2019).

Third, the dissertation advances the theoretical understanding of SMEs by challenging the traditional portrayal of these firms as structurally disadvantaged or passive adopters of external innovations. Instead, this research highlights the proactive role of SMEs as experimental, reflexive, and context-aware agents within complex industrial ecosystems. Rather than framing small scale as a liability, the thesis underscores how it enables organizational agility, rapid iteration, and human-centered governance, especially in the implementation of Lean practices and digital tools. The empirical cases (Chapters III and IV) demonstrate that SMEs can act as laboratories for integrated innovation, capable of testing and refining socio-technical solutions in ways that are often inaccessible to larger, bureaucratic firms. Theoretically, this shifts the lens from a structural deficit model toward a relational and processual interpretation of innovation in SMEs, where knowledge flows, participatory decision-making, and cross-functional integration are central mechanisms. By focusing on how innovation is socially constructed within SME environments, the thesis aligns with and extends contemporary organizational theories that view small firms as embedded, adaptive, and sustainability-oriented actors, rather than passive recipients of top-down innovation policy (Del Giudice *et al*., 2021; Le and Ikram, 2022; Omowole *et al*., 2024).

Fourth, the interdisciplinary architecture of the thesis, spanning innovation management, organizational theory, and sustainability studies, offers a methodological contribution to academic inquiry. By combining a systematic literature review with single and multiple case studies, the research exemplifies how multi-level, interpretive approaches can generate rich, contextualized insights into complex innovation phenomena. This is in line with recent scholarly efforts calling for more holistic, embedded, and actor-sensitive frameworks in studying Industry 4.0 transformations (Nguyen *et al*., 2024; Tura *et al*., 2024).

Fifth, the project also introduces a multi-level innovation analysis that bridges traditionally fragmented areas of research, namely, systemic paradigms, organizational practices, and strategic experiences. While much of the existing literature operates at a single level of analysis, this research contributes a holistic, integrative perspective that acknowledges the complex, multi-layered nature of innovation processes in SMEs. The analysis advanced in this thesis accounts for the ways in which innovation unfolds across multiple dimensions: i) Systemic-theoretical: at the theoretical level, innovation is conceptualized as a socio-technical process, where technological integration is not an isolated event but a systemic shift that aligns technological, human, and organizational factors; ii) Operational: at the operational level, digital tools like AI are positioned as mechanisms for knowledge democratization, employee engagement, and human-centered improvement; iii) Strategic: the focus shifts to how SMEs leverage these innovations for global competitiveness, addressing barriers to AI adoption, and exploring its role in decision-making processes. By recognizing that innovation is not linear, but iterative and context-sensitive, the framework emphasizes that true organizational transformation requires an integration of technological, cultural, and human factors at all levels.

Finally, this dissertation offers a novel conceptualization of AI not merely as a technological enabler, but as a socio-organizational phenomenon that reshapes organizational dynamics, knowledge flows, and decision-making processes. In existing literature, AI is often positioned as a tool for automation or efficiency enhancement. However, this thesis repositions AI within the broader social sustainability and human-centered transformation discourse, arguing that AI has the potential to transform the workplace itself. Indeed AI, when embedded in organizational systems, does not only automate processes, but also alters power dynamics, decision-making practices, and organizational learning. As the case studies in this dissertation reveal, AI tools can be used to enhance employee learning, improve transparency in decision-making, and support more inclusive organizational practices. At the same time, the potential risks of AI, such as job displacement, skill gaps, and increased surveillance, require careful consideration. Thus, the study emphasizes the need for a critical, reflective approach to AI integration in organizations, one that balances its potential for enhancing productivity with its capacity to support inclusive and empowering workplaces.

3. MANAGERIAL IMPLICATIONS

The findings of this research offer several critical managerial implications for SMEs operating within the increasingly complex intersection of Lean production systems, digital transformation, and sustainability imperatives. Drawing on the three studies that underpin this thesis, a set of integrated managerial insights emerges, cutting across strategic, operational, and cultural-human dimensions.

From a *strategic perspective*, the integration of AI within SMEs must transcend the narrow view of AI as a purely technical enhancement. Instead, it must be embedded as a core component of decision-making processes, influencing activities from market sensing and resource allocation to partner evaluation and business model innovation. The research demonstrates that AI's value is unlocked when it is not treated as a detached instrument, but rather as an enabling force that operates in synergy with human judgment. To this end, managers are encouraged to cultivate AI literacy across all organizational levels, ensuring that decision-makers comprehend the strengths, limitations, and implications of algorithmic reasoning. Enhancing trust in digital systems through explainable AI models and participatory implementation strategies is equally essential. This strategic embedding must align AI deployment with the organization's broader vision, leveraging digital tools not merely for operational gains, but to reinforce strategic positioning and long-term competitiveness.

Building on this foundation, the study extends the analysis to the strategic domain, demonstrating that AI's transformative potential is maximized when its human-centered integration translates into strategic intelligence. When AI systems are embedded within organizational decision-making frameworks, they not only enhance efficiency but also expand managerial foresight and strategic agility. In this regard, the research shows that the firms most capable of managing dynamic international markets are those that treat AI not as an add-on, but as a strategic infrastructure implemented with reflexivity and ethical foresight. Indeed, Chapter IV shows that when properly deployed, AI systems support SMEs in identifying new markets, evaluating entry strategies, and managing global uncertainty. This implies that digitalization should not be limited to operational processes but extended to strategic functions such as foresight, planning, and risk management. Thus, managers should invest in AI capabilities not only for efficiency gains but also for enhancing data-driven agility and international competitiveness (Del Giudice *et al*., 2021; Le and Ikram, 2022).

On the *operational front*, the thesis emphasizes how AI-powered learning platforms offer transformative potential in democratizing access to Lean knowledge, particularly for SMEs that often lack structured training systems. Yet, the efficacy of these tools depends on their thoughtful integration within comprehensive change management efforts. Over-reliance on digital resources, without accompanying social support mechanisms, risks diminishing engagement and learning outcomes. Managers must thus promote hybrid learning ecosystems that blend technology with human facilitation, combining self-paced digital modules with mentoring, peer-to-peer collaboration, and face-to-face reinforcement. Such an approach sustains not only the transmission of technical competencies but also the diffusion of Lean's foundational values: collaboration, autonomy, and continuous improvement. Crucially, this process must be inclusive. Addressing digital inequality by ensuring that all employees, regardless of age, digital fluency, or organizational role, have equitable access to tools, time, and support, is fundamental for creating a performance-enhancing learning culture that strengthens organizational adaptability.

Moreover, and perhaps most significantly, the thesis calls attention to the cultural and human imperatives of technological innovation, advocating for the institutionalization of social sustainability as a strategic axis within the firm. Rather than relegating it to the realm of corporate social responsibility, social sustainability must shape the very logic of technological adoption and organizational transformation. For managers, this entails placing employee well-being, participation, and equity at the core of operational and strategic decisions. It requires a recognition that technological shifts bring not only productivity gains but also psychological, emotional, and ethical ramifications for workers. To face this complexity, innovation processes should be designed as inclusive and co-constructed pathways, embedding the voices, experiences, and concerns of employees from the outset. When people are involved as agents (and not merely recipients) of change, organizations can cultivate trust-based cultures where transformation becomes a shared trajectory. In such environments, resistance diminishes, commitment strengthens, and innovation becomes a collective pursuit, rather than a top-down obligation. The research underscores the critical importance of integrating social sustainability into digital innovation strategies. As demonstrated in the case study on AI-driven training platforms (Chapter III), the success of technological tools in improving performance depends significantly on how they are perceived and experienced by employees. Managers are encouraged to adopt a human-centered approach to technology implementation, prioritizing transparency, inclusiveness, and skill development. This is particularly relevant for SMEs seeking to enhance digital maturity while maintaining employee trust and engagement (Rana *et al.*, 2021; Ghaithan *et al.*, 2023). Establishing a culture of experimentation and psychological safety is a precondition for Lean-AI integration. As small firms often operate under tight margins and with limited formal infrastructures, the fear of failure can inhibit innovation and discourage the iterative experimentation required by Lean systems. Managers must actively invest in the development of environments where employees feel safe to test ideas, question assumptions, and participate in improvement initiatives without fear of penalization. Such a climate of openness and trust is not only culturally desirable but empirically essential, as psychological safety represents the underlying mechanism that enables learning-oriented behaviors to emerge. In this sense, psychological safety has been shown to positively correlate with employee engagement, knowledge sharing, and innovation success (Edmondson and Lei, 2014). In this context, sustainability must be translated into measurable and operational objectives. While many SMEs express commitment to sustainability, it often remains at the level of corporate rhetoric or marketing positioning. Instead, managers should incorporate environmental and social metrics into performance dashboards, including energy efficiency, emissions, employee well-being, and equity in access to training and development. Therefore, the integration of AI systems enables real-time monitoring of such indicators, thus making sustainability a tangible and trackable part of the innovation process.

Building on the strategic, operational, and cultural insights discussed above, the thesis further emphasizes the implementation perspective, outlining how the integration of Lean, AI, and social sustainability can be practically enacted within SMEs. This second set of managerial implications focuses on organizational mechanisms and enablers that support the effective and ethical realization of digital transformation.

First, the thesis emphasizes the strategic role of Lean culture as a foundational enabler of digital transformation. Managers should view Lean not merely as a toolkit for operational efficiency, but as a cultural infrastructure that facilitates structured experimentation, continuous improvement, and employee empowerment. Particularly in SMEs, where resource constraints are pronounced, Lean methodologies can amplify the effectiveness of digital investments by ensuring that technological solutions are embedded within stable, participatory, and process-oriented environments (Womack and Jones, 1996; Dombrowski and Mielke, 2013; Vinodh *et al.*, 2020).

Second, managers must begin to reframe AI not as a purely technological solution, but as a strategic enabler of learning and continuous improvement. In Lean environments, AI can enhance the effectiveness of feedback loops, reduce decision-making latency, and support predictive capabilities in production planning and quality control. However, to unlock these benefits, firms must embed AI systems into their operational routines and Lean cycles, rather than treating them as external or specialized tools. This requires building cross-functional teams in which AI outputs are interpreted and acted upon by empowered operators, line managers, and process designers.

Third, the project suggests that SMEs can overcome structural limitations, such as lack of capital or technical expertise, by engaging in collaborative innovation networks. By building relationships with technology providers, universities, and institutional actors, SMEs can access critical knowledge and resources while mitigating the risks of digital transformation. This aligns with recent literature on ecosystem-based innovation and highlights the importance of open, participatory, and policy-supported learning environments (Balder *et al.*, 2024; Ferreira *et al.*, 2023; Hamburg, 2020). Indeed, the transformation of SME capabilities requires the development of hybrid professional profiles. Lean transformation and AI implementation demand employees who understand both process efficiency and technological possibilities. Managers should implement cross-training programs that combine Lean thinking with digital literacy, enabling operational staff to interpret AI insights and data specialists to design tools aligned with Lean priorities. Investing in such hybrid competences can reduce resistance to change and accelerate the adoption of new practices.

Moreover, ethical considerations must be embedded into both technological and managerial decisions. While AI can enhance performance, it also introduces risks such as algorithmic bias, privacy violations, and job displacement. Lean thinking, with its emphasis on respect for people, offers a valuable ethical foundation for mitigating such risks. Managers must ensure that digital tools are implemented in ways that support human dignity, inclusivity, and participation. This may include ethical impact assessments, inclusion of employees in decision-making around automation, and transparent communication of how AI systems are designed and used.

Further managerial implications can be outlined to support the concrete application of its findings. Building on the preceding insights, these implications highlight how SMEs can operationalize the integration of Lean, AI, and social sustainability through practical, adaptive, and ethically grounded strategies.

First, managers are encouraged to adopt a pilot-based experimentation model for AI integration, aligned with Lean's incremental logic of continuous improvement. Instead of implementing AI systems at full scale from the outset, SMEs can identify specific processes, such as quality inspection, inventory control, or scheduling, that are well-suited for low-risk digital experimentation. Such "Lean-AI pilots" enable organizations to validate the usefulness of a solution in a contained environment, while also facilitating employee learning and feedback collection (Qureshi *et al*., 2022). Over time, such iterative experimentation nurtures organizational confidence, accelerates learning cycles, and reinforces a culture of structured innovation.

At the same time, sustainability should be explicitly embedded into daily operational routines and Lean practices. Managers can leverage traditional Lean mechanisms, such as Gemba walks and Kaizen events, to assess not only productivity-related issues but also environmental and social parameters, including energy use, material efficiency, ergonomics, and workplace inclusivity. Incorporating these dimensions into routine shop-floor observation not only supports triple-bottom-line performance but also reinforces a culture of integrated responsibility among employees (Sajan *et al*., 2017).

Moreover, human-centered digitalization also represents a crucial implication of this research. Managers are encouraged to leverage AI for workforce well-being, particularly through sentiment analysis tools that monitor employee feedback and identify psychosocial risks. Weekly pulse surveys, analyzed using natural language processing, can provide real-time insights into job satisfaction, stress levels, and engagement. These digital tools serve as early warning systems and support a proactive approach to social sustainability, reinforcing Lean's foundational respect-for-people principle (Ajirotutu *et al*., 2024).

A related implication concerns the development of AI-assisted skills management systems. AI algorithms can support dynamic competence mapping by analyzing operator performance, error rates, and training history. This enables the creation of adaptive, personalized training programs aligned with Lean objectives such as standardization and multi-skilling. Managers can thus ensure that training investments are targeted, impactful, and inclusive, especially critical in SMEs where formal HR structures may be limited (Faisal, 2025). However, technological tools for competence development can only reach their full potential when embedded in a broader culture of collective learning and open communication. In this sense, the effective use of AI for skills management must be complemented by mechanisms that enhance knowledge exchange between human and digital actors, as well as across hierarchical and functional boundaries. To enhance organizational learning and enhance mutual understanding, SMEs should institutionalize cross-learning forums between technical and non-technical staff. Regular "Lean-Digital Circles" can provide structured opportunities for shop-floor operators to share experiential insights, while data scientists can explain AI system outputs and limitations. This bi-directional knowledge exchange builds trust, demystifies technology, and increases the accuracy and relevance of digital interventions (Naerac *et al*., 2024).

In support of holistic transformation, incentive systems must also evolve. Managers should align performance and reward mechanisms with integrated objectives, combining traditional metrics such as productivity and cost reduction with social and environmental KPIs. For instance, teams may be rewarded for achieving reductions in carbon emissions, improvements in safety metrics, or increases in employee cross-skilling rates. Such multi-dimensional performance frameworks help institutionalize sustainability and inclusivity as central tenets of operational excellence (Nawanir *et al*., 2020).

Moreover, given the ethical complexities associated with AI adoption, managers must adopt ethical deployment protocols as part of standard innovation governance. These include pre-deployment checklists that assess risks related to algorithmic bias, data privacy, inclusivity, and potential job displacement. Embedding such foresight into Lean and digital decision-making not only enhances legitimacy but also reinforces a socially sustainable and human-centered approach to innovation (Siegel *et al*., 2024).

From a scaling perspective, the lessons suggest that SMEs should avoid rigid template replication. Even highly successful pilot projects often faltered when transposed to different lines or subsidiaries because of subtle differences in routines, worker mindsets, or shopfloor constraints. The more effective strategy is to treat innovation as modular, generative, and context-adjustable. Managers should create "internal innovation cells" that adapt core design principles to local micro contexts, preserving the underlying logic but allowing variation in form.

Finally, managers are encouraged to adopt a multi-dimensional and evolutionary view of innovation, recognizing that the integration of Lean, digitalization, and sustainability is not a linear process but a dynamic journey shaped by continuous learning and contextual adaptation. This mindset enables organizations to remain resilient in the face of volatility while enhancing inclusive growth models that align with broader societal objectives.

The managerial contributions of this thesis provide a practical roadmap for SMEs aiming to drive responsible innovation through the synergistic integration of Lean principles, digital tools, and social sustainability values. Managers are invited to cultivate inclusive organizational cultures, leverage technology for strategic agility, and embed sustainability into the core of their innovation trajectories.

4. RESEARCH LIMITATIONS AND AVENUES FOR FUTURE DIRECTIONS

Despite the theoretical richness and the empirical grounding of this dissertation, several limitations must be acknowledged. These delineate the boundaries of generalizability, transferability, and internal coherence within which the findings should be interpreted. Recognizing these limitations is critical for ensuring methodological transparency and for positioning the contributions of the work within the broader scientific discourse on human-centered innovation in SMEs.

A first set of limitations relates to the context-specific nature of the empirical data. The research draws on case studies conducted primarily within European SMEs, situated within industrial sectors where Lean and digital technologies were already present or emergent. This introduces a geographical and sectorial limitation that may limit the applicability of the findings to other regions or industries, particularly in developing economies or in non-manufacturing domains. While this choice was deliberate, given the structural characteristics and relevance of SMEs in the Italian industrial sector, it narrows the scope of application. Future research should explore whether the insights presented here hold in other national or regional contexts, including non-European economies or emerging markets where digital and sustainability transitions face distinct socio-institutional constraints (Nguyen *et al*., 2024; Malik and Jasińska-Biliczak, 2018).

A second limitation concerns the temporal dimension of the study. The research was conducted over a finite period, and it cannot fully account for the long-term evolution of AI and Lean integration. Transformational processes, especially those involving cultural change, tacit knowledge diffusion, and governance reconfiguration, often unfold over multi-year timeframes. As such, this dissertation captures only a snapshot of ongoing transformations, with the risk of overemphasizing early adoption dynamics while underrepresenting long-term institutionalization, erosion, or unintended consequences.

Thirdly, there are important methodological limitations tied to the use of qualitative, interpretive methods. While the richness of insight, semi-structured interviews allow for a granular understanding of lived experiences and informal dynamics, it also introduces subjectivity in data interpretation. The researcher’s positionality, background, and interaction with the field inevitably shape the construction of meaning, even under conditions of reflexivity and triangulation. Although theoretical saturation was pursued, and data were triangulated across sources and stakeholders, there remains an unavoidable element of constructivist bias in the narratives co-produced with participants. Moreover, the small-N design, while optimal for in-depth exploration, does not lend itself to statistical generalization. The study privileges depth over breadth, which is appropriate given its theory-building aim, but nonetheless imposes limits on predictive validity.

Another significant limitation concerns the treatment of AI itself. Given the speed at which AI technologies evolve, any analysis is inevitably subject to technological obsolescence. Tools, platforms, and algorithms discussed in the work may already be outdated or have evolved considerably. More importantly, the dissertation primarily treats AI as a managerial and organizational artifact, and while it references technical affordances and system architectures, it does not engage with deep technical analyses of AI models, nor with computational performance metrics. This could be seen as a limitation for readers expecting a technically grounded account of AI deployment. However, this choice was coherent with the socio-technical orientation of the research, which prioritizes interpretive, human-centered perspectives over deterministic or techno-centric narratives. As such, further research could explore specific AI functionalities, such as machine learning algorithms, natural language processing, or predictive analytics, and assess their differentiated impacts on organizational structures, employee roles, and strategic capabilities (Ghani, 2024; Del Giudice *et al*., 2021).

From a conceptual perspective, one limitation lies in the thesis's deliberate emphasis on social sustainability. While this focus responds to a clear gap in existing literature, it may have underemphasized the complex trade-offs between the three sustainability pillars, namely, social, environmental, and economic. Future studies could adopt multi-objective frameworks to examine how digital-Lean integration impacts all three dimensions simultaneously, potentially uncovering tensions or synergies between them (Bonilla *et al*., 2018; Fleacă *et al*., 2023).

Additionally, the thesis focused primarily on internal organizational dynamics (e.g., employee empowerment, AI adoption, decision-making). However, in line with the ecosystem perspective highlighted in recent literature (Ferreira *et al*., 2023), future research should examine how SMEs interact with external stakeholders, including customers, suppliers, policymakers, and technology providers. In particular, understanding how SMEs co-create value within digital and sustainable innovation networks would enrich current theoretical models and offer practical insights into building resilient, collaborative ecosystems.

4.1. Suggested future research avenues

The limitations and boundaries identified in this dissertation are not merely constraints; they also suggest fertile territories for future inquiry. Building on the theoretical synthesis and empirical insights of this research, several promising avenues emerge for advancing both the scholarly understanding and practical application of human-centered innovation at the intersection of Lean, advanced digitalization, and social sustainability in SMEs. This agenda articulates a multi-dimensional research strategy, spanning micro, and macro levels, and calling for methodological, conceptual, and empirical innovation.

A first and critical direction involves the development of longitudinal studies that track socio-technical transformations over extended periods. The insights of this dissertation are situated in a temporal snapshot of change, yet transformations involving AI deployment, Lean reconfiguration, and cultural shifts unfold over years. Future studies could employ process tracing, panel-based ethnography, or real-time intervention research to examine how SME ecosystems evolve through phases of technological adoption, routinization, resistance, and institutionalization. Such work would be invaluable in uncovering the temporal dynamics of trust formation, skill adaptation, and governance evolution, particularly as AI systems shift from experimental to operational status within organizations.

A second and complementary research trajectory should address the cross-cultural transferability and adaptation of the proposed socio-technical model. While this dissertation focused on European SMEs, the dynamics of human-centered innovation may vary significantly across geographies marked by different labor regimes, digital infrastructures, and socio-cultural expectations. Comparative studies across regions, such as Sub-Saharan Africa, Southeast Asia, or Latin America, could explore how SMEs in distinct institutional environments negotiate the tensions between automation, informality, and inclusion.

Closely linked to this is the need for more intersectional research that explores how socio-technical transformations affect and are affected by workers' identities, including gender, age, ethnicity, and educational background. AI systems and Lean workflows do not interact with generic "users" or "operators," but with embodied subjects embedded in specific power relations and historical trajectories. There is an urgent need for empirical studies that examine how digitalization in SMEs intersects with gendered labor patterns, youth employment, or migrant precarity, and how inclusive design practices can mitigate risks of marginalization. This would contribute to a richer contribution, expanding the theoretical scope of both innovation studies and organizational theory.

A fourth area of inquiry lies in the operationalization and empirical testing of the integrative framework developed in this dissertation. While the framework is grounded in qualitative evidence, its translation into measurable constructs and testable hypotheses remains an open field. Future research could develop mixed-methods approaches, combining ethnographic depth with survey-based generalization, to evaluate the efficacy of the design principles proposed here. This could include the development of tools, models, or index-based evaluations that assess how well SMEs are aligning

Lean, AI, and sustainability logics in practice. These instruments could also inform policymaking, standard-setting, and capacity-building programs aimed at digitally lagging SMEs.

Moreover, future studies should consider the role of policy ecosystems and institutional incentives in shaping SME transformation paths. While this dissertation touched on ecosystem logics, a deeper political economy perspective is needed to understand how funding structures, digital readiness programs, tax regimes, and labor protections influence which transformation strategies are adopted, and by whom. Comparative institutional research could explore how different governance regimes (e.g., centralized vs. decentralized innovation policy) mediate the integration of Lean, AI, and sustainability in SMEs. There is also scope for action research in policy design, where scholars collaborate with public actors to develop more adaptive, inclusive, and SME-responsive frameworks for digital innovation.

In conclusion, this research opens multiple frontiers for inquiry, each of which challenges dominant assumptions in management and innovation literature. By shifting the analytical gaze from tools to tensions, from performance to purpose, and from systems to subjects, future scholarship can continue the work begun here: constructing a critical, inclusive, and context-aware theory of socio-technical transformation for the small enterprise of the 21st century.

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