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ABSTRACT

This study advances the understanding of Lean Six Sigma 4.0 (LSS4.0) as a strategic framework for enhancing energy performance in industrial operations. A scoping review identified 29 barriers and 30 drivers, which were refined through focus group interviews into twelve critical barriers and seven key drivers. Empirical techniques, Fuzzy Delphi and Fuzzy DEMATEL, were applied to prioritize these factors and reveal their causal interrelations. Key results indicate that training and technical qualification influence at least five major barriers, including resistance to change and lack of standardization. At the same time, production cost reduction emerged as the most significant driver, overcoming capital investment constraints. These interdependencies informed the development of a research agenda, followed by a structured implementation roadmap aligned with the DMAIC cycle and tailored to varying levels of digital maturity. The roadmap incorporates operational and sustainability KPIs, such as cycle time reduction, energy consumption per unit, and carbon footprint, to guide continuous improvement under energy-efficiency goals. The study contributes both theoretically and practically by offering a replicable framework that supports the integration of LSS4.0 into diverse industrial contexts, bridging gaps in empirical evidence and providing actionable insights for organizations undergoing digital and sustainable transformation.

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Lean Six Sigma; Fuzzy logic; Delphi study; energy efficiency; Industry 4.0; DMAIC roadmap

1. Introduction

Currently, managing energy has gained significant importance in companies' business strategies globally (Cerciello, Busato, and Taddeo 2023; Fontoura et al. 2025). This trend stems from the imperative to trim costs across organizations' value chain processes, ultimately enhancing competitiveness and driving profitability (Shokri et al. 2022). Among accelerating climate concerns and stringent regulatory pressures, firms are under growing demand not only to reduce operational costs but also to minimize environmental impact through optimized energy management (Mishra and Singh 2023). The key to achieving these objectives is the adoption of effective methodologies tailored to professionals, such as Lean and Six Sigma (Mittal et al. 2023). Over the past decade, these methodologies have evolved into highly promising continuous improvement strategies in production and service sectors worldwide (Agnese et al. 2023; Singh et al. 2021). These methodologies can eradicate non-value-added tasks and mitigate process variations, guaranteeing operational efficiency and delivering superior quality (Camacho, Caro, and Peña 2023; Nascimento et al. 2019).

Despite extensive research on Lean Six Sigma (LSS) and Industry 4.0 (I4.0) in isolation, very few studies have proposed a unified framework that harnesses their synergy specifically for energy efficiency. While Chiarini and Kumar (2021) demonstrated LSS and I4.0 integration in Italian manufacturing, Pongboonchai-Empl et al. (2024) provided a systematic review of I4.0 technologies within the DMAIC cycle, and Skalli et al. (2025) developed a design-science LSS4.0 framework, none of which explicitly addresses sustainable energy goals. A search in Web of Science and Scopus confirms this scarcity of LSS4.0 literature with an energy focus (Ibrahim and Kumar 2024; Skalli et al. 2025). Moreover, empirical evidence remains sparse on how LSS4.0 concretely transforms production processes and enhances energy efficiency.

The interdependencies between drivers and barriers are poorly understood, as several authors highlighted the importance of studies that delve into the advantages, drivers, critical success factors, and barriers associated with utilizing LSS4.0 to enhance energy efficiency (Farrukh, Mathrani, and Sajjad 2022).

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To systematically explore these dimensions, we derived our Research Questions (RQs) directly from themes identified in the literature, ensuring alignment between theoretical constructs and empirical investigation (Cohen et al. 2015). Therefore, it seeks to address the following Research Questions (RQs):

RQ1: How does LSS4.0 impact production performance and energy efficiency in industrial settings?

RQ2: Which driver and barrier interrelationships most strongly influence LSS4.0 adoption with an energy focus?

RQ3: What strategic directions and priorities should guide future research on LSS4.0 for enhanced energy performance?

This study aims to construct and validate an integrated LSS4.0 implementation framework by combining literature insights and expert-based methods to identify critical barriers and drivers, define research priorities, and develop a time-based roadmap that aligns DMAIC phases with operational and energy KPIs across diverse organizational contexts. Theoretical contributions include quantifying the top barriers, mapping their influence against drivers using Fuzzy Delphi (FD) and Fuzzy DEMATEL (FDEM). Practically, we deliver managers and policymakers a concrete framework, a KPI dashboard prototype, and a step-by-step roadmap to streamline LSS4.0 implementation. This study addresses three key novelties: a mixed-methods ranking of drivers and barriers via FD and FDEM (Fontoura et al. 2023), a proposed standardization framework combining ISO and IEEE benchmarks (Trigo et al. 2014), and a practitioner-oriented KPI dashboard prototype for energy-efficient LSS4.0 deployment (Pietukhov et al. 2023). By bridging this gap, we aim to provide both theoretical contributions and actionable guidance to managers operating under varying digital maturity levels (Farrukh, Mathrani, and Sajjad 2022).

The study was organized as follows: This section provides background information and outlines the research gap, questions, and the underlying motivation driving this research. Section 2 introduces the conceptual terminology that informed the research and literature background. Section 3 presents the research design, providing a detailed explanation of the methodology adopted. Section 4 reports the theoretical and empirical findings, including barrier-driver interrelationships and the standardization framework. Section 5 offers a qualitative analysis through methodological triangulation, proposing the practitioner-oriented KPI dashboard and managerial insights. Finally, Section 6 concludes, discusses research limitations, and outlines a future research agenda towards LSS5.0.

2. Background

Modernizing production methodologies is a pressing necessity in response to emerging market requirements. While LSS approaches have seen extensive adoption, a distinct shift is evident towards embracing the advancements of I4.0, necessitating the integration of advanced technologies like Augmented Reality (AR), Virtual Reality (VR), and enhanced learning techniques that foster greater adaptability (Kumar et al. 2021). Recent advancements, such as Digital Twins, Industrial Internet of Things (IIoT), and machine learning, have been shown to synergize with LSS principles to further streamline processes and enable predictive maintenance, thereby supporting energy-efficiency goals (Skalli et al. 2025). Integrating I4.0 technologies catalyses LSS, primarily enhancing the value and dependability of industries, reducing lead times, and effectively addressing defects (Yeen Gavin Lai et al. 2019). Incorporating I4.0 technologies and principles in operations with sustainability initiatives significantly enhances resource efficiency, boosts production flexibility, reduces energy consumption (Beier, Niehoff, and Xue 2018; Ghobakhloo 2020) as well as improving diagnosis and accurate visualizations of production processes (Posada et al. 2015), allowing the elimination of redundant steps, reducing costs and improving energy efficiency, thus optimizing general operational sustainability (Shrouf et al. 2014).

The drivers for embracing quality initiatives are manifold, but the predominant ones involve implementing methodologies like LSS. This approach aims to enhance efficiency and performance, curb expenses and setbacks, and bolster market presence and customer satisfaction (Skalli et al. 2023). In addition, organizational digital maturity and leadership commitment have emerged as critical enablers for successful LSS4.0 implementation, enabling rapid scaling of energy-saving measures across plant operations (Swarnakar et al. 2023). Hence, it is imperative to identify the most influential factors driving organizational management and integrate them effectively into corporate strategies. This ensures that companies have the necessary motivation to confront market challenges head-on. Evaluating and gauging the organization's readiness for integrating continuous improvement methodologies and embracing I4.0 technologies is crucial. This assessment helps identify critical drivers and aids in selecting the most suitable projects, which can transform these methodologies into sustainable, results-driven implementations geared towards LSS4.0 (Shokri and Li 2020; Skalli et al. 2023, 2025). To support this, we propose a readiness assessment framework combining ISO 50001 energy management principles and IEEE P2801 benchmarks to evaluate an organization's digital and energy maturity levels (Jovanović and Filipović 2016). The integration of LSS with I4.0 technologies to form LSS 4.0 is an emerging trend in both academia and the industrial sector (Pongboonchai-Empl et al. 2024). The primary economic motivators propelling the adoption of LSS4.0 within product sectors include cost minimization, financial incentives, safeguarding profit margins, and adapting to changes in competitive standings (Farrukh, Mathrani, and Sajjad 2022).

If left unidentified and unaddressed, barriers can deter a beneficial implementation of LSS4.0 and significantly impact quality methodologies. Several barriers can be found in the literature, including financial constraints, inadequate management support, limited awareness, resistant organizational cultures, and skills gaps (Kamble et al. 2019). Legacy IT infrastructures and complex regulatory compliance requirements have also been identified as significant impediments to seamless LSS4.0 deployment (Kaswan et al. 2023; Pickett et al. 2020). Understanding the obstacles and the profound impact within organizations is essential, enabling their strategic mitigation or neutralization. By aligning with the company's critical challenges, this approach minimizes adverse outcomes while maximizing positive results (Mohan et al. 2022; Skalli et al. 2023; Yadav et al. 2021). Hence, we can outline the primary obstacles to the implementation of LSS4.0 in industrial contexts, as identified in the literature, as follows: resistance to change and fear factors (Dieste, Sauer, and Orzes 2022; Shokri et al. 2022), lack of commitment from top management, and insufficient training on LSS in the context of I4.0 (Kumar et al. 2023; Yadav et al. 2021).

2.1. Theoretical framework

To strengthen the theoretical foundation of this study, it is essential to position the proposed LSS4.0 framework in relation to prior models that have explored the integration of LSS with Digital Transformation (DT) and Industry 4.0 (I4.0). While these studies vary in scope and methodological orientation, they consistently highlight the potential of combining continuous improvement methodologies with digital technologies to enhance operational excellence. However, most frameworks remain limited in their explicit treatment of sustainability and energy-efficiency outcomes. Table 1 summarizes the main contributions of selected studies, outlining their objectives, the connection between LSS and DT, and their key findings.

As shown in Table 1, existing frameworks on LSS 4.0 have made incremental contributions by exploring its interface with digital technologies such as IoT, robotic process automation, big data analytics, and artificial intelligence. These efforts, while reporting localized gains in productivity, quality, and operational agility—and occasionally suggesting links to energy efficiency—remain inadequate to guide organizations towards a holistic transformation. To date, no framework has provided a structured and transferable roadmap that systematically embeds sustainability-oriented KPIs into the continuous improvement process. Current approaches are fragmented, overly context-dependent, and conceptually narrow, as they treat digitalization primarily as a technological upgrade rather than as a lever for achieving verifiable sustainability outcomes. This study addresses this critical gap by proposing a framework that integrates energy and environmental metrics directly into the DMAIC cycle. By doing so, it shifts LSS 4.0 from a technology-driven paradigm to a sustainability-oriented improvement pathway, with the potential to significantly impact the sustainable production field. The framework is designed to be replicable across sectors, offering both a clear roadmap and a coherent set of actionable KPIs that enable organizations to align digital transformation initiatives with broader environmental and energy-efficiency objectives.

3. Research design

The research process consisted of five distinct phases (Fontoura et al. 2023), delineated in the figure available in the supplementary materials at https://zenodo.org/records/16275594. Commencing the methodology was the scoping review (Nascimento et al. 2022), which sought to elucidate the integration of LSS methodologies and I4.0 technologies within industrial sectors to enhance energy management practices. It aimed to identify existing models, alongside key obstacles (barriers) and facilitators (drivers), for successful implementation. In the second stage, a focus group (Kontio et al. 2008), involving experts, was utilized to investigate their perspectives and opinions on implementing LSS4.0 while also analysing all barriers documented in the literature. During the third phase, a distinct questionnaire (Garcia-Buendia et al. 2024) was developed in collaboration with experts, different from the focus group, to gather demographic information and solicit their views on the most pertinent barriers. Additionally, it sought to discern the strongest interrelationships between these barriers and drivers. In the fourth stage, a Delphi study (de Mattos Nascimento et al. 2024; Fontoura et al. 2023) was conducted, comprising two distinct methods: FD and FDEM. FD was employed to pinpoint the most significant barriers. At the same time, FDEM was utilized to ascertain which drivers would most effectively eliminate these barriers while implementing LSS4.0 in industries. Finally, in the fifth phase, the findings were used to develop a comprehensive research agenda that informs and guides future investigations on this subject, followed by a time-based roadmap integrating DMAIC phases and FDEM results.

3.1. Scoping review

The scoping review is a comprehensive literature review that draws upon evidence syntheses to identify research gaps. It offers a broad overview of the content covered in the identified works without delving into specific details, and highlights critical aspects relevant to a review (Armstrong et al. 2011; Munn et al. 2018), synthesizing complex and heterogeneous themes (Farrukh, Mathrani, and Sajjad 2022; Franciosi et al. 2018). This research utilized the Scopus and WoS databases to compile the final portfolio. These selected databases were preferred for their extensive coverage of pertinent literature in operations management (de Mattos Nascimento et al. 2022). The scoping review process used in this research was divided into six distinct phases (Fontoura et al. 2023): (i) identify the research questions, (ii) identify relevant studies, (iii) study selection, (iv) chart the data, (v) validation and data coding, and (vi) collate, summarize, and report.

Providing a comprehensive account of the entire review process is crucial, as emphasized by Saunders et al. (2012). To (i) identify relevant questions, discussions among authors with different areas of expertise, brainstorming sessions, and thorough literature analyses were applied. The main objective was to understand cutting-edge methodologies, LSS, I4.0 technologies, and energy-efficiency issues for the industry. Additionally, efforts were made to identify the most commonly used models. The scoping review not only furnished a solid theoretical foundation (Okoli and Schabram 2010; Saieg et al. 2018) but also highlighted key research gaps (Webster and Watson 2002). To (ii) identify relevant studies, a portfolio was built from the listed documents, utilizing a word tree

Table 1. Representative models connecting Lean Six Sigma with digital transformation.

Author	Objective	LSS ↔ DT	Key contributions
(Skalli et al. 2025)	To develop a structured framework for systematically incorporating Industry 4.0 into Lean Six Sigma practices	Systematic integration of digital tools (IoT, automation, data analytics) into the LSS improvement cycle	14-step framework validated by experts and applied in case studies (automotive and mining); improvements in quality, efficiency, and a 20% energy-efficiency gain
(Sahoo and Upadhyay 2024)	To analyze the combined impact of I4.0, Lean Six Sigma practices, and CSCM on triple bottom line (economic, environmental, social) performance	Shows that I4.0 impacts economic performance directly, while environmental and social performance require mediation through LSSP and CSCM	Empirical evidence from 224 manufacturing firms highlights that LSSP and CSCM mediate sustainability outcomes and provide a strategic framework for TBL improvements
(Huang et al. 2024)	To apply the Lean Six Sigma DMAIC approach and integrate Robotic Process Automation (RPA) to improve hospital medical claims processes	Combines Lean Six Sigma's structured problem-solving with digital automation (RPA), representing a Lean digital transformation	Reduced process time by 380 min; improved Process Cycle Efficiency (PCE) from 69.07% to 95.54%; validated real-world digital LSS application in healthcare
(Shahin et al. 2024)	To leverage GPT-3.5 Turbo NLP for extracting Voice of Customer (VoC) data from digital interactions (Twitter) and link insights to LSS4.0 practices	Integrates AI-enabled NLP into LSS4.0, extending Digital Transformation through customer-centric, real-time data analytics	Demonstrates improved contextual understanding of customer sentiment; showcases multilingual, large-scale VoC processing; enhances decision-making for LSS4.0 in Industry 4.0
(Ibrahim and Kumar 2024)	To identify critical Industry 4.0 technologies that can be integrated with Lean Six Sigma for improved manufacturing processes	Uses fuzzy DEMATEL to prioritize technologies such as AI/ML, big data analytics, automation, smart sensors, and simulation, aligning them with LSS methodologies	Highlights how AI enables predictive analysis, smart sensors improve energy efficiency, and robots support flexibility; links integration to sustainability, safety, and workforce upskilling
(Tissir et al. 2024)	To develop a comprehensive, step-by-step framework to guide organizations in implementing LSS4.0	Integrates Lean Six Sigma with I4.0 technologies via a 15-step DMAIC-based approach, aligning digitalization with process improvement	Provides a structured roadmap for managers; validated through an expert panel and an automotive case study; prevents digitalization without purpose by linking tool adoption to DMAIC phases

technique, as shown in Figure 1, locating 143 documents before applying the inclusion and exclusion criteria.

In the (iii) study selection phase, rigorous criteria were employed to choose the most pertinent literature for the ultimate compilation. Inclusion and exclusion criteria were set to reduce selection bias (Siddaway 2014). Only documents published up to January 2023 in English-language journals and conference proceedings were deemed appropriate for inclusion, given their reliability in facilitating rigorous literature reviews (Siddaway et al. 2019). Regarding exclusion criteria, any documents from the intersection of LSS and I4.0 technologies that lacked integration of at least one I4.0 technology into LSS, as well as any documents from the intersection of LSS and energy efficiency that failed to showcase energy-efficiency enhancements, were discarded. The selected papers underwent a rigorous three-stage evaluation process in which their titles, abstracts, and keywords were reviewed (Fontoura et al. 2023). Subsequently, the methodology, findings, and conclusions were examined. The ultimate phase encompassed a thorough reading of the selected documents. Additionally, supplementary research incorporated other papers into the final portfolio, bringing the total number of publications for this research to 52, as shown in the supplementary document.

To (iv) chart the data, the documents were organized in Mendeley and categorized into folders for easier filtering. Subsequently, this data was transferred to a spreadsheet containing the authors, publication year, study location, objectives, findings, methodological overview, results, drivers, barriers, and technological approaches. The collected information was scrutinized for comparison during the (v) validation and data coding, wherein discussions were facilitated to resolve any discrepancies that arose, ensuring the reliability of the data while minimizing potential errors and biases among the evaluators (Caiado et al. 2025). The processes of (vi) collating, summarizing, and reporting were carried out, complemented by a thorough content analysis (Garza-Reyes 2015), which was selected as the preferred analytical approach.

3.2. Focus group

In the study's second phase, a focus group methodology was employed to facilitate a structured discussion aimed at investigating a specific set of questions. To ensure a rich diversity of perspectives, we selected twelve domain experts from industry and academia using purposeful sampling, considering their educational credentials, professional track records in operations and supply chain management, as well as their expertise in LSS and I4.0 technologies (Woods et al. 2013). The Focus Group consisted of four 80-minute sessions (320 minutes total), each moderated using a predefined discussion guide and supplemented by real-time data coding in Excel to capture qualitative insights and interrelationships among constructs (Langford and McDonagh 2002). The primary objective of this stage was to meticulously analyze and comprehend the perspectives of domain experts concerning the research findings revealed through the content analysis. The sessions were organized under the guidance of a moderator to encourage discussion and foster mutual understanding among participants, adhering to a predefined set of guidelines.

The selection of specialists from both the general market and academia with experience in LSS was based on their involvement in project partnerships led by the authors, focusing on implementing LSS methodologies and adopting

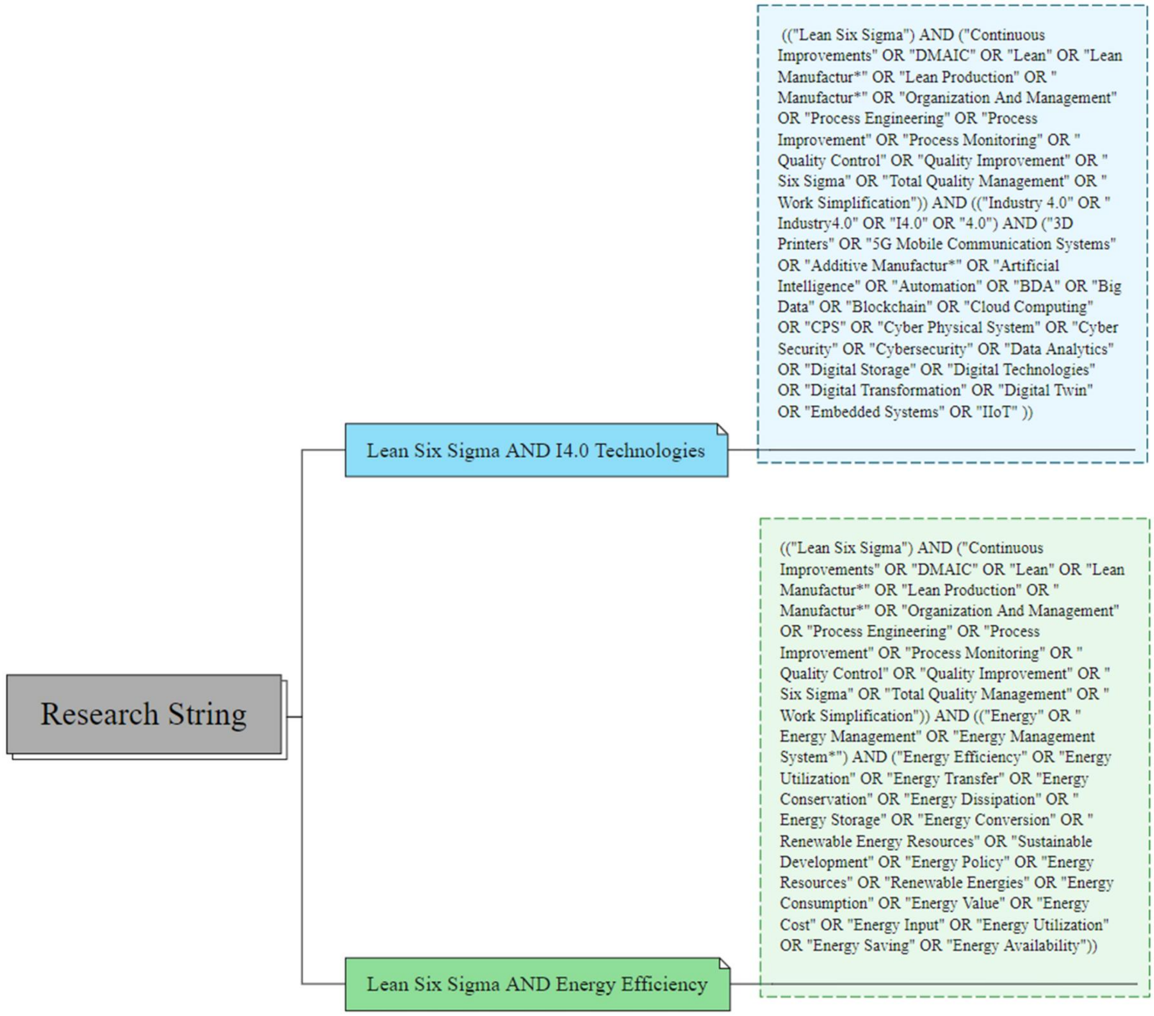

Figure 1. Research string using word tree.

I4.0 across various companies, particularly in the electricity sector. Candidates were selected based on their established expertise, assessed through their educational credentials, substantial research or professional experience in operations and supply chain management, sustainability, and their proficiency in technology. This purposeful sampling approach considered individual characteristics relevant to the session's topics. It selected 12 participants who best aligned with the protocol established for the group discussions, considering their history, age, experience, and knowledge. Focus Group sessions should include at least three participants and a maximum of twelve participants (Kontio et al. 2008). Therefore, the Focus Group utilized in this research involved the engagement of twelve experts hailing from Brazil's industrial and electrical energy sectors. The group setting enables participants to expand upon the responses and ideas of others within the group, thereby enhancing the depth and significance of the information gathered (Langford and McDonagh 2002), as detailed in Table 2.

The Focus Group sessions were conducted across four intensive sessions that explored the integration of LSS methodologies with I4.0 technologies in industrial settings. The initial session explored the current energy consumption patterns within the industrial sector and identified ways the proposed research agenda could promote enhanced energy efficiency. The subsequent second and third sessions focused on a comprehensive discussion of the 29 barriers and 30 drivers to implementing I4.0 technologies identified in the literature, emphasizing their potential to facilitate improved energy efficiency in industrial settings. The final session synthesized the main drivers and barriers, emphasizing their strong interrelationships during the implementation of LSS and I4.0 technologies, which were deemed crucial for effective energy management. Additionally, the session cross-referenced the various factors discussed, using an Excel spreadsheet for data analysis, which helped prioritize quantitative results and participants' qualitative feedback. As a result, a list of drivers and barriers was created based on expert feedback regarding their interrelationships. The strongest relationships were highlighted, identifying 12 barriers and 7 drivers during the fourth session.

3.3. Questionnaire design

The third phase entailed developing and validating the questionnaire instrument employed in the research. It encompassed two stages aimed at categorizing and elucidating all pertinent study details for participant comprehension. Based

Table 2. Focus group expert panel - adapted from Fontoura et al. (2023).

Code	Experience	Specialties	Degree	Expertise	Country
A1	30 years	Sustainable Management Systems	Bachelor	Practitioner	Brazil
A2	15 years	Sustainable Management System	Doctorate	Academic	Spain
A3	31 years	Operation and Maintenance Planning	Bachelor	Practitioner	Brazil
A4	20 years	Operation and Maintenance Planning	Bachelor	Practitioner	Brazil
A5	18 years	Operation and Maintenance Planning	Bachelor	Practitioner	Brazil
A6	17 years	Operation and Maintenance Planning	Bachelor	Practitioner	Brazil
A7	15 years	Operation and Maintenance Planning	Bachelor	Practitioner	Brazil
A8	10 years	Operation and Maintenance Planning	Bachelor	Practitioner	Brazil
A9	15 years	Information Technology	Bachelor	Practitioner	Brazil
A10	16 years	Engineering	Bachelor	Practitioner	Brazil
A11	30 years	Industrial Management	Bachelor	Practitioner	Brazil
A12	22 years	Industrial Management	Master	Practitioner	Brazil

Table 3. Delphi study expert's panel - adapted from Fontoura et al. (2023).

Characteristics	n (%)
Experiences	
Less than 10 years	4 (16.66)
From 10 to 20 years	7 (29.17)
More than 20 years	13 (54.17)
Specialties	
Management (Director, Manager and Coordinator)	17 (70.83)
Technician (Application Engineer, Industrial Engineer, and Technical Consultant)	7 (29.17)
Expertise	
Practitioners	24 (100)
Academics	0 (0)
Academic background	
Engineering	17 (70.83)
Others	7 (29.17)

on themes identified in the Focus Group, we generated 68 questionnaire items and organized them into barrier and driver categories, which were reviewed for content validity by three independent experts. Initially, a concise exposition elucidating the concepts of LSS and I4.0 technologies was provided to ensure a comprehensive grasp of the research, succeeded by the solicitation of demographic particulars concerning the academic and vocational backgrounds of the participants (Garcia-Buendia et al. 2024) encompassing specialized areas of expertise, educational attainment, and practical familiarity with LSS methodologies or I4.0 technologies within industrial or energy sector contexts.

Following the acquisition of demographic data, participants were prompted to respond to evaluate the perceived significance of barriers impeding the adoption of the LSS4.0 model within organizational settings and the interrelationship between drivers found in the literature and these most relevant barriers. Although no strict guidelines exist regarding the optimal number of experts required for a Delphi study (Moktadir et al. 2020), an additional twenty-four experts, distinct from those involved in the Focus Group, were selected using a similar process based on their background, age, experience, and knowledge, as outlined in Table 3.

Their professional experience ranged from six to thirty years; all had implemented or adopted LSS4.0 as part of their management practices. The experts represented twenty companies across various sectors in Brazil and Argentina, including consulting, energy, and manufacturing, ensuring diverse perspectives and comprehensive experience in different processes. To assess and categorize the significance of the foremost impediments identified in the literature and highlighted by the Focus Group experts for the implementation of an LSS4.0 model, a 5-point Likert scale was utilized, ranging from 1, indicating 'no relevance', to 5, representing 'extreme relevance' (Garcia-Buendia et al. 2024). The focus centred on amalgamating LSS principles with the technological advancements in I4.0. This assessment employed a linguistic scale encompassing categories such as 'no influence', 'low influence', 'moderate influence', 'high influence', and 'extreme influence', abbreviated as NI, LI, MR, HI, and EI, respectively (Fontoura et al. 2023). Notably, all twenty-four experts actively participated in both rounds of the survey.

3.4. Delphi study

The Delphi study integrated the FD and Decision-making Trial and Evaluation Laboratory (DEMATEL) methods to enhance the analysis of critical barriers, drivers, and relevant I4.0 technologies for improving the implementation capabilities of LSS4.0. The FD method was employed to identify critical factors and prioritize barriers that impede the adoption of LSS4.0. Two iterative rounds of FD were conducted, with experts revising their judgments after receiving group feedback, resulting in a convergence of responses (a reduction in standard deviation of more than 20%) (Montes et al. 2023). However, FD alone cannot assess the dependencies or feedback loops between dimensions or criteria. To address this, we applied FDEM using Triangular Fuzzy Numbers (TFNs) to model the causal relationships between drivers and barriers; TFNs were chosen for their transparency and ease of interpretation by stakeholders (Kahraman et al. 2003). FDEM assessed the importance and causal relationships between drivers and barriers, identifying the most influential criteria for implementing LSS4.0 in industrial environments. The proposed extended research framework, integrating FD and FDEM, enabled the analysis and identification of key barriers and drivers in real-world settings. This framework developed a matrix highlighting the strongest interrelationships, indicating which drivers should be prioritized to resolve LSS4.0 implementation challenges while supporting continuous and incremental improvements in energy efficiency within organizations.

Two iterations, FD and FDEM, involved twenty-four domain specialists, different from the Focus Group experts. This mechanism operates as a group decision-making process, necessitating the expertise of individuals with profound subject matter understanding, thereby transcending the reliance on statistical sampling endeavours to achieve population representativeness (Okoli and Pawlowski 2004). Moreover, it is advisable to administer the identical questionnaire multiple times to experts within each round to ensure convergence of their prognostications (Ishikawa 1993). The FD method stage was conducted in two rounds to consolidate expert consensus regarding the barriers to LSS4.0 implementation. In the first round, experts evaluated each item using a five-point Likert scale, and the results were subsequently refined based on feedback provided in the second round. After consolidating the final responses, the instrument's internal consistency was assessed using Cronbach's alpha coefficient. Values above 0.85 were sought, as coefficients exceeding this threshold are generally interpreted as indicative of high reliability and internal consistency within psychometric assessments (Goetz et al. 2008). This reinforces the reliability of the data collected and supports the validity of the expert judgments used in the subsequent stages of analysis.

By integrating the FD method for consensus building with the FDEM ability to analyze the relational structure of criteria, a more robust evaluation is enabled, leading to more precise decision-making in environments characterized by high complexity and uncertainty, where traditional fuzzy methods may fail to capture the interactions between criteria adequately (Radin Umar et al. 2024). The use of TFNs was adopted in this research due to their ease of comprehension and ability to facilitate effective communication among stakeholders, and it was employed to represent linguistic terms to capture the uncertainties inherent in the questionnaire responses (Fontoura et al. 2023). Their frequent pairing with linguistic terms in research is due to their capability to quantify subjective assessments while preserving a clear and structured framework, making them particularly well-suited for scenarios where ambiguity and vagueness must be systematically addressed (Kahraman et al. 2003).

3.4.1. Fuzzy Delphi (FD)

The FD method extends the traditional Delphi method by incorporating fuzzy logic to overcome uncertainties in the decision-making process (Fontoura et al. 2023). The Delphi methodology ensures anonymity among participants, thereby mitigating groupthink by affording equal weight to responses gathered from experts, resulting in a balanced outcome. The most relevant barriers to implementing LSS4.0 within organizations are identified and classified through quantitative analysis employing the FD technique. This technique integrates Fuzzy set theory with traditional Delphi principles, aiming to address and reduce uncertainties inherent in expert judgments (Garcia-Buendia et al. 2024; Ishikawa 1993). By introducing membership functions, which translate ambiguous linguistic preferences into quantifiable values while preserving their qualitative essence, each participant's perspective is carefully considered and incorporated to achieve consensus in group decision-making (Sadeghi et al. 2016). After the questionnaire stages, all linguistic terms were converted into TFNs using the concept of membership function (Zadeh 1965), as presented in Table 4. The significance value of an attribute b is evaluated by the respondent a as $j = (x_{ab}, y_{ab}, z_{ab})$, $a = 1, 2, 3, \ldots, n$, and $b = 1, 2, 3, \ldots, m$. Thus, the j_b weight of the b attribute is calculated as $j_b = (x_b, y_b, z_b)$, $x_b = \min(x_{ab})$, $y_b = \left(\prod_1^n y_{ab}\right)^{\frac{1}{n}}$ and $z_b = \max(z_{ab})$ (Wang et al. 2020).

Table 4. TFNs to relevance scales, adapted from Fontoura et al. (2023).

Scale	Linguistic terms	TFNs
1	No relevance (NR)	(0; 0; 0.25)
2	Low relevance (LR)	(0; 0.25; 0.50)
3	Moderate relevance (MR)	(0.25; 0.50; 0.75)
4	High relevance (HR)	(0.50; 0.75; 1.0)
5	Extreme relevance (ER)	(0.75; 1.0; 1.0)

The value of the convex combination D_b is calculated using an α-cut, typically set at 0.5 but can be adjusted based on the experts' degree of optimism or pessimism, ranging from 0 to 1 (Fontoura et al. 2023). Lambda (λ) represents the decision-makers optimism level and balances extreme judgments, providing a nuanced approach to decision-making (Garcia-Buendia et al. 2024). Finally, $\delta = \sum_{a=1}^{n} \frac{D_b}{n}$ serves as the attribute filter's threshold (Caiado et al. 2025). If $D_b \geq \delta$, attribute b is accepted; otherwise, it is rejected. The calculation of the value of the convex combination can be generated as follows, demonstrated in Equation (1):

$$D_b = \int (u_b, l_b) = [\lambda u_b + (1 - \lambda) l_b] \tag{1}$$

where: $u_b = z_b - \alpha(z_b - y_b); l_b = x_b - \alpha(y_b - x_b); b = 1,2,3,\ldots,m;$ $\alpha =$ the expert's level of opinion; $\lambda =$ the decision-makers level of optimism.

Therefore, each linguistic term provided by experts (e.g. 'high relevance') was converted into a TFN according to the scale in Table 4. For each barrier, TFNs were then aggregated across all experts by calculating the average of the lower, middle, and upper values. For example, if three experts assigned 'moderate relevance' (0.25, 0.50, 0.75), 'high relevance' (0.50, 0.75, 1.0), and 'extreme relevance' (0.75, 1.0, 1.0), the aggregated TFN would be (0.25, 0.72, 1.0). Defuzzification was performed using the centroid method, computing the crisp value. This crisp value was then compared to the threshold to determine whether each barrier was retained or discarded.

3.4.2. Fuzzy DEMATEL (FDEM)

DEMATEL (Decision-Making Trial and Evaluation Laboratory) is a methodology designed for modelling and analysing structural models to elucidate the influence relationships among complex criteria (Fontoura et al. 2025). DEMATEL is widely regarded as one of the most effective methods for exploring causal relationship structures (Falatoonitoosi et al. 2013). Employing matrices or digraphs, it transforms the interconnections between causes and effects into a transparent and interpretable structural model of the system (Si et al. 2018). The inherent subjectivity in human assessments of these critical factors is mitigated through the adoption of a propitious methodology that integrates Fuzzy set theory with the DEMATEL method, facilitating the segmentation of critical factors crucial to decision-making processes (Garcia-Buendia et al. 2024). The linguistic terms alongside their respective TFNs representations are shown in Table 5. In the FDEM, defuzzification converts qualitative inputs into Fuzzy linguistic representations, yielding precise numerical values derived from Fuzzy numbers (Fontoura et al. 2023). Subsequently, the computation involving the minimum and maximum Fuzzy numerical representations facilitates the determination of left and right values (Chang, Chang, and Wu 2011).

According to Fontoura et al. (2025), fuzzy membership functions $f_{ij}^{k} = (f_{lij}^{k}, f_{mij}^{k}, f_{rij}^{k})$ are employed to generate the weighted total values. Assuming that k experts participated in the evaluation process, f_{ij}^{k} means the diffuse weight of the attribute effect i^{th} in the attribute j^{th} as assessed by a specialist k^{th}. The resultant crisp numerical values were subsequently synthesized into a comprehensive direct total matrix, enabling the construction of a diagram to streamline the analytical outcomes. This framework organizes distinct attributes into cause-and-effect groups, delineating structured interrelationships and pivotal effects (Garcia-Buendia et al. 2024). A set of attributes *(F)* is defined, and specific interrelationships between attribute pairs are utilized to establish the corresponding mathematical relations (Wang et al. 2020). In practice, each expert's pairwise evaluation is first expressed as a TFN, which is then normalized to place all responses on a standard scale. The fuzzy values are subsequently defuzzified into crisp influence scores, which are integrated across experts to generate a single value for each relationship. These aggregated values are then used to build the generalized direct relation matrix, from which the total relation matrix is derived, enabling both direct and indirect causal effects to be captured. The proposed FDEM method is organized into six distinct steps, following the framework outlined by Fontoura et al. (2023), as detailed below:

Step 1. Normalize the Fuzzy numbers:

$$F_{ij}^{k} = \left(f_{l_{ij}}^{k}, f_{m_{ij}}^{k}, f_{r_{ij}}^{k}\right) = \left[\frac{l_{ij}^{k}\text{-min}\left(l_{ij}^{k}\right)}{\Delta}, \frac{m_{ij}^{k}\text{-min}\left(m_{ij}^{k}\right)}{\Delta}, \frac{r_{ij}^{k}\text{-min}\left(r_{ij}^{k}\right)}{\Delta}\right] \tag{2}$$

$$\Delta = \max\left(r_{ij}^{k}\right) - \min\left(l_{ij}^{k}, m\ r_{ij}^{k}, r_{ij}^{k}\right) \tag{3}$$

Table 5. TFNs to influence scales, adapted from Garcia-Buendia et al. (2024).

Scale	Linguistic terms	TFNs
VLI	Very Low Influence	(0; 0,10; 0,30)
LI	Low Influence	(0,1; 0,30; 0,50)
MI	Moderate Influence	(0,3; 0,50; 0,70)
HI	High Influence	(0,5; 0,70; 0,90)
VHI	Very High Influence	(0,7; 0,90; 1,00)

where: l_{ij}^{k} = Left TFN values; m_{ij}^{k} = Mean TFN values; r_{ij}^{k}= Right TFN values.

Step 2. Calculate the right (rv) and left (lv) normalized values:

$$\left(lv_{ij}^{k}, rv_{ij}^{k}\right) = \left[\frac{f_{m_{ij}}^{k}}{1 + f_{m_{ij}}^{k} - f_{l_{ij}}^{k}}, \frac{f_{r_{ij}}^{k}}{1 + f_{r_{ij}}^{k} - f_{m_{ij}}^{k}}\right] \tag{4}$$

where: f_{lij}^{k} = Normalized Minimum Fuzzy Number; f_{mij}^{k} = Normalized Average Fuzzy Number; f_{rij}^{k} = Normalized Maximum Fuzzy Number.

Step 3. Compute the normalized crisp values (x):

$$x_{ij}^{k} = \frac{\left[lv_{ij}^{k}\left(1 - lv_{ij}^{k}\right) + \left(rv_{ij}^{k}\right)^{2}\right]}{\left(1 - lv_{ij}^{k} + rv_{ij}^{k}\right)} \tag{5}$$

where: lv_{ij}^{k}= calculated left normalized value; rv_{ij}^{k}= calculated right normalized value.

Step 4. Integrate the crisp values ($\tilde{x}$):

$$\tilde{x}_{ij} = \frac{x_{ij}^{1} + x_{ij}^{2} + \ldots + x_{ij}^{k}}{K} \tag{6}$$

where: x_{ij}^{k} = Normalized crisp value computed; K = Total number of respondents.

Step 5. Arrange the generalized direct relation matrix (G):

$$G = \left[\tilde{x}_{ij}\right]_{i\times j} \tag{7}$$

where: $\tilde{x}_{ij}$ = Integrated crisp values.

Step 6. Compute the normalized total direct relation matrix (T):

$$T = \tau \otimes G \tag{8}$$

$$\tau = \frac{1}{\max\left(\sum_{i=1}^{l}\tilde{x}_{ij}\right)} \tag{9}$$

where: G = Generalized direct relation matrix; $\tilde{x}_{ij}$ = Integrated crisp values.

3.5. Research agenda and roadmap

A research agenda serves as a potent tool for researchers, facilitating focused analyses and diagnostics accompanied by critical reflections or participatory dialogues concerning gaps in existing knowledge (De Angelis, Howard, and Miemczyk 2018). Moreover, it enables the formulation of actionable proposals or suggestions for future investigations, thereby enhancing the comprehensiveness of research endeavours. Within this context, the research agenda is pivotal in steering and delineating objectives, mainly supporting the scientific community in collaboration with broader societal stakeholders, notably businesses (Carayol 2003). Given that a research agenda inherently embodies a forward-looking proposition, articulated in the present with a keen eye towards the future, it necessitates the selection of thematic domains earmarked for subsequent investigation (Hummers-Pradier et al. 2009).

We conducted a rigorous content analysis of the Focus Group transcripts, Delphi rankings, and DEMATEL matrices using Python. This process involved coding recurrent themes, such as training needs, standardization gaps, and digital infrastructure demands, and quantifying their co-occurrence to identify the most prominent driver and barrier relationships. Examples include the link between training and resistance to change, as well as the relationship between capital investment and production cost reduction. These empirical patterns served as the foundation for the thematic pillars of the proposed research agenda. We translated those empirical findings into a structured conceptual framework by mapping each DMAIC phase to both operational and energy KPIs (cycle time reduction, energy consumption per unit, carbon footprint reduction, and resource efficiency score). Therefore, the roadmap was developed by integrating the empirical findings from the Focus Group, FD, and FDEM outcomes.

The most critical barriers and their causal relationships with key drivers were identified, establishing a foundation for targeted intervention. These relationships informed the selection of priority actions aimed at overcoming high-impact barriers using the most influential drivers. To ensure practical relevance, the roadmap was structured across three levels of digital maturity (low, medium, and high) based on existing frameworks and the progressive nature of digital transformation. Finally, these actions were aligned with the DMAIC cycle, embedding the roadmap within a structured LSS logic that guides implementation from problem statement definition to sustained control. This approach ensures that the roadmap is adaptable to different organizational contexts and stages of readiness, while maintaining methodological coherence.

4. Results

4.1. LSS4.0 outcomes

All 52 documents identified in the scoping review underwent thorough examination, during which the factors facilitating and hindering the adoption of I4.0 technologies were meticulously analyzed. These findings, along with an enumeration of the primary drivers and barriers, were chosen for deliberation by the focus group. These selected elements were subjected to rigorous discussion, particularly regarding the integration of LSS methodologies and the imperatives surrounding the incorporation of I4.0 technological apparatus within industrial management paradigms, answering RQ1. The Focus Group experts conveyed their perspectives concerning the impediments encountered in organizational management, including managerial disengagement from processes (Shokri et al. 2022), resistance towards cultural transformations (Skalli et al. 2023), diminished competitive edge (Sodhi 2020), inefficiencies in waste reduction (Farrukh, Mathrani, and Sajjad 2022), absence of standardized processes (Singh and Bhanot 2020), imperative for supply chain automation (Zekhnini et al. 2020), energy inefficiencies (Kamble et al. 2019), dearth of dependable data (Sahoo et al. 2023), inadequate data for informed decision-making (Komkowski et al. 2023), all of which are intricately linked to the sustainability and profitability dynamics of enterprises (Dieste, Sauer, and Orzes 2022).

Among the primary hurdles identified by the Focus Group experts in integrating LSS methodologies alongside the adoption of I4.0 technologies lies the formidable challenge of resistance to change (Bag et al. 2021; Moktadir et al. 2020). This resistance stems from entrenched employee paradigms that significantly influence project trajectories. However, addressing this obstacle entails leveraging various catalysts such as training and skill enhancement initiatives (Swarnakar et al. 2023), unwavering commitment from senior management (Gholami et al. 2021), heightened emphasis on customer satisfaction (Sony and Naik 2020; Sordan et al. 2022), fostering organizational flexibility and agility (Bhat, Bhat, and Gijo 2021), and bolstering competitiveness (Amorim Santos and Martins 2020), among other factors. These drivers mitigate or potentially eradicate the barriers mentioned above, frequently impeding the realization of anticipated enhancements (Patel et al. 2022). It is consensually agreed among experts that most impediments can be surmounted through strategic investments (Zuberi et al. 2020).

Despite the substantial investment requirements, the Focus Group underscored the paramount significance of promptly embracing I4.0 technologies, particularly in data collection, storage, quantity, and analysis domains. Such integration enhances organizational adaptability and responsiveness to evolving market demands, facilitating the adoption of decentralized architectures with robust interoperability, digitalization of supply chains, bolstering competitiveness, and fortifying LSS methodologies when amalgamated with these technologies. According to literature, I4.0 technologies exhibiting remarkable synergy with LSS methodologies encompass (i) the Internet of Things (IoT) for real-time data exchange within machinery and industrial production processes, (ii) Edge Computing to expedite data storage and processing, (iii) Cloud Computing for secure data storage and retrieval across machinery and equipment; (iv) Big-Data Analytics (BDA) for comprehensive data processing and analysis; (v) Web technologies serving as digital interfaces bridging users and process data; (vi) Cybersecurity measures ensuring network information security; and (vii) Interoperability mechanisms facilitating seamless communication across networked devices through neutral protocols, structures, and formats.

4.2. Relevant barriers to implementing LSS4.0 in organizations

After completing the two rounds of questionnaires, convergence of responses was observed, indicating a satisfactory level of agreement among the participating experts. This convergence suggests that the iterative feedback process inherent to the FD method was effective in refining and aligning the participants' evaluations. To assess the internal consistency of the final set of responses, Cronbach's alpha coefficient was calculated. The result obtained was $\alpha = 0.870$, which exceeds the commonly accepted threshold of 0.85, thereby indicating a high level of internal consistency and reliability among the evaluated items (Goetz et al. 2008). The

FD method was employed by Equation (1) to ascertain the most relevant barriers. Responses from experts are delineated in Appendix B, utilizing linguistic scales NR, LR, MR, HR, and ER ('no relevance', 'low relevance', 'moderate relevance', 'high relevance', and 'extreme relevance') (Fontoura et al. 2023), as elucidated in Table 4. Parameters α and ? were set at 0.5 and 1, respectively. The calculated threshold (δ) value stood at 0.828, with barriers exhibiting convex combinations (D_b) below δ being discarded, as depicted in Table 6.

Lack of commitment from senior management (B1); Insufficient qualification and technical knowledge (B2); Lack of strategic alignment in selecting LSS (B3); Lack of operational and managerial information (B4); Lack of standardization of process and data information (B5); Quality of suppliers (B6); Resistance to change (B7); Poor Information Technology (IT) infrastructure (B8); Cyber security risk and data privacy issue (B9); Capital investment (B10); Lack of adequate recognition and rewards for the LSS team (B11); Government rules and regulations (B12).

The analysis revealed that out of the twelve barriers reviewed, only four were deemed non-relevant and were rejected: Quality of suppliers, Poor Information Technology (IT) infrastructure, Cybersecurity risk and data privacy issues, and Government rules and regulations. The foremost barrier identified about organizational criteria was resistance to change, while for management and strategic criteria, lack of senior management commitment emerged as the most significant. Insufficient qualifications and technical acumen were highlighted as paramount in the sociocultural domain. Interestingly, no barriers were deemed relevant under the general criterion, suggesting that extraneous factors do not impede LSS4.0 implementation within organizations.

4.3. Interrelations between drivers and barriers

As delineated in Table 5, a novel investigation addressed RQ2. This investigation aimed to discern the strongest interrelationships between drivers and barriers through the FDEM technique, assessing the influence of drivers upon barriers, thereby mitigating or obviating the impact of barriers on the implementation of continuous improvement in the production processes. The initial phase involved the construction of the initial direct relations matrices, utilizing insights garnered from expert assessments. The responses provided by participants were employed to construct individual initial direct relation matrices (I) (Garcia-Buendia et al. 2024). As illustrated in Table 5, experts were tasked with ranking the influence of drivers and barriers utilizing the linguistic scale. The Fuzzy linguistic variable design methodology enables the transformation of the initial relational matrices into TFN by applying the data presented in Table 5. Each linguistic variable is systematically replaced with its corresponding numerical value (see Appendix C). Subsequently, the defuzzification process is performed using Equations (2) and (4). The resultant crisp values are then applied to Equation (5) to derive the direct relation matrices D. Equation (6) calculates the mean values of the matrices D. The generalized direct relation matrix G, representing the drivers and barriers identified in LSS4.0 implementations, is constructed using Equation (8). The total direct relation matrix T, which encapsulates the interrelationships between drivers and barriers, is computed through Equations (8) and (9). The resulting matrix, summarized in Table 7, comprehensively represents the interconnections between drivers and barriers within the context of LSS4.0 implementations.

4.4. Research agenda

As illustrated in Figure 2, a comprehensive research agenda was developed by synthesizing qualitative insights from the Focus Group with the quantitative results derived from the FD and FDEM methods. From an initial list of 29 barriers and 30 drivers identified through a scoping literature review, the Focus Group discussions enabled a refinement to 12 critical barriers and 7 key drivers considered most relevant to LSS4.0 implementation within the context of energy-efficient industrial operations. To ensure analytical rigour, the research agenda was grounded in the strongest causal relationships identified in the FDEM results, specifically those whose convex combination values exceeded the 80th percentile threshold (0.1444). These pronounced interrelations guided the formulation of empirical priorities by revealing the most influential connections between drivers and barriers. The analysis showed, for instance, that training and technical qualification influenced at least five critical barriers, including resistance to change, lack of standardization, and insufficient

Table 6. Selection of the most relevant barriers.

Author	Barriers	u	l	Db	Decision
(Ben Ruben, Vinodh, and Asokan 2017)	Lack of commitment from senior management	0.912	−0.412	0.912	Accepted
(Dieste, Sauer, and Orzes 2022)	Insufficient qualifications and technical knowledge	0.889	−0.014	0.889	Accepted
(Gholami et al. 2021)	Lack of strategic alignment in selecting LSS projects	0.862	−0.362	0.862	Accepted
(Komkowski et al. 2023)	Lack of operational and managerial information	0.864	−0.364	0.864	Accepted
(Tripathi et al. 2021b)	Lack of standardization of the process and data information	0.895	−0.395	0.895	Accepted
(Kumar et al. 2023)	Quality of suppliers	0.823	−0.323	0.823	Rejected
(Skalli et al. 2023)	Resistance to change	0.928	0.322	0.928	Accepted
(Yadav et al. 2021)	Poor Information Technology (IT) infrastructure	0.823	−0.323	0.823	Rejected
(Kumar et al. 2023)	Cybersecurity risk and data privacy issue	0.717	−0.342	0.717	Rejected
(Caiado et al. 2025)	Capital investment	0.862	−0.362	0.862	Accepted
(Sahoo et al. 2023)	Lack of adequate recognition and rewards for the LSS team	0.858	−0.358	0.858	Accepted
(Dieste, Sauer, and Orzes 2022)	Government rules and regulations	0.500	0.000	0.500	Rejected
	Threshold = 0.828				

Table 7. Interrelationship between drivers and barriers.

Barriers/drivers	D1	D2	D3	D4	D5	D6	D7
B1	0.1233	0.0696	0.1317	0.1202	0.1352	0.135	0.1483
B2	0.1473	0.1062	0.1227	0.1185	0.1185	0.1619	0.1323
B3	0.1287	0.1184	0.1266	0.1053	0.1079	0.1444	0.1316
B4	0.1251	0.1404	0.1138	0.1413	0.1053	0.117	0.1084
B5	0.1384	0.1472	0.123	0.1608	0.1332	0.1477	0.1123
B7	0.1488	0.1244	0.137	0.1457	0.1355	0.1511	0.1255
B10	0.1503	0.1274	0.1424	0.1427	0.1638	0.1364	0.137
B11	0.1413	0.1303	0.114	0.141	0.1312	0.1259	0.1253
Moderate influence (60 percentile)							
Strong influence (80 percentile)							

Flexible and agile companies (D1); Digitized supply chain (D2); Decentralized architectures and interoperability (D3); I4.0 Technologies (D4); Reduction of production costs (D5); Training and technical qualification (D6); Customer, supplier and company satisfaction (D7).

technical knowledge. This finding highlights the need for future research to explore integrative training strategies that address both technical upskilling and behavioural adaptation under digital transformation.

Another crucial insight from the agenda is the centrality of reducing production costs in overcoming the barrier of capital investment constraints. This suggests that further studies should focus on how LSS4.0 adoption can be economically justified by linking technological investment to performance indicators such as energy cost per unit and return on sustainability-related assets. Moreover, the driver related to organizational agility emerged as a fundamental factor in reducing inertia and fostering adaptability, particularly in digitally evolving environments. Research is needed to better understand how structural and cultural agility influence the success of LSS4.0 deployment and whether they act as moderating variables across different organizational sizes or maturity stages.

The digitization of processes and data flows also proved to be a high-leverage driver, especially in tackling the barrier associated with the absence of process standardization. This reinforces the demand for further investigation into digital modelling, interoperable platforms, and data management standards that facilitate LSS4.0 implementation while enhancing traceability and energy-related KPIs. Taken together, these relationships informed the formulation of eight interconnected research guidelines, which range from training design and digital maturity modelling to the integration of circular economy principles and the development of green digital frameworks.

These guidelines collectively answer RQ3 by proposing a forward-looking agenda that connects empirical evidence with conceptual gaps. The agenda builds upon the causal structure identified in this study to propose lines of enquiry that are both theoretically meaningful and practically actionable. It also anticipates new directions by recommending that LSS4.0 research be articulated with broader strategic initiatives such as green manufacturing, digital resilience, and agile energy systems. These connections reflect a convergence between the technological and environmental dimensions of modern industrial management, thus contributing to the construction of a robust theoretical and operational foundation for future studies. Ultimately, this research agenda provides the empirical and conceptual foundation for the implementation roadmap outlined in the subsequent section. While the agenda identifies the key domains and variables that require further exploration, the roadmap translates these into concrete actions aligned with the DMAIC cycle. This progression from agenda to roadmap ensures that the knowledge produced in this study is not only theoretically grounded but also operationally viable, supporting organizations seeking to integrate LSS4.0 into their digital transformation and energy-efficiency strategies.

5. Discussion

5.1. Training and technical qualification as pillars of LSS4.0 adoption

The theoretical and empirical findings from the study were utilized to examine the interplay between drivers and barriers influencing LSS, identifying critical success factors essential for the effective implementation of LSS4.0. Consequently, a research agenda was developed to address the gaps identified in the scoping review, emphasizing organizations' energy-efficiency perspectives. The driver related to training and technical qualification exhibits influences with five distinct barriers: insufficient qualification and technical knowledge, a lack of strategic alignment in selecting LSS projects, a lack of standardization of process and data information, resistance to change, and capital investment. During Focus Group deliberations, considerable emphasis was placed on the significance of training and team qualifications. It was observed that trained employees transform their analytical behaviours, enhancing the outcomes of products and services derived from their processes. This transformation necessitates access to comprehensive information to enable employees to address challenges reliably (Ben Ruben, Vinodh, and Asokan 2017; Swarnakar et al. 2023).

During discussions, prioritizing training related to I4.0 technologies was particularly concerning. This type of qualification entails a behavioural shift and cultural adaptation, requiring employees to embrace technologies as new tools for work. Adequate training on LSS and its facilitators, as highlighted by Mohan et al. (2022), Skalli et al. (2023), and Tripathi et al. (2021a), leads to a notable increase in the successful implementation of methodologies. Familiarity with available tools empowers employees to contribute actively to project improvement, enhancing their understanding of

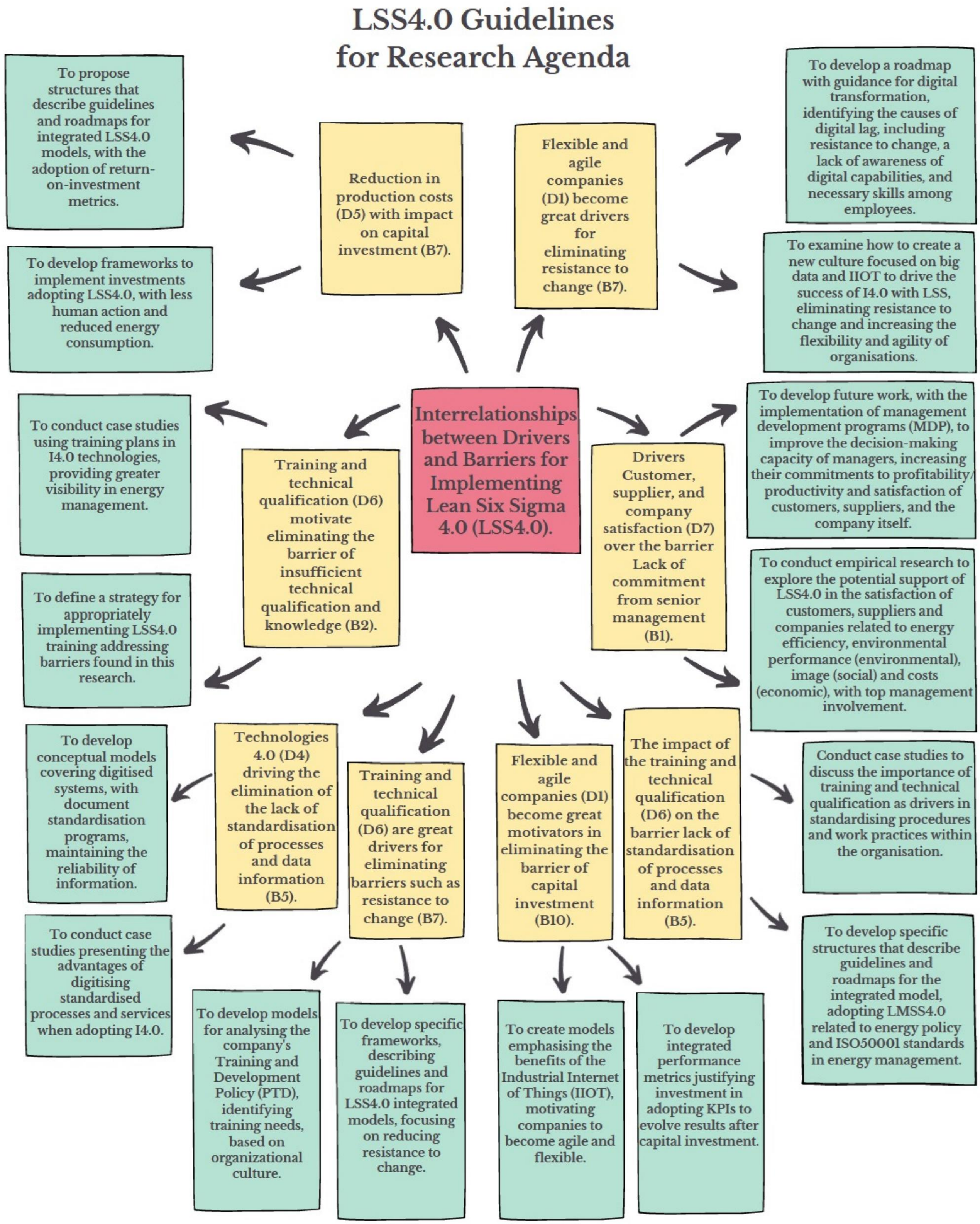

Figure 2. LSS4.0 guidelines for research agenda.

production processes. This understanding facilitates various improvements, such as cost reduction, optimization of resource consumption, elimination of non-value-added activities, and ultimately, improved project outcomes and environmental benefits (Ben Ruben, Vinodh, and Asokan 2017; May et al. 2015).

5.2. Measurement gaps and the case for standardization

However, a significant discussion gap pertains to the lack of metrics for validating proposed LSS4.0 models across case studies. This is essential for aligning with Lean project objectives and consolidating sustainable results. This gap underscores the importance of providing practical data on the training and technical qualification level, as it influences other interrelated barriers, such as reducing resistance to change among employees. Metrics and case studies enable managers to evaluate demands effectively, facilitating more informed decision-making. Additionally, the need for standardization in data and information is underscored, emphasizing the importance of precise and reliable standards to support effective decision-making processes. With the adoption of well-trained methodologies and technologies, improvements in production processes can also be observed since the tools facilitate critical analyses, focusing on reducing production costs (Jayaram 2016; Kale et al. 2022; Tay and Loh 2022), enabling the optimization of the consumption of electricity, fuel, water and other inputs, elimination of non-value-added activities, reduction of unnecessary steps, making them more effective and energy efficient, as well as better results, operational and environmental benefits (Ben Ruben, Vinodh, and Asokan 2017; May et al. 2015).

Concerning I4.0 technologies, a strong relationship was observed between these technologies and barriers related to the Lack of standardization of process and data information and employee resistance to change. The focus group emphasised the need for accurate and standardized information to avoid project uncertainties and undesirable outcomes (Dieste, Sauer, and Orzes 2022; Kamble et al. 2019). Addressing these challenges requires organizational changes and cultivating new skills and cultures, particularly transitioning to I4.0 practices (Psarommatis et al. 2023; Rahardjo et al. 2023). The delay in the industry's digital transformation towards I4.0 and integration of LSS lean production stems from the absence of clear guidance, inadequate digital awareness among stakeholders, and a lack of requisite skills, underscoring pertinent gaps for future research (Bhamu and Singh Sangwan 2014; Hermann et al. 2015).

Building on the strong emphasis placed by the focus group on the lack of standardization, this study highlights the potential for adopting hybrid standardization frameworks to support LSS4.0 implementation. Drawing from established benchmarks such as ISO 9001 (quality management) (Sá et al. 2022), ISO 50001 (energy management) (Mkhaimer et al. 2017), ISA-95 (integration of enterprise and control systems) (Guerrero et al. 2011), and IEEE P2801 (data governance in AI systems), organizations may develop integrated approaches that ensure interoperability, reliable energy metrics, and consistent process monitoring. Such frameworks enable more accurate data collection and improved comparability of Key Performance Indicators (KPIs), such as control chart stability and energy consumption per unit, particularly when deploying LSS4.0 tools across heterogeneous environments. While these references provide a foundational direction, further empirical validation in diverse organizational contexts is recommended to confirm their effectiveness and return on investment.

Additionally, there is a dearth of case studies that rigorously test and validate proposed frameworks, as well as a lack of development of integrated performance indicators to assess outcomes during and after implementation, especially in the realm of energy, environment, social, economic, and cultural domains. In the context of energy efficiency, the focus group highlighted the absence of standardized processes and data management, which hinders the complete automation and digitalization of operations (Suhail et al. 2023). This lack of standardization complicates the optimization of critical supply chain steps that could effectively monitor and control electricity and other resource consumption, thereby improving energy management within industries (Rahardjo et al. 2023).

5.3. Sectoral readiness and tailored training strategies

Recognizing the diversity in learning curves and cultural readiness across industry sectors, the proposed Research Agenda advocates for adaptable training strategies tailored to different levels of digital maturity. Instead of assuming a uniform approach, it emphasises the importance of a tiered continuum of training formats. This includes foundational workshops for low-maturity environments, such as traditional utilities, as well as blended AR and VR simulations for intermediate-level manufacturing firms, and advanced prescriptive analytics laboratories for digitally mature service organizations. Aligning training design with each sector's specific readiness helps mitigate cultural resistance, accelerate capability development, and support the effective integration of energy-conscious LSS4.0 practices. These adaptive strategies also contribute to a more seamless transition towards future LSS5.0 innovations.

In addition to the I4.0 tools discussed, emerging technologies are increasingly relevant to the transition towards LSS5.0. Artificial intelligence (AI) enables predictive analytics for energy consumption, anomaly detection in production processes, and optimization of multi-variable systems, thereby supporting more proactive continuous improvement initiatives. Collaborative robots (cobots) are being piloted in several manufacturing sectors to enhance flexibility and human-machine integration, particularly in energy-intensive tasks such as assembly and material handling, where they contribute to reduced waste and energy savings. Recent pilot implementations in manufacturing and logistics contexts demonstrate that AI and cobots not only enhance process efficiency but also promote human-centric and sustainable production systems, which are at the core of the LSS5.0 paradigm.

Discussions on flexible and agile companies revealed barriers such as insufficient qualifications and technical knowledge, resistance to change, and capital investment. The conclusion was that fostering adaptability and resilience among employees is paramount for organizational flexibility and agility. Employees must embrace cultural changes and new methodologies to meet evolving market demands (Kumar et al. 2023; Skalli et al. 2023; Yadav et al. 2021). The analysis revealed that flexible and agile companies serve as significant drivers in overcoming resistance to change, thereby facilitating the adoption of I4.0 technologies during digital transitions (Lal Bhaskar 2020; Shokri et al. 2022). Moreover, the flexible and agile production driver underscores the need for capital investment in digitalization and training to enhance responsiveness to customer needs and market variability. This investment enables reconfigurable production systems operated by skilled employees (Sodhi 2020). Notably, agile production facilitates swift responses to new product development, enables dynamic capacity allocation, and provides competitive advantages through mass customization (Bhat, Bhat, and Gijo 2021; Sony and Naik 2020).

Furthermore, agile companies prioritize environmental management, ecological product design, and resource conservation, all of which contribute to energy efficiency (Mishra 2022; Skalli et al. 2023). However, there is a notable scarcity of studies investigating the impact of LSS on I4.0, as well as the development of integrated KPIs for assessing employee performance in adopting new tools (Tripathi et al. 2021a). Key drivers for agile companies encompass supplier certification for environmental management systems, collaborative environmental initiatives with customers and suppliers, ecological product design, reduction of energy consumption, reuse and recycling of materials and packaging, implementation of reverse logistics, effective waste treatment, comprehensive evaluation of product and system designs, and adherence to corporate social responsibility principles (Mishra 2022; Skalli et al. 2023). These factors play a significant role in enhancing energy efficiency.

5.4. Managerial insights

This research provides strategic insights for managers, policymakers, and stakeholders aiming to integrate LSS4.0 into their organizational practices, particularly in contexts that demand enhanced energy efficiency and digital maturity. Rather than presenting a prescriptive implementation plan, this study proposes a structured research agenda based on the analysis of interrelationships between key drivers and barriers. A central insight from this analysis is the role of organizational agility in overcoming critical obstacles such as capital investment constraints and resistance to change. The findings suggest that companies demonstrating flexibility and adaptability are better positioned to adopt I4.0 technologies and achieve improvements in energy performance. This highlights the importance of investing not only in technological infrastructure but also in cultivating resilient teams and adaptive cultures.

Another managerial implication lies in the emphasis on training and technical qualification as strategic enablers of transformation (Maisiri and Van Dyk 2021). The research agenda recommends investing in customized learning strategies that integrate LSS principles with immersive I4.0 tools such as augmented reality and simulation-based environments to help teams navigate technological transitions, reduce resistance, and strengthen analytical capabilities. Additionally, the agenda highlights the importance of developing integrated performance metrics (KPIs) that can simultaneously capture operational efficiency, energy consumption, quality, and environmental impacts (Pérez-Fortes et al. 2016). Although still underexplored in empirical studies, such metrics are essential for aligning continuous improvement with sustainability outcomes. Future research should pursue the development of these indicators, ideally informed by frameworks such as ISO 50001 and IEEE P2801 (Mkhaimer et al. 2017), which offer internationally recognized standards for assessing energy and digital maturity.

Notably, the research agenda also suggests that future efforts should focus on developing roadmaps to guide digital transformation, particularly by identifying barriers such as low digital awareness, limited technical skills, and cultural resistance to change. The agenda outlines the need for structured guidance that can support organizations through the complex processes of LSS4.0 adoption and sustainable innovation. While the research agenda outlines strategic directions applicable across organizational contexts, it is essential to acknowledge the disparity in resources between large corporations and small to medium-sized enterprises (SMEs). Flexible and agile organizations are presented as key enablers of LSS4.0 adoption (Saleeshya and Binu 2019). However, SMEs may face structural limitations such as limited access to capital, digital infrastructure, or skilled personnel, which constrain their capacity to engage in large-scale transformation initiatives (Matarazzo et al. 2021).

To address these constraints, SMEs may benefit from modular and resource-sensitive approaches. For instance, phased rollouts that begin with low-cost, IoT-enabled monitoring of energy use can provide quick wins without requiring significant capital investment. In contrast, later phases may incorporate cloud analytics or digital twins as digital maturity increases. Simplified KPI dashboards, focused on essential indicators such as energy consumption per unit and resource efficiency score, can reduce complexity and training demands. Public-private partnerships, including government innovation vouchers and industry-university pilot programmes, may also help SMEs overcome financial and technical barriers. These strategies can enable SMEs to gradually adopt LSS4.0 practices in line with their resources, while still contributing to energy efficiency and sustainability goals.

Beyond identifying barriers, effective change management strategies are crucial for the successful adoption of LSS 4.0. Organizations should anticipate resistance to digital tools and KPI-driven accountability and address it proactively through transparent communication of goals, strong leadership commitment, and the establishment of pilot projects that demonstrate early wins. Tailored training programmes at different organizational levels, combined with incentive systems that reward energy-efficient behaviours, can foster engagement and build trust. Embedding these practices within organizational routines helps shift culture towards continuous improvement, ensuring that LSS4.0 implementation is not perceived as a disruptive imposition but as a collective pathway to sustainable operational excellence.

Established change management frameworks can further support these strategies. For instance, Kotter's 8-Step Model provides a structured sequence (Schmutz 2022), from establishing urgency and building a guiding coalition to anchoring change in organizational culture, which can guide practitioners through digital transformation journeys. Similarly, the ADKAR model (Awareness, Desire, Knowledge, Ability, Reinforcement) provides a practical tool for managing individual-level transitions (Da Veiga 2018), ensuring that workforce alignment accompanies technological adoption. Embedding such frameworks into LSS4.0 implementation enhances managerial capacity to mitigate resistance, foster cultural resilience, and sustain improvements over time.

Future research should therefore explore how the research agenda's recommendations can be adapted or phased to suit the specific realities of SMEs, possibly through modular implementations, public-private partnerships, or sector-specific support frameworks. Addressing this gap is essential to ensuring that LSS4.0 strategies promote inclusive and scalable improvements across diverse organizational settings. In summary, while the research agenda primarily addresses academic gaps, it also offers valuable direction for managerial reflection. By focusing on agility, workforce readiness, roadmap-based planning, and robust evaluation frameworks, organizations can better prepare for the complex yet necessary transition to LSS4.0, underpinned by sustainable and energy-conscious practices.

5.5. Bridging theory and practice

To transition from conceptual models to impactful industry applications, it is recommended to launch cross-functional pilot projects under a structured change management framework (Sánchez-Rodríguez and Spraakman 2012). These pilots should bring together operations, IT, and sustainability teams to co-design data pipelines and training curricula. Performance milestone reviews and ROI (Return on Investment) demonstrations at each stage help secure leadership buy-in and maintain momentum. Establishing communities of practice further supports ongoing refinement and improvement. For example, manufacturing stakeholders can share lessons on integrating predictive analytics into process mapping, while service providers compare approaches to measuring energy consumption per transaction. Such forums foster peer learning, enabling the framework to evolve in response to real-world challenges.

In parallel, embedding action-research cycles that combine quantitative KPI tracking with qualitative interviews ensures that each pilot both validates the framework's generalizability and uncovers context-specific adjustments (Morandi et al. 2014). This evidence-based approach bridges the gap between academic theory and operational reality, accelerating adoption and continuous improvement. Following the conceptual framework, Table 8 presents the full definitions, formulas, and data sources for our integrated KPIs, enabling balanced performance management across Lean, Six Sigma, and energy targets.

The KPIs listed in Table 8 were selected not only for their alignment with LSS and I4.0 objectives but also because they reflect widely recognized benchmarks in industrial and sustainability assessment. Cycle time reduction and defect-per-million opportunities (DPMO) are standard LSS indicators for operational performance and quality control. Energy consumption per unit and energy cost per unit are consistent with energy management practices established under ISO 50001 and widely applied in industrial energy audits. Carbon footprint reduction and the carbon intensity index follow international sustainability reporting frameworks, including the Greenhouse Gas Protocol and the UN Sustainable Development Goals. Water usage per unit and waste diversion rate are recognized indicators in environmental management and circular economy practices. The green material ratio supports evaluation of renewable and recyclable inputs in supply chains, while the resource efficiency score integrates multiple resource dimensions in line with eco-efficiency approaches. By explicitly linking each KPI to established industrial and sustainability benchmarks, the proposed framework reinforces both its theoretical validity and its practical applicability.

Despite the robustness of the selected KPIs, collecting accurate and reliable data across heterogeneous industrial environments presents several challenges. Variations in data quality between legacy systems and modern ERP/EMS platforms can create inconsistencies, while incomplete metering of resources such as energy and water may hinder precise

Table 8. Detailed KPI definitions.

KPI	Definition	Formula	Data Source
Cycle Time Reduction	Percentage decrease in average process cycle time	(Baseline CT – Current CT) / Baseline CT * 100%	ERP / MES system
Defect-per-Million Opportunities (DPMO)	Number of defects per one million opportunities	(Defects / Opportunities) * 1,000,000	Quality inspection reports
Energy Consumption per Unit	Kilowatt-hours consumed per unit produced	Total kWh / Total units	Energy management system, production logs
Carbon Footprint Reduction	Percentage reduction in CO_2 emissions per unit	(Baseline CO_2 – Current CO_2) / Baseline CO_2 * 100%	Emissions monitoring system
Water Usage per Unit	Litres of water used per unit	Total litres / Total units	Utility metering, production data
Waste Diversion Rate	Percentage of waste diverted from landfill	(Waste diverted / Total waste) * 100%	Waste management records
Energy Cost per Unit	Cost of energy consumed per unit	Total energy cost / Total units	Financial system, energy invoices
Green Material Ratio	Proportion of sustainable and renewable materials used	(Green material weight / Total material weight) * 100%	Procurement database; BOM records
Carbon Intensity Index	CO_2 emissions per monetary value of output	Total CO_2 emissions / Revenue	Emissions monitoring, financial records
Resource Efficiency Score	Composite index of resource utilization (energy, water, materials)	Weighted sum of normalized resource metrics	Combined ERP, EMS, and utility data

measurement. Organizational resistance to disclosing sensitive cost or emissions information also limits transparency. To mitigate these issues, companies may adopt harmonized data standards (e.g. ISO 50001 reporting protocols), employ sensor-based monitoring to reduce manual data entry errors, and use cross-validation from multiple data sources (e.g. utility metres, production logs, and financial systems). Additionally, phased data integration strategies and staff training programmes can improve data reliability and reduce measurement bias, enhancing the robustness of KPI-based decision-making.

5.6. Towards a practical roadmap for LSS4.0 implementation

The empirical results of this study, based on FD and FDEM, revealed interdependencies among critical drivers and barriers to the adoption of LSS4.0. These interrelations were used not only to construct a research agenda but also to inform the proposal of a practical roadmap to guide real-world implementation. Unlike prescriptive maturity models, this roadmap aims to integrate the most influential variables into a structured, adaptive approach that supports the progressive deployment of LSS4.0 principles across various organizational contexts. The phase-to-phase design of the roadmap is directly informed by the causal structure revealed through the FDEM analysis. In the Define phase, the prioritization of project lead time is justified by the strong influence of capital investment over the need for production cost reduction. This relationship highlights the importance of basing early-stage decisions on return-on-investment and time-to-value considerations. In the Measure phase, the inclusion of standardized energy metrics, such as energy consumption per unit, responds to the influence of the lack of standardization in process and data information, aiming to achieve a digitized supply chain. This highlights the need for consistent and structured data collection practices to enable digital integration and traceability. The Analyse and Improve phases reflect the interplay between resistance to change and the need for training and technical qualification. The roadmap addresses this causal relationship by embedding technical training efforts and pilot experimentation, thereby reducing behavioural resistance and fostering readiness for technological adoption. In the Control phase, the emphasis on energy KPI dashboards is supported by the observed impact of inadequate recognition and rewards for the LSS team on customer, supplier, and company satisfaction. The implementation of monitoring and visibility tools at this stage aims to support accountability, promote team engagement and ensure the continuity of sustainable performance improvements. These empirically derived interrelations reinforce the alignment between the roadmap's structure and the dynamics uncovered through the FDEM analysis. Table 9 presents a structured view of this integration, mapping each DMAIC phase to its respective activities, operational KPIs, and sustainability metrics. This serves as a visual synthesis of the implementation logic outlined above.

To operationalize this framework, the roadmap includes three integrated stages. First, a readiness assessment phase should be conducted using standards such as ISO 50001 and IEEE P2801 to evaluate energy and digital maturity, while also mapping organizational culture, skills, and available infrastructure. This diagnostic step enables a tailored deployment strategy that accounts for the organization's specific baseline. Second, the implementation of modular training programmes is recommended. These may range from introductory workshops to immersive simulations, depending on organizational maturity, to reduce resistance to change and foster capabilities in LSS4.0 tools. Finally, the roadmap includes the deployment of a dashboard that integrates Lean, Six Sigma and energy-efficiency KPIs, enabling real-time tracking, cross-functional coordination, and continuous improvement cycles. This stage provides the necessary visibility for decision-makers and supports ongoing performance validation. Figure 3 illustrates the roadmap that integrates DMAIC phases and FDEM results.

In Figure 3, the DMAIC-aligned roadmap has been augmented with visual cues to illustrate how energy KPIs and digital maturity levels interact dynamically across the implementation phases. For example, in the Define and Measure stages, KPIs such as energy consumption per unit and energy cost per unit are established as baselines. At the same time, digital maturity is still low, often limited to basic data collection. As the roadmap progresses through Analyse and Improve, the integration of advanced Industry 4.0 tools (e.g. IoT sensors, cloud analytics) enables higher digital maturity and supports real-time KPI tracking and optimization. In the Control phase, both energy KPIs and digital maturity are monitored continuously through dashboards, reinforcing a cycle of ongoing improvement.

Beyond these technical aspects, the roadmap incorporates feedback loops from operational data. Continuous

Table 9. Structured conceptual framework for LSS4.0.

DMAIC Phase	Key Activities	Operational Metrics	Sustainability Metrics	Key Barrier Addressed
Define	Project charter, stakeholder alignment	Project lead time	Baseline kWh per unit	Capital investment
Measure	Data collection, process mapping	Cycle time, defect rate	Energy consumption per unit	Lack of standardization of the process and data information
Analyse	Root-cause analysis	DPMO, process capability	Carbon footprint per batch	Resistance to change
Improve	Solution design, pilot tests	Yield improvement	Percentage of energy saved post-change	Resistance to change
Control	Standardization, control plans	Control chart stability	Energy KPI dashboard monitoring	Lack of adequate recognition and rewards for the LSS team

DMAIC Phase	Barrier → Driver	Expected KPI Outcomes	Key Actions		Horizon
Define	**Capital investment → Reduction of production costs** This justifies the need to align investment with time-to-value analysis	- Structured project baseline - Initial energy maturity benchmark	Conduct readiness assessments using ISO 50001 and IEEE P2801; align stakeholders and define project lead time	Apply ISO 50001 / IEEE P2801 checklist	Short-term
				Align internal stakeholders and departments	Medium-term
				Define scope, timeline, and implementation plan	Long-term
Measure	**Lack of standardisation of process and data information → Digitised supply chain** This supports structured energy data collection and metric reliability.	- Comparable, traceable energy and process metrics	Diagnose digital infrastructure, establish data standardisation protocols, and select KPIs such as energy consumption per unit	Map existing data sources and formats	Short-term
				Establish standardisation rules and architecture	Medium-term
				Define energy KPIs and implement baseline metrics	Long-term
Analyse	**Resistance to change → Training and technical qualification** This emphasises the need for workforce development during diagnostics	- Validated improvement opportunities - Cause-effect mapping	Perform root cause analysis based on DPMO, capability indices, and carbon footprint metrics	Train team in diagnostics and root cause analysis	Short-term
				Collect and analyse DPMO and energy metrics	Medium-term
				Map causes using process flow and capability charts	Long-term
Improve	**Resistance to change → Training and technical qualification** Skills development directly enables behavioural and process improvements	- Increased yield - Percentage energy saved post-change	Deploy technical training, conduct pilot tests, implement yield-enhancing and energy-saving solutions	Deliver focused technical workshops	Short-term
				Execute pilot projects for key process changes	Medium-term
				Monitor outcomes and prepare for full-scale deployment	Long-term
Control	**Lack of adequate recognition and rewards for the LSS team → Customer, supplier and company satisfaction** This validates the role of real-time dashboards in ensuring impact	- Sustained performance - Ongoing visibility and accountability	Implement cross-functional KPI dashboards integrating Lean, Six Sigma, and energy indicators; formalise control plans and continuous review loops	Design and implement real-time KPI dashboard	Short-term
				Integrate dashboard with LSS and energy indicators	Medium-term
				Establish review loops and incentive mechanisms	Long-term

Figure 3. Time-based LSS 4.0 roadmap integrating DMAIC phases and FDEM results.

monitoring of energy KPIs ensures not only performance control but also provides input for iterative DMAIC cycles, allowing organizations to recalibrate objectives, strategies, and digital maturity pathways dynamically. This cyclical mechanism reinforces the adaptability of LSS4.0 and embeds continuous improvement into daily operations. Moreover, the success of LSS4.0 adoption depends on effective change management and cultural alignment. Resistance to digitalization and KPI-based accountability can be mitigated through transparent communication of objectives, visible leadership commitment, and the use of pilot projects that demonstrate quick wins. Tailored training programmes across organizational levels and incentive systems that reward energy-efficient practices can further strengthen workforce engagement. These strategies ensure that LSS4.0 is perceived not merely as a technological transition but as a collective journey towards sustainable operational excellence.

The roadmap structure is designed to be scalable and customisable, ensuring applicability across both manufacturing and service sectors. In highly automated contexts, integrating with existing digital systems, such as Manufacturing Execution Systems (MES) and Enterprise Resource Planning (ERP), can support KPI measurement. In contrast, service-oriented environments may require more qualitative methods and longitudinal tracking. In both cases, the roadmap promotes the use of mixed methods, combining quantitative performance tracking with stakeholder feedback to inform adjustments to implementation paths. This flexible approach supports the translation of research findings into sector-specific innovations while preserving alignment with the LSS4.0 principles.

6. Conclusions

Therefore, integrating various research methodologies, including Scoping Reviews, Focus Group discussions, FDEM, and research agendas, significantly enriched our understanding of implementing LSS4.0 in companies to improve energy efficiency. However, despite the increasing interest in this domain, a significant lack of empirical studies remains to examine the integration of LSS with I4.0 technologies. This gap is particularly evident regarding critical success factors, including drivers, barriers, and their interrelationships, with a specific focus on enhancing energy efficiency within organizations. This study addressed the three proposed research questions in a structured and evidence-based manner. RQ1, which explored the impacts of LSS4.0 on production performance and energy efficiency, was answered through an extensive literature review and empirical analysis, demonstrating that the integration of LSS methodologies with I4.0 technologies such as IoT, Big Data, and cloud computing results in significant process improvements, waste reduction, and more efficient energy use. RQ2 was addressed through the application of FD and FDEM methods, which identified the most critical barriers to LSS4.0 adoption and mapped the causal interrelationships between key drivers and barriers. Notably, the drivers Training and technical qualification, Flexible and agile companies, and I4.0 Technologies exerted strong influence over barriers such as insufficient knowledge, lack of standardization, resistance to change, and capital investment. Finally, RQ3 was answered by developing a comprehensive and practice-oriented research agenda based on the observed interdependencies, outlining strategic directions for advancing both the theoretical foundations and practical implementation of LSS4.0 with a focus on energy performance. This includes the creation of standardized performance indicators, tailored roadmaps according to digital maturity levels, and sector-specific recommendations to support the scalable and effective adoption of LSS4.0 across diverse industrial settings.

6.1. Theoretical and practical implications

From a theoretical perspective, this study fills a key gap in the literature by consolidating an initial set of 29 barriers and 30 drivers into a refined subset of eight barriers and seven drivers, using a Focus Group followed by the FD method. By subsequently mapping the interdependencies among these factors through FDEM analysis, the research offers a structured understanding of the causal dynamics that shape LSS4.0 adoption. This contributes to theory by moving beyond fragmented factor lists and advancing a prioritized and relational model of barriers and enablers. The analysis identified the most influential causal relationships between drivers and barriers, enabling a prioritized and evidence-based roadmap for LSS4.0 adoption. The proposed conceptual framework incorporates four key sustainability performance indicators: cycle time reduction, energy consumption per unit, carbon footprint reduction, and resource efficiency score. These indicators are integrated within each DMAIC phase, offering a coherent model that directly links process improvement to energy performance. This work advances theoretical understanding by moving beyond isolated case studies towards a scalable, metrics-based approach, establishing a foundation for future developments in LSS 5.0, including AI-powered forecasting and digital twin simulations.

From a practical perspective, this study offers a structured approach for organizations seeking to implement LSS4.0 with an energy performance focus. By identifying the most critical drivers and barriers through expert consensus and mapping their causal relationships, the research provides managers with clear priorities for action, such as investing in technical training, fostering organizational agility, and promoting the integration of I4.0 technologies. The proposed framework also offers a ready-to-use KPI structure embedded within the DMAIC cycle, enabling practitioners to track sustainability outcomes alongside process improvements. Furthermore, the roadmap developed in this study supports decision-makers in planning LSS4.0 deployment according to their digital maturity level, ensuring more effective resource allocation and higher chances of success. These insights are particularly relevant for industries aiming to align operational excellence with energy-efficiency goals and broader sustainability targets.

6.2. Limitations and future works

While our mixed-methods approach, based on expert panels from Brazil and Argentina, provides robust initial insights, the findings are inevitably influenced by the specific regulatory frameworks, industrial maturity levels, and cultural characteristics of Latin America. These contextual features may not fully align with those in other regions, such as Europe, North America, or Asia, where differences in energy pricing structures, compliance requirements, and organizational practices can shape both the prioritization of drivers and the applicability of KPIs. Accordingly, while the transferability of our results requires careful consideration, the framework offers a robust foundation that can be further refined through multi-regional case studies. Future research should therefore aim to validate and adapt the proposed roadmap across diverse economic and cultural settings, thereby enhancing its broader applicability.

Additionally, the review was limited to English-language literature, which may have excluded relevant contributions published in languages other than English. Another important limitation lies in the absence of longitudinal tracking of key performance indicators, which restricts the ability to evaluate the sustained impact of LSS4.0 implementation over time. To address this limitation, future research should include longitudinal studies and pilot implementations that test the durability and impact of the proposed LSS4.0 roadmap and KPIs over time. Longitudinal analysis would enable the assessment of whether improvements in energy efficiency and digital maturity are sustained beyond initial adoption. At the same time, pilot projects across different sectors could validate adaptability and scalability. These efforts would provide robust empirical evidence, strengthening the roadmap's applicability in diverse industrial contexts.

Beyond regional generalization, methodological adjustments may also be required to adapt the proposed roadmap and KPI framework to diverse industrial sectors and contexts. For energy-intensive industries such as steel, cement, or chemicals, benchmarking against sector-specific standards (e.g. IEA energy intensity targets, ISO 50001 implementation guides, or Global Cement Sustainability Initiative metrics) would provide stronger comparability. In contrast, for SMEs and low-capital sectors, simplified KPI dashboards and modular roadmaps may be necessary to reflect resource constraints and limited digital maturity. At the regional level, calibration of KPIs should consider differences in energy pricing, regulatory compliance schemes, and cultural readiness for digitalization. Such methodological adaptations would strengthen the applicability of LSS4.0 initiatives and enhance the global transferability of the proposed framework.

Building on the current findings, future research should explore how emerging Industry 5.0 technologies can expand the potential of LSS4.0 initiatives. The integration of Gen-AI into the roadmap may enable prescriptive analytics that can recommend optimal process settings in real-time, thereby reducing energy waste and improving productivity. In the Measure phase, AI models could analyze live KPI streams, such as energy cost per unit and resource efficiency score, to anticipate performance losses and suggest timely interventions. Digital twins could complement this by simulating 'what-if' scenarios, allowing teams to virtually test improvements before implementing them. Furthermore, collaborative robots that respond to KPI thresholds can autonomously adjust machine parameters or support operators in repetitive tasks, thereby enhancing process resilience and worker well-being. When integrated with real-time dashboards, these tools can move organizations closer to autonomous operations, a defining element of LSS5.0. Future studies should pilot these technologies across diverse sectors to assess their combined impact on productivity, environmental performance, and social outcomes. Integrating circular economy principles into this evolution would further reinforce the transition towards truly sustainable, energy-efficient industrial systems.

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