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CASE REPORT

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Integrating Lean Six Sigma with life cycle and value stream level of RAMI 4.0

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ABSTRACT
This study integrates the Lean Six Sigma (LSS) DMAIC (design, measure, analyze, improve, control) methodology with the Life Cycle and Value Stream Level of RAMI 4.0 by proposing a systematic structure that includes LSS 4.0 tools and techniques for each level. The fuzzy Entropy Weighting method is used to evaluate LSS 4.0 tools and techniques for each level, and a sample implementation of the proposed structure is conducted in a high-technology electronics firm. The results indicated that the proposed structure effectively integrates the LSS and DMAIC methodology with the Life Cycle and Value Stream Level of RAMI 4.0. The results suggest that although the DMAIC methodology is applicable for each life cycle stage, the most important approaches vary for each life cycle level. Therefore, DMAIC implementation for each level should be conducted separately for each life cycle and LSS 4.0 tools and techniques should be chosen according to the specific needs. This article proposes a novel systematic structure that includes LSS 4.0 tools and techniques for each DMAIC stage and that can be used for LSS implementation in RAMI 4.0. The proposed structure will contribute to systemizing the complex structure of Industry 4.0 in the implementation phase of smart factories.

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Introduction

In today's dynamic business environment, organizations face significant challenges, such as the need for new technology integration, management of large data sets, new skills, potential supply chain disruptions, and the need to adopt a new market environment. Therefore, they continuously update their processes based on these new requirements. In this manner, manufacturing organizations are critical in building the economy by supplying goods and services. Their main aim is to maximize their profit while satisfying customer demands (Swarnakar, Tiwari, and Singh 2020). The adoption of Industry 4.0, also known as the Fourth Industrial Revolution, is one of these challenges affecting the manufacturing sector as it requires a transition toward digital and smart factories (El-Breshy et al. 2024).

A transformation to an Industry 4.0 smart factory includes digitalizing and integrating the entire value chain through the life cycle of products and processes (Ghobakhloo 2020). Therefore, systematic guidelines that cover the entire life cycle and value chain with multiple levels are required for a successful transition and implementation. With this view, reference architectures for Industry 4.0 have been proposed. In this line, one of the most well-known is the Reference Architecture Model Industry 4.0 (RAMI 4.0). RAMI 4.0 was developed as part of the "Industrie 4.0" initiative by the German Federal Ministry of Education and Research (BMBF). The objective of the "Industrie 4.0" initiative is to facilitate the digitization and networking of industrial production. In this context, RAMI 4.0 is a contextual framework that facilitates in a structured manner the implementation of Industry 4.0 concepts and technologies in manufacturing and related industries. RAMI 4.0 aims to enable companies to design, implement, and manage Industry 4.0 technologies more effectively through a standardized framework for organizing and integrating industrial systems, which leads to increased efficiency, flexibility, and innovation in manufacturing and other related industries. Thus, RAMI 4.0 has been proposed as a

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solution to effectively facilitate the adoption of Industry 4.0.

In particular, RAMI classifies and identifies the areas of Industry 4.0 by integrating three dimensions, that is, hierarchy levels, life cycle and value stream, and layers (Wang, Towara, and Anderl 2017). Vertical integration, horizontal integration, and end-to-end engineering are the baselines of RAMI 4.0, where each element is engaged at different levels (Pisching et al. 2018). The main idea behind RAMI 4.0 can be expressed as a structure for breaking down the complex interrelations of Industry 4.0 into small clusters by considering all elements and encouraging further technological developments. The success of RAMI 4.0 is based on its suitability to cover the entire value chain and handle the life cycle from development and deployment to maintenance (Corradi et al. 2019). RAMI 4.0 has a three-dimensional structure, that is, a layers axis, hierarchy levels axis, and life cycle and value stream axis (Hankel and Rexroth 2015).

However, the adoption of RAMI 4.0 is still emerging and it can pose several challenges for organizations due to its complexity, technical requirements, organizational implications, cost, and resource constraints. Nevertheless, using current operational excellence practices, such as Lean Six Sigma (LSS), and integrating them with RAMI 4.0 would benefit its smoother adoption and transition to Industry 4.0.

LSS is a hybrid business improvement approach that integrates lean and Six Sigma and aims to maximize stakeholder value by improving speed, quality, customer satisfaction, and cost management (Vimal et al. 2023). Lean Six Sigma (LSS) shares common goals with Industry 4.0, for example, increasing production efficiency and quality, contributing to workers' health and safety, and integrating production systems with supply chain stakeholders (Ibrahim and Kumar 2024; Kaswan, Rathi, Cross, et al. 2023). Tissir et al. (2022) explained the joint features of LSS and Industry 4.0: "*LSS and I4.0 share the same final aims since they are oriented towards customer satisfaction and focus on productivity and quality improvement*." Different methods are used in LSS, for example, value stream mapping, root cause analysis, statistical tools, etc., for its implementation, but the DMAIC (design, measure, analyze, improve, control) approach is one of the most commonly employed. DMAIC is used in LSS projects as a problem-solving methodology to evaluate each process with an organized procedure. The flexibility and adaptability of the DMAIC methodology make it one of the most popular business strategies for achieving continuous improvement in the manufacturing and service sectors (Panayiotou and Stergiou 2020). The DMAIC methodology can optimize processes by integrating information systems in an Industry 4.0 environment (Arcidiacono and Pieroni 2018).

Due to its nature, LSS can simplify the implementation of RAMI 4.0 using the DMAIC methodology. By applying the DMAIC methodology within the RAMI 4.0 framework, organizations can systematically identify, analyze, and address challenges, optimize processes, and enhance performance, reliability, and efficiency. DMAIC provides a structured approach to problem-solving and process improvement that complements the principles and objectives of RAMI 4.0, enabling organizations to realize the full potential of digital transformation and achieve sustainable competitive advantage. However, different tools and techniques are essential for following the DMAIC stages while integrating them into the RAMI 4.0 model.

From these points of view, this study aims to answer the below research questions:

RQ1: How can LSS be integrated with RAMI 4.0?
RQ 2: Which LSS Tools and Techniques can be used in DMAIC stages in RAMI 4.0, and how can organizations prioritize these tools and techniques according to their needs?

This study contributes to the theory and practice of LSS and Industry 4.0 by proposing a systematic structure that includes LSS 4.0 tools and techniques for each DMAIC stage and that can be used for LSS implementation in RAMI 4.0. A generic structure is proposed while the life cycle and value stream level of RAMI 4.0 are the main focus areas in this study. To prioritize these tools and techniques for each DMAIC stage with a focus on the life cycle and value stream level of RAMI 4.0, the Fuzzy Entropy Weighting (FEW) method is employed. FEW is a valuable method for presenting decision-maker's preferences and revealing elements' relative priority order (Zhang et al. 2019). A case study is conducted to test the procedure of the proposed structure in a high-technology electronics company. The results of this study are valuable for practitioners and academics in terms of integrating LSS with Industry 4.0 in a structured manner.

This article is organized as follows: After the introduction, a review of Industry 4.0 and LSS is presented. Section Proposed structure for integrating Lean Six Sigma DMAIC and RAMI 4.0 includes the proposed structure. Section Methodology—fuzzy entropy weighting covers the methodology. Section Discussion and implications presents the study's implementation.

Finally, Section Conclusions discusses the implications, and the final section is the conclusion.

Industry 4.0 and Lean Six Sigma

Industrial revolutions trigger a complete transformation in the supply chains, and the manufacturing industry can be seen as the most affected part. As the manufacturing sector evolves according to the digitalization under Industry 4.0, current practices for operational excellence, such as Lean and LSS, become more technologically enabled. Industry 4.0 technologies can facilitate LSS 4.0 (Antony et al. 2022). As an accepted fact by researchers and practitioners, digital technologies and Industry 4.0 applications have significant potential when integrated with LSS to increase the performance of organizations (Kasem et al. 2024).

In this study, the review area is limited to studies that solely focused on LSS and Industry 4.0, where the current literature related to LSS and Industry 4.0 has a rapidly increasing trend, and researchers follow different approaches. Systematic reviews, framework proposals, and technological implementations especially come to the forefront. One of the earliest studies that integrated LSS and Industry 4.0 in global supply chain management was conducted by Jayaram (2016), focusing on the industrial Internet of Things. To continue with some review studies, Vinodh et al. (2020) conducted a review focusing on Industry 4.0 and continuous improvement that covers lean, Six Sigma, kaizen, and Industry 4.0 as strategies, and a conceptual framework that integrates these concepts was presented. A recent review on the evolution and future of LSS in Industry 4.0 was conducted by Antony et al. (2022), and the potential benefits and motivations of this integration were presented.

Similarly, Tissir et al. (2022) also conducted a literature review on integrating LSS and Industry 4.0 to demonstrate gaps in the literature, present future research direction, and propose a framework that categorizes the results. Furthermore, Pongboonchai-Empl et al. (2023) made a systematic literature review on integrating Industry 4.0 technologies and DMAIC and proposed a conceptual framework for DMAIC 4.0. In addition, Skalli et al. (2023) made a bibliometric analysis that covered lean, six Sigma, and Industry 4.0 and presented LSS 4.0 trends. Similarly, Citybabu and Yamini (2023) reviewed LSS and Industry 4.0 and presented a conceptual framework.

On the other hand, from a more practical implementation point of view for LSS and Industry 4.0 integration, Arcidiacono and Pieroni (2018) applied DMAIC in the healthcare sector with a particular focus on Industry 4.0 technologies. They conducted several case studies to show the impacts on supply processes and reduced waste. Chiarini and Kumar (2021) focused on operational excellence through LSS and Industry 4.0 integration, where reinvented mapping tools and horizontal, vertical, and end-to-end integration are needed. They interviewed different manufacturing companies in Italy, and in the end, they classified Industry 4.0 technologies under the DMAIC stages (Chiarini and Kumar 2021). Furthermore, Dogan and Gurcan (2018) approached the subject from a data perspective, intending to improve quality and different methods for each DMAIC stage by covering the concepts of statistics, quality tools, data mining, big data, and process mining. In addition, Anvari, Edwards, and Agung (2021) presented the results of an ongoing study that aims to show mutual support between Industry 4.0 and LSS. They provided combined components and tools for LSS and Industry 4.0 for each DMAIC step and suggested a new methodology called "Total Equipment Energy Effectiveness." In addition, Samanta et al. (2023) analyzed the critical success factors of integration of LSS and Industry 4.0 and revealed the causal relationship between these factors for organizational excellence.

From a more technology-based perspective, Sony (2020) focused on cyber-physical system (CPS) architectures under Industry 4.0 and integrated LSS principles in the design of 8C (connection, conversion, cyber, cognition, coalition, customer, and content) architecture of CPS, and explained the DMAIC cycle of each C's. In another technology-based study, Bhat, Bhat, and Gijo (2020) worked on simulation-based LSS integrating Industry 4.0, where the DMAIC methodology is applied to improve performance. On the other hand, Ibrahim and Kumar (2024) made an Industry 4.0 technology selection for LSS integration.

Due to the direct connection between LSS and quality management, some studies have integrated these concepts with Industry 4.0. For instance, Yadav, Shankar, and Singh (2020) surveyed the impacts of Industry 4.0 technologies on different organizational performance indicators under LSS and quality management systems. Furthermore, two consecutive studies related to critical success factors were conducted, where critical success factors for LSS in quality under Industry 4.0 are presented (Yadav, Shankar, and Singh 2021a), and the hierarchy of these factors is analyzed (Yadav, Shankar, and Singh 2021b).

Considering sustainability, sustainable manufacturing, and green issues while integrating LSS and

Industry 4.0 is another promising area, and different authors have conducted some initial studies. For instance, Titmarsh, Assad, and Harrison (2020) proposed a framework for achieving sustainability by using LSS in the Industry 4.0 environment, and they mainly worked on the impact of ICT on the relationship between sustainable manufacturing and LSS DMAIC. Furthermore, Khanzode, Sarma, and Goswami (2021) worked on identifying enablers of LSS for sustainability implications with a perspective of circular economy and Industry 4.0 integration and proposed managerial implications. On the other hand, Ganjavi and Fazlollahtabar (2021) developed a sustainable Industry 4.0 production value measurement approach, where leanness and LSS are extracted under quality elements and analyzed deeply. Finally, a recent review was conducted by Kaswan, Rathi, Antony, et al. (2023) on green LSS Industry 4.0 with a focus on COVID-19 to develop a framework.

As can be seen from the review related to LSS and Industry 4.0, authors follow different approaches, and both theoretical and practical studies have been conducted. However, the literature lacks an integration of LSS and a reference model for Industry 4.0. From this point of view, this study aims to incorporate one of the well-known architectural models, that is, RAMI 4.0, with the LSS DMAIC methodology to address this gap in the literature. The following section includes the proposed structure that is presented for this purpose.

Proposed structure for integrating Lean Six Sigma DMAIC and RAMI 4.0

In this study, the RAMI 4.0 model is integrated with the LSS DMAIC methodology with a special emphasis on the "Life Cycle and Value Stream" dimension, which focuses on the entire life cycle of the products or processes. The life cycle and value stream dimensions divide a smart factory into different levels by including macro, medium, and micro processes, where lean tools can be useful in optimizing the system to increase efficiency, eliminate waste, and reveal value-added activities.

The proposed structure can be seen as the initial work, starting from one dimension of RAMI 4.0, and future research will focus on each dimension individually. It is flexible in terms of application in different sectors. The usefulness of tools and techniques may vary according to the sectoral and organizational needs. In addition, although the DMAIC methodology can be applied to each stage of the RAMI 4.0 individually, the importance level of different LSS 4.0 tools and techniques may change according to the presented life cycle and value stream processes.

According to the given information, the proposed structure for the study is schematized in Figure 1.

In the proposed structure, the first part includes the details of RAMI 4.0. The life cycle and value stream level of RAMI 4.0 covers all the products and processes, from the design and development phases to their production and maintenance (Corradi et al.

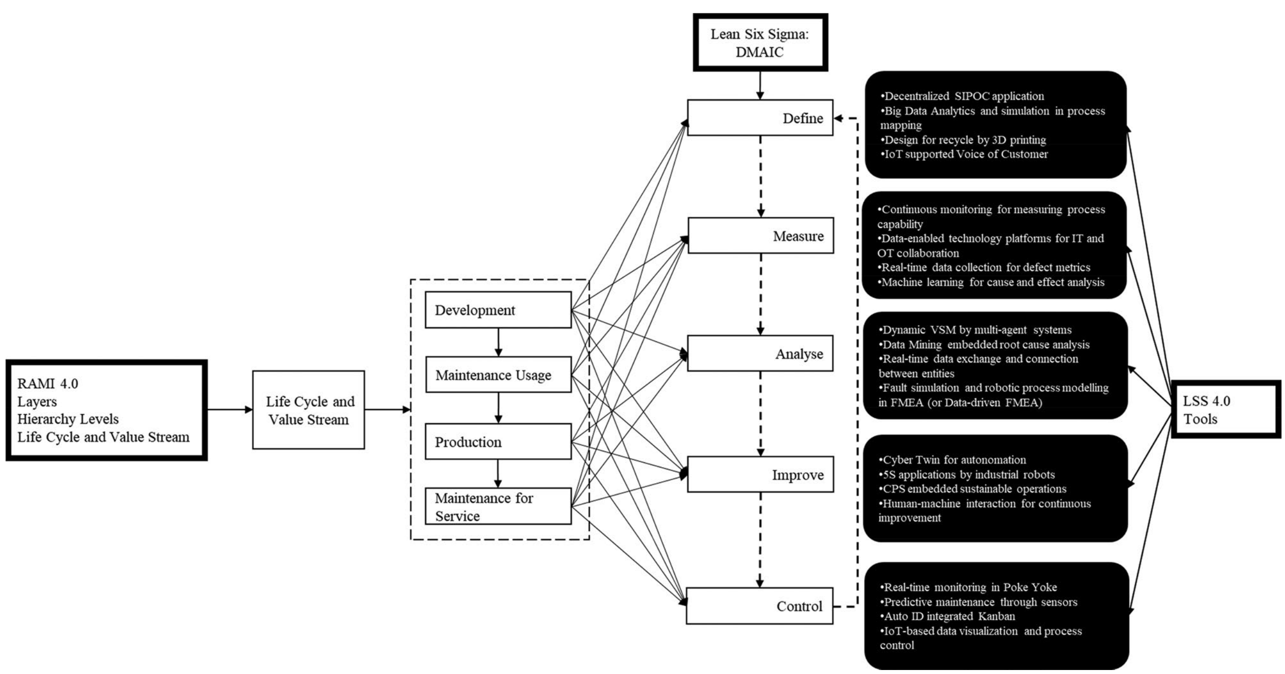

Figure 1. Proposed structure for RAMI 4.0 and LSS integration.

2019). This level is based on a draft standard for guideline life cycle management called IEC 62890 and characterizes the life cycle of entities, including products, workpieces, and facilities (Pisching et al. 2018). The initial categorization under this level is the type phase and instance phase. The type phase is where the product is under development, and the instance phase is where it is in production (Resman et al. 2019). The type phase transforms into the instance phase when the design and prototyping are completed and production starts (Hankel and Rexroth 2015). These phases include development and maintenance usage under the type phase and production and maintenance for service under the instance phase. These four levels are considered for evaluation in this study.

The explanation of these levels can be made as follows (Bastos et al. 2021): *The development* level includes the conceptualization of the product, simulation, and prototyping, and most research and development activities are covered at this level. *Maintenance usage* consists of the activities directly related to the product, not the production processes and this level covers system updates, instruction manuals, and product changes. *Production level* refers to the manufacturing stage, the factory's most critical part. Finally, *maintenance for servic*e, also known as instance maintenance and usage, includes manufacturing maintenance, optimization of process updates, after-sale services, and end-of-life treatments.

The second part of the proposed structure includes DMAIC stages and LSS 4.0 tools and techniques. Due to its nature, the DMAIC methodology is suitable for analyzing the production phase's entire life cycle and value stream. The circular structure of DMAIC shares a common understanding with the stages of the life cycle and value stream dimension. Therefore, applying the DMAIC methodology is expected to be useful for resource efficiency, increasing value-added activities through the value chain, and optimizing the system. Thus, the main reason behind focusing on the life cycle and value stream dimension while integrating the DMAIC methodology is to initially cover the product life cycle at the production level.

From a managerial implementation perspective in LSS, to make process improvements and solve problems *via* the DMAIC methodology, the most critical part is to find appropriate tools to use in each stage (Uluskan 2016). To get practical outcomes from the DMAIC methodology, the theoretical models should be validated by practical applications in businesses (Kumar, Singh, and Bhamu 2021). Current expectations and changes should be integrated into the DMAIC methodology. Therefore, tools and techniques used in each stage of DMAIC should be clearly defined. From this point of view, tools and techniques that include the features of Industry 4.0 and LSS are presented for each DMAIC stage and named "LSS 4.0 Tools and Techniques" in the model. These proposed tools and techniques integrate traditional LSS tools and Industry 4.0 technologies and approaches. They are the author's contributions, which are also supported by the previous studies.

To start with the initial stage of the DMAIC methodology, *define*, four tools and techniques are proposed. The define stage aims to make a problem description and objective definition. For this purpose, several tools and techniques are used. In this study, traditional tools and techniques are integrated with Industry 4.0-related approaches and presented as "LSS 4.0 Tools." The tools and techniques related to the define phase are coded with a letter "D" and explained below:

Blockchain-based decentralized SIPOC application (D1)

Decentralization is one of the design principles of Industry 4.0, which refers to moving from a centralized organizational structure to self-organized entities (Beier et al. 2020). Blockchain technology supports decentralization by providing trust and transparency between stakeholders and optimizing the distribution of resources. These features can be integrated into the SIPOC methodology for defining and describing the problem during the define phase (Kumar, Singh, and Bhamu 2021).

Big data analytics and simulation in process mapping (D2)

Process mapping is a standard tool used during the define phase (Farrukh, Mathrani, and Sajjad 2021), which requires a high amount of data related to the current system. In an Industry 4.0 environment, these data can be derived from big data analytics and simulation methods can be integrated into process mapping to deal with dynamic systems.

Design for circularity by 3D printing (D3)

To deal with a circular life cycle of the processes and products, it is essential to design the entire system by considering the end-of-life phase (Berwald et al. 2021). With Industry 4.0, design for circularity is a crucial term. It can be supported by 3D printing to eliminate waste caused during the design and minimize the faults, which would be considered in the define phase.

IoT supported voice of customer (D4)

VOC is important to understand customer needs and product or service expectations and expresses customer desires at every level (Wartati et al. 2021). IoT can be used to understand customer needs and support customer relationships in real-time (Yerpude and Singhal 2018). It can also be integrated with the VOC.

The second stage of the DMAIC methodology is the measure phase, which aims to determine the causes of problems, measure the system, and establish the initial process capability. In this study, four LSS 4.0 tools and techniques are presented related to the measuring stage and coded with the letter "M" and explained below:

Continuous monitoring for measuring process capability (M1)

Measuring process capability is critical in this phase, where data is needed to capture the current state (Kumar, Singh, and Bhamu 2021). Continuous monitoring through digital technologies would be beneficial in identifying the current system's critical aspects and providing up-to-date process capability measurement.

Data-enabled technology platforms for IT and OT collaboration (M2)

Information Technology (IT) and Operational Technology (OT) became two integrated areas after Industry 4.0 and created new industrial systems (Hahn 2016). In this integrated structure, data-enabled technology platforms enable data exchange and real-time measurement between the shop floor and business users (Rao et al. 2020).

Real-time data collection for defect metrics (M3)

Quality parameters are defined in the measure phase (Kumar, Singh, and Bhamu 2021), where defect metrics are crucial. Real-time data collection related to faults and defects would increase the efficiency and help to achieve the zero defect goal.

Machine learning for cause and effect analysis (M4)

Machine learning could be useful for making a connection between entities, making intelligent decisions, and providing a deeper understanding of the system (Dogan and Gurcan 2018). In a cause-and-effect analysis, data derived from machine learning can be used to make dynamic decision-making and forecast potential causes of errors.

The third stage of the DMAIC methodology is the analyze phase. This stage analyzes the current performance by conducting root cause analysis and revealing the faults. Analyze stage-related LSS 4.0 tools and techniques are codded with the letter "A" and presented below:

Dynamic VSM by multi-agent systems (A1)

VSM is a beneficial technique for analyzing the current state, revealing the continuous improvement areas, and suggesting a future state. Industry 4.0 requires dynamic mapping tools supported by multi-agent systems, which can be integrated into the VSM method (Huang et al. 2019) and used in the analysis phase.

Data mining embedded root cause analysis (A2)

Appropriate exploratory techniques are essential to analyze hidden causes of errors and different patterns. For this purpose, data mining provides an associative analysis, clustering, classification, and prediction of the system (Dogan and Gurcan 2018), and it is applicable for root cause analysis in terms of providing relevant data.

Real-time data exchange and connection between entities (A3)

To analyze the system appropriately, it is essential to provide a link between relevant entities. Real-time data exchange through smart technologies is an important characteristic of the Industry 4.0 environment (Ali et al. 2021), which can be helpful for making this connection simultaneously.

Data-driven FMEA (A4)

Failure Modes and Effect Analysis (FMEA) is a standard tool in the analysis phase of DMAIC methodology for analyzing and preventing failures. In the Industry 4.0 environment, data-driven FMEA can be applied by integrating fault simulation and robotic process modeling into the process, which can predict fault probabilities (Filz et al. 2021).

The improve phase is the fourth stage of the DMAIC methodology, which focuses on improving the current system and eliminating waste. LSS 4.0 tools and techniques related to the improve stage are named with the letter "I" and explained below:

Cyber twin for autonomation (Jidoka) (I1)

A cyber twin for each component in the system is used for providing self-awareness and self-prediction by collecting time and machine records and integrating them for future steps (Lee, Bagheri, and Kao 2015). In intelligent autonomation or Jidoka, sensors allow autonomous correction, where Industry 4.0 has an excellent potential for this predictive approach to improve quality (Deuse et al. 2020). From this point of view, cyber twin integration in autonomation would increase prediction performance and avoid quality problems.

5S applications by industrial robots (I2)

In the traditional lean applications, 5S (sort, set in order, shine, standardize, and sustain) is an approach that is particularly important for manual workstations; however, in Industry 4.0 smart factory, industrial robots may collaboratively apply 5S for process improvement (Stadnicka and Antonelli 2019).

CPS embedded sustainable operations (I3)

Integrating Industry 4.0 technologies to achieve sustainable operations is crucial to resource efficiency, minimizing long-term effects on nature, and providing continuous improvement in the system. CPS-embedded sustainable operations would optimize system efficiency throughout the life cycle and help eliminate non-value-adding activities.

Human-machine interaction for continuous improvement (I4)

The role of the workforce has changed tremendously with Industry 4.0, and human-machine interaction has become an indispensable element of the manufacturing environment (Nardo, Forino, and Murino 2020), which has a strong connection with LSS. To achieve continuous improvement in smart factories, human-machine interaction should be provided in a balanced way.

The final stage of the DMAIC methodology is the control phase, which aims to control the improved system with relevant tools. In this study, LSS 4.0 tools and techniques related to the control stage are shown with the letter "C" and presented below:

Real-time monitoring in Poka-Yoke (C1)

Poka-Yoke, or mistake proofing, is a well-known lean tool to avoid human errors in the system. In smart factories, real-time monitoring would enable avoiding errors before happening and could improve the traditional poka-yoke approach (Widjajanto, Purba, and Jaqin 2020).

Predictive maintenance through sensors (C2)

Predictive maintenance is a critical tool in LSS applications to avoid errors. Intelligent sensors in Industry 4.0 can control the system in real-time and in predictive maintenance (Pech, Vrchota, and Bednář 2021).

Auto ID integrated kanban (C3)

Kanban is a signaling mechanism for controlling processes and resource needs. In Industry 4.0, Kanban systems can be digitalized by Auto-ID systems to track and simulate inventory levels and replenishment times (Rao et al. 2020).

IoT-based data visualization and process control (C4)

To provide data gathering, process stability, and connecting computers and processes, IoT is a key technology and can be integrated with LSS (Efimova et al. 2021). Therefore, IoT-based approaches can be applied for process control, visualization, and sustaining improvement areas.

Furthermore, resource requirements vary depending on the life cycle stage and the need for data to define critical issues. To do that, using appropriate measuring techniques, well-developed analysis procedures, continuous improvement in the entire life cycle, and controlling the system to avoid waste and failures is crucial to providing resource efficiency. With this view, resource allocation for each stage also depends on the priorities of each level, where data acquisition through Industry 4.0 technologies enables successful resource allocation and scheduling during the life cycle and contributes to adding value (Zheng et al. 2021). Therefore, systematic prioritization is essential to provide unique suggestions for different sectors and organizations. With this aim, the FEW method is suggested for the proposed structure to evaluate all layers. Firstly, each of the DMAIC stages should be evaluated for each of the life cycle and value stream levels, that is, development, maintenance usage, production, and maintenance for service, and the DMAIC stages that need greater attention for each life cycle and value stream level should be revealed. Secondly, all the life cycle and value stream levels should be handled individually, and under each DMAIC stage, proposed tools and techniques should be evaluated. Although the proposed procedure requires some detailed analysis and may take time, results are expected to be valuable for the organizations in terms of detailed suggestions from macro to micro perspectives for DMAIC methodology implementation for each life cycle and value stream level.

The following section includes the methodological explanation of the FEW method.

Methodology—fuzzy entropy weighting

Entropy weighting originated from thermodynamics and is applied to information systems, where information entropy is defined as the uncertainty of signals in communication procedures (Ji, Huang, and Sun 2015). It is a common method for obtaining weights for the objective criteria, especially in multi-criteria decision-making applications. In the entropy method, the size of the information is expressed by the entropy, where a higher amount of information results in a higher difference between attribute values and higher entropy weight (He et al. 2016). On the other hand, most MCDM approaches require experts' opinions and linguistic variables used for evaluation. The fuzzy Entropy Weighting method (FEW) is derived from entropy weighting, which uses linguistic terms to assess the criterion and convert them into fuzzy linguistic variables. FEW is a practical and relatively easy method, compared to other methodologies, to evaluate the weights of criteria, and it includes three main stages (Ighravwe and Oke 2017). Before explaining these stages, trapezoidal fuzzy numbers are used in this study, which are defined as $A = (a, b, c, d)$. The linguistic variables and trapezoidal fuzzy numbers are shown in Table 1.

The explanation related to FEW applications is presented below by using Ding (2011), Ighravwe and Oke (2017), and Ji, Huang, and Sun (2015):

Stage 1: Creating a decision matrix

Suppose there are m decision makers or alternatives for hierarchical structures and n criteria to evaluate. Then, the decision matrix is shown as $D = (x_{ij})_{mxn}$. Defuzzification of the trapezoidal fuzzy numbers is the initial stage to provide a crisp data set for FEW approaches. The graded mean integration representation method converts trapezoidal fuzzy numbers presented in Table 2 to crisp values using Eq. [1].

$$x_{ij} = \frac{a + 2b + 2c + d}{6} \quad [1]$$

After that, the normalization procedure can be conducted for each criterion using Eq. [2].

$$d_{ij} = \frac{x_{ij}}{\sum_{j=1}^{n} x_{ij}} \quad [2]$$

Stage 2: Entropy value determination

Entropy values, E_j, are calculated by using Eq. [3].

$$E_j = -(\ln m)^{-1} \sum_{i=1}^{m} d_{ij} \ln d_{ij} \quad [3]$$

Stage 3: Obtaining criterion weights

Criterion weights w_j obtained by using Eq. [4], where $0 \leq w_j \leq 1$, and $\sum_{j=1}^{n} w_j = 1$

$$w_j = \frac{\left(1 - E_j\right)}{n - \sum_{j=1}^{n} E_j} \quad [4]$$

Table 1. Linguistic expressions and trapezoidal fuzzy numbers.

Linguistic expression	Trapezoidal fuzzy number
Very highly important	(0.7, 0.8, 0.9, 1.0)
Highly important	(0.6, 0.7, 0.8, 0.9)
Slightly important	(0.5, 0.6, 0.7, 0.8)
Important	(0.4, 0.5, 0.6, 0.7)
Neither important nor unimportant	(0.3, 0.4, 0.5, 0.6)
Unimportant	(0.2, 0.3, 0.4, 0.5)
Slightly unimportant	(0.1, 0.2, 0.3, 0.4)
Highly unimportant	(0.0, 0.1, 0.2, 0.3)

Table 2. Information related to decision makers (DM).

	Year of experience	Department	Position
DM1	4	Production	Senior Production Engineer
DM2	7	Research and Development	Senior Engineer
DM3	9	Research and Development	Team Leader (Engineer)
DM4	11	Research and Development	Team Leader (Engineer)
DM5	18	Production	Production Manager

The implementation of the proposed structure in high-technology electronics company

This study was conducted in an international high-technology electronics company with a broad market share and extensive product range. The reason for choosing this company was that it has applied LSS for more than three decades in the organization and has worked on the transition to Industry 4.0. Their LSS implementation included total productive maintenance, operational excellence, lean production, and total quality management. In their smart factory transition process, investments in research and development come to the forefront. Furthermore, advanced robotics in the production processes and strong interconnectivity between machines are applied in the company through the Industry 4.0 transition. In addition, building the digital twin of the production processes to increase traceability is one of their plans. The company also tends to integrate LSS principles with its new smart factory structure to eliminate waste, improve quality, and have leaner production processes.

The company's features make it suitable for the sample implementation of the proposed structure related to LSS and the RAMI 4.0 model. The implementation aimed to give an example of using the proposed structure in an organization or sector. Therefore, it was not aimed to reflect the macro environment but to guide future applications to show how to prioritize DMAIC stages and LSS 4.0 tools and techniques for the company's life cycle and value stream levels. These results would vary depending on the organization's expectations, limitations, infrastructure, transition capacity, and current processes. Therefore, although the proposed structure is easy to generalize and flexible in terms of applying to different sectors and organizations, the results of this implementation are unique for the selected case company in this study.

They were carried out with the participation of five company decision-makers (DM). These decision-makers work in different departments and have different expertise, but all of them are familiar with the production processes, LSS tools and techniques, and Industry 4.0 concepts. Information related to decision-makers is given in Table 2.

Due to the nature of this study, the evaluation procedure in this study was significantly long. DMs were asked to use linguistic variables that were presented in Table 2. To avoid misunderstandings of the concepts and to save time, short interviews based on questions and answers were conducted with DMs individually, and evaluation tables were filled based on the collected data. Each DM was firstly asked to prioritize the DMAIC stages (i.e., define, measure, analyze, improve, control) for each life cycle and value stream level (i.e., development, maintenance for usage, production, and maintenance for service). The data table for this initial phase is presented in Table 3. This part aimed to reveal the most important DMAIC stage for each life cycle and value stream stage to define the priorities.

After that, these linguistic evaluations were transformed into the related trapezoidal fuzzy numbers using Table 1. Equations [1] and [4] were applied, respectively, to determine the weights for each DMAIC stage for each life cycle and value stream level. Table 4 summarizes the results of the initial evaluation stage, where D_j refers to the normalized values, E_j to the entropy values, and w_j to the weights.

The results of the first evaluation stage revealed that the most critical DMAIC stage for the development level is "define," which is understandable due to the main activities in the new process or product development level. In the maintenance for usage level, the "define" stage appeared to be the most important, followed closely by the "measure" stage. "Analyze" is the most important DMAIC stage for the production level. Finally, "improve" was the most critical stage for the maintenance of the service level. As can be understood from the results, although the DMAIC methodology applies to all levels of the life cycle and value stream, the importance of stages varies. This leads to different approaches and may guide future investments based on prioritization.

The same evaluation procedure and fuzzy entropy weighting implementation were used to prioritize LSS 4.0 tools and techniques for each life cycle and value stream level. Table 5 presents the data table that includes linguistic DM evaluations.

Table 3. Evaluation of DMAIC for each life cycle and value stream level.

	Development					Maintenance for usage					Production					Maintenance for service				
	D	M	A	I	C	D	M	A	I	C	D	M	A	I	C	D	M	A	I	C
DM1	EI	HI	I	U	I	U	EI	SI	HI	HI	I	HI	I	SI	HI	U	I	I	HI	HI
DM2	HI	HI	I	NC	SI	I	HI	HI	SI	SI	HI	HI	I	U	EI	SU	I	HI	EI	HI
DM3	HI	HI	I	I	I	I	EI	I	I	HI	I	EI	HI	I	HI	I	SI	SI	I	SI
DM4	EI	HI	SI	I	I	U	EI	HI	HI	EI	SI	HI	I	I	HI	NC	I	I	SI	EI
DM5	EI	I	SI	SI	I	I	HI	I	I	HI	I	I	HI	SI	I	U	I	I	HI	I

Table 4. Summary of the results of evaluation of DMAIC stages for each life cycle and value stream level.

	Development			Maintenance for usage			Production			Maintenance for service		
	D_j	E_j	w_j	D_j	E_j	w_j	D_j	E_j	w_j	D_j	E_j	w_j
Define (D)	4.840	−2.724	0.310	4.459	−2.223	0.272	3.400	−0.717	0.142	2.337	0.395	0.060
Measure (M)	3.448	−0.731	0.144	4.388	−2.023	0.255	3.526	−0.821	0.151	3.657	−1.053	0.202
Analyze (A)	3.730	−1.192	0.183	3.214	−0.479	0.125	5.057	−3.110	0.340	3.870	−1.310	0.228
Improve (I)	3.759	−1.295	0.191	3.214	−0.479	0.125	4.014	−1.605	0.216	4.885	−2.799	0.375
Control (C)	3.657	−1.053	0.171	4.109	−1.662	0.224	3.526	−0.821	0.151	3.142	−0.373	0.135

Table 5. Evaluation of LSS 4.0 tools and techniques for each life cycle and value stream level.

	Development				Maintenance for usage				Production				Maintenance for service			
Define	D1	D2	D3	D4	D1	D2	D3	D4	D1	D2	D3	D4	D1	D2	D3	D4
DM1	EI	HI	NC	EI	I	HI	U	I	I	HI	U	U	I	U	I	HI
DM2	HI	HI	I	SI	I	SI	NC	U	U	EI	SU	U	I	U	I	EI
DM3	EI	HI	I	HI	U	I	SU	I	SI	HI	NC	SU	NC	NC	SI	EI
DM4	EI	SI	U	HI	SI	I	I	SI	I	I	NC	U	U	I	HI	HI
DM5	SI	SI	SU	SI	NC	I	U	U	I	SI	U	U	U	U	SI	EI
Measure	M1	M2	M3	M4	M1	M2	M3	M4	M1	M2	M3	M4	M1	M2	M3	M4
DM1	HI	HI	U	I	HI	I	HI	I	HI	HI	EI	I	HI	U	I	I
DM2	I	EI	U	U	I	I	EI	I	I	HI	HI	HI	HI	I	I	U
DM3	I	HI	I	NC	I	I	I	HI	I	SI	HI	HI	I	NC	U	SU
DM4	I	I	I	I	HI	HI	HI	HI	HI	I	SI	I	I	U	U	U
DM5	HI	HI	U	U	HI	I	HI	HI	I	I	SI	I	SI	SU	NC	NC
Analyze	A1	A2	A3	A4	A1	A2	A3	A4	A1	A2	A3	A4	A1	A2	A3	A4
DM1	I	I	I	I	I	HI	I	HI	HI	U	HI	I	NC	I	I	I
DM2	EI	I	I	HI	SI	HI	I	SI	HI	SU	EI	SI	I	SI	U	HI
DM3	EI	HI	SI	HI	I	SI	I	SI	SI	I	HI	SI	U	SI	U	HI
DM4	HI	HI	I	I	I	SI	SI	I	I	I	SI	I	U	I	I	SI
DM5	HI	I	U	I	SI	EI	I	I	SI	U	HI	SI	I	HI	I	I
Improve	I1	I2	I3	I4	I1	I2	I3	I4	I1	I2	I3	I4	I1	I2	I3	I4
DM1	HI	I	HI	I	SI	U	I	U	HI	I	EI	EI	I	I	U	I
DM2	HI	I	HI	SI	I	NC	I	I	EI	HI	HI	EI	I	SI	SU	U
DM3	SI	SI	I	SI	I	I	SI	SU	EI	HI	HI	HI	U	SI	NC	I
DM4	SI	I	I	I	U	SU	U	I	HI	I	I	HI	U	U	U	I
DM5	EI	SI	SI	HI	I	U	I	U	I	I	HI	HI	I	I	U	U
Control	C1	C2	C3	C4	C1	C2	C3	C4	C1	C2	C3	C4	C1	C2	C3	C4
DM1	U	I	U	I	I	I	U	I	HI	EI	HI	HI	I	U	U	I
DM2	SU	U	SU	I	HI	I	SU	I	EI	EI	SI	EI	I	SU	SU	I
DM3	U	U	U	SI	HI	SI	U	HI	EI	HI	SI	HI	U	U	SU	SI
DM4	U	NC	U	I	I	SI	I	HI	HI	HI	I	EI	I	I	U	I
DM5	I	I	U	SI	SI	I	U	SI	HI	HI	SI	HI	SI	U	U	I

After applying Eqs. [1] and [4], Table 6 presents the results after evaluating LSS 4.0 tools and techniques for each life cycle and value stream level.

This implementation prioritized LSS 4.0 tools and techniques under each DMAIC stage for each life cycle and value stream level. To start with the results related to the development level, Big Data Analytics and simulation in process mapping (D2) were revealed as the most important LSS 4.0 approach under the define stage. For the measure stage, continuous monitoring for measuring process capability (M1), for analyzing stage Dynamic VSM by multi-agent systems (A1), for improving stage Cyber Twin for autonomation (Jidoka) (I1), and for control stage IoT-based data visualization and process control (C4) was found as the most critical LSS 4.0 tools and techniques.

When the results related to maintenance for usage level were analyzed, it was revealed that similar to the initial level, Big Data Analytics and simulation in process mapping (D2) was the most critical LSS 4.0 approach for the define phase. On the other hand, real-time data collection for defect metrics (M3) was the most critical part of the measure phase. Data Mining embedded root cause analysis (A2) had the highest weight for the analysis phase. In the improve stage, Cyber Twin for autonomation (Jidoka) (I1) and CPS embedded sustainable operations (I3) shared the first rank with equal weights. Finally, IoT-based data visualization and process control (C4) was revealed as the most important approach for the control stage, similar to the previous level.

As in the first two levels, Big Data Analytics and simulation in process mapping (D2) had the highest weight under the defined stage for the production level. Real-time data collection for defect metrics (M3) for the measure phase, real-time data exchange and connection between entities (A3) for the analyze phase, and CPS embedded sustainable operations (I3)

Table 6. Results of evaluation of LSS 4.0 tools and techniques for each life cycle and value stream level.

		Development			Maintenance for usage			Production			Maintenance for service		
		D_j	E_j	w_j	D_j	E_j	w_j	D_j	E_j	w_j	D_j	E_j	w_j
Define	Blockchain based decentralized SIPOC application (D1)	3.856	−1.262	0.273	2.589	0.174	0.210	3.442	−0.819	0.259	3.094	−0.326	0.162
	Big Data Analytics and simulation in process mapping (D2)	4.367	−1.989	0.360	3.870	−1.310	0.587	5.012	−2.938	0.561	2.134	0.586	0.051
	Design for circularity by 3D printing (D3)	2.419	0.411	0.071	2.061	0.621	0.096	2.250	0.466	0.076	3.524	−0.910	0.233
	IoT supported Voice of Customer (D4)	3.985	−1.458	0.296	2.176	0.581	0.106	2.438	0.277	0.103	5.380	−3.551	0.555
Measure	Continuous monitoring for measuring process capability (M1)	5.057	−3.110	0.401	4.126	−1.731	0.277	3.135	−0.398	0.147	4.641	−2.417	0.445
	Data-enabled technology platforms for IT and OT collaboration (M2)	5.772	−4.171	0.504	2.977	−0.237	0.126	4.081	−1.573	0.270	2.265	0.528	0.061
	Real-time data collection for defect metrics (M3)	2.205	0.534	0.045	4.445	−2.144	0.319	4.472	−2.130	0.328	3.693	−1.122	0.276
	Machine learning for cause and effect analysis (M4)	2.276	0.488	0.050	4.126	−1.731	0.277	3.975	−1.442	0.256	3.276	−0.663	0.217
Analyze	Dynamic VSM by multi-agent systems (A1)	4.550	−2.287	0.419	4.266	−1.914	0.249	4.765	−2.587	0.319	4.291	−2.001	0.286
	Data Mining embedded root cause analysis (A2)	3.135	−0.398	0.178	5.540	−3.849	0.414	2.134	0.570	0.038	5.057	−3.107	0.391
	Real-time data exchange and connection between entities (A3)	2.554	0.275	0.092	3.219	−0.518	0.129	5.127	−3.140	0.369	3.116	−0.473	0.140
	Data-driven FMEA (A4)	3.975	−1.442	0.311	3.975	−1.439	0.208	4.391	−2.078	0.274	3.581	−0.921	0.183
Improve	Cyber Twin for autonomation (Jidoka) (I1)	5.540	−3.849	0.317	4.957	−2.905	0.384	3.603	−0.910	0.146	4.459	−2.223	0.368
	5S applications by industrial robots (I2)	4.266	−1.914	0.191	3.551	−0.916	0.189	3.975	−1.442	0.187	5.121	−3.143	0.474
	CPS embedded sustainable operations (I3)	4.641	−2.417	0.224	4.957	−2.905	0.384	5.772	−4.171	0.395	2.550	0.181	0.094
	Human-machine interaction for continuous improvement (I4)	5.057	−3.107	0.269	2.134	0.570	0.042	4.760	−2.569	0.273	2.347	0.436	0.064
Control	Real-time monitoring in Poka-Yoke (C1)	3.610	−1.172	0.280	4.641	−2.417	0.463	4.760	−2.569	0.265	3.887	−1.447	0.447
	Predictive maintenance through sensors (C2)	3.506	−0.955	0.252	3.310	−0.615	0.219	4.760	−2.569	0.265	1.988	0.664	0.061
	Auto ID integrated Kanban (C3)	2.438	0.277	0.093	1.988	0.664	0.045	4.641	−2.414	0.254	2.324	0.361	0.117
	IoT-based data visualization and process control (C4)	4.266	−1.914	0.375	3.617	−1.018	0.273	4.295	−1.901	0.216	3.657	−1.053	0.375

for the improve phase were found to be the most critical approaches. When the results related to the control stage are investigated, Real-time monitoring in Poka-Yoke (C1) and Predictive maintenance through sensors (C2) share the highest weight.

Finally, the results showed that IoT-supported Voice of Customer (D4) is the most important define phase approach for the maintenance of service level. Prioritization was followed by Continuous monitoring for measuring process capability (M1) for the measure stage, Data Mining embedded root cause analysis (A2) for the analyze stage, 5S applications by industrial robots (I2) for the improve stage, and Real-time monitoring in Poka-Yoke (C1) for control stage.

In the following section, the discussion and implications are presented.

Discussion and implications

Industries operating in the globalized manufacturing landscape encounter numerous challenges, such as improving quality, reducing costs, and minimizing lead times. Consequently, they must prioritize continuous improvement and performance enhancement methodologies. The integration of LSS with Industry 4.0 emerges as a critical technique to address these issues effectively (Samanta et al. 2023).

From the theoretical implications point of view, this study contributes to the literature by providing LSS 4.0 tools and techniques for each DMAIC stage, which integrate the features of Industry 4.0 and LSS in general. Although some studies integrate Industry 4.0 and LSS (Arcidiacono and Pieroni 2018; Ibrahim and Kumar 2024; Jayaram 2016; Sony 2020; Antony et al. 2022; Yadav, Shankar, and Singh 2021a) only a few of them provide Industry 4.0 technologies for DMAIC each stage (Anvari, Edwards, and Agung 2021; Chiarini and Kumar 2021). On the other hand, to the best of our knowledge, only one study integrated lean automation with RAMI 4.0, which solely focused on the business layer of the model to provide information related to human-robotic material handling teams to other levels (Pantano et al. 2020). Therefore, this study fills the knowledge gap by presenting a systematic structure that can be used for organizations to apply the DMAIC methodology in RAMI 4.0. This contribution also points to the gap presented by Skalli et al. (2023) "lack of specific frameworks describing guidelines and roadmaps for LSS and Industry 4.0" by providing the proposed structure.

This study may also be used to extend the operational excellence of the organizations, which is defined as the integration of Industry 4.0, reverse logistics, and lean approaches (Dev, Shankar, and Qaiser 2020), by providing specified LSS 4.0 tools and techniques, especially integrated with life cycle and value stream of the products. This is also directly related to reverse operations and circularity. Therefore, besides the applicability, this study contributes to the theoretical knowledge associated with Industry 4.0 and LSS integrations. Furthermore, the proposed methodology to implement the structure is easy to use and can be integrated with other methods (Wang, Li, and Li 2021) to investigate further.

Furthermore, the proposed structure in this study may have many implications for practitioners and managers when integrating the LSS DMAIC methodology with the RAMI 4.0 model. The proposed structure's general nature reveals the need to prioritize according to the company's needs. As a well-known and accepted fact, the Industry 4.0 transition requires high investments and tremendous transformations in the current system (Raj et al. 2020), as well as positioning the workforce on the smart factory floor. Therefore, technology selection and investment decisions are critical for organizations to sustain in the competitive environment. It is essential to avoid any kind of waste in the dynamic and complex structure of the smart factory. Hence, organizations should find ways to make them leaner while making them technologically developed.

As it can be understood from the previous studies and the proposed LSS 4.0 tools and techniques in this study, data dependency is one of the most crucial during the life cycle of the processes for both LSS and Industry 4.0 applications (Anvari, Edwards, and Agung 2021). Organizations must build a solid infrastructure for continuous data collection and analysis during the entire life cycle. This enables big data analytics through the system and may provide data to make decisions, prevent errors and failure, optimize the system, and reveal the areas for continuous improvement. With this view, Product Life Cycle Management (PLM) software can be supported by Industry 4.0 technologies to manage the entire life cycle of the products and processes.

Due to the interconnected nature of the Industry 4.0 environment, stakeholder participation during the life cycle is another important aspect. The decentralized structure of Industry 4.0 reveals the importance of data sharing, transparency, connectivity, and real-time interaction between participants of the value chain, which can be provided by Blockchain technology. In this sense, stakeholder theory is one of the most relevant theories, focusing on stakeholder relationships (Pinheiro et al. 2022). It can be integrated with Industry 4.0 technologies to derive data and provide a baseline for lean methods, such as SIPOC or VSM.

From a customer relations and integration point of view, the first and last level of the life cycle and value stream is directly related to customer desires and after-sale expectations. Therefore, while dynamic data is integrated into the voice of the customer, an information technology integration should also be made, and Customer Relationship Management (CRM) should be enriched by the data collected through Industry 4.0 technologies.

Employee collaboration and acceptance are other factors related to LSS and Industry 4.0. In the traditional applications of LSS, labor-intensive decision-making and tasks were the priority. However, with the Industry 4.0 transition, most of the labor-intensive jobs can be performed through robotic systems. Human-machine interaction has become an important topic for organizations. Training and education-related new systems that include technical knowledge and an attitude toward data security should be part of managerial implications.

At the smart factory level, using sensors and RFID is crucial to take preventative actions. Continuous monitoring of each process would contribute to defect prevention and improve quality. Furthermore, eliminating eight wastes, namely over-production, over-processing, waiting, defects, unnecessary transportation, unnecessary inventory, unnecessary motion, and talent, can easily be supported by Industry 4.0 technologies and increase factory-level efficiency.

The proposed structure provides a holistic view of applying the LSS DMAIC methodology at each lifecycle level individually and suggests LSS 4.0 tools and techniques based on organizations' priorities. A strong commitment from internal and external partners is essential to this integration. While embarking on the RAMI 4.0 for a systematic transition, LSS principles should be followed to sustain continuous improvement. In essence, embracing RAMI 4.0 and LSS represents a strategic imperative for organizations seeking to thrive in the digital era, fostering agility, resilience, and excellence in manufacturing practices.

Conclusions

LSS and Industry 4.0 mutually support each other, and their integration contributes to the performance of organizations in terms of increasing quality, eliminating waste, and reaching operational excellence. Combining LSS tools and techniques and Industry 4.0 principles is important for successful implementation.

Integrating reference architectures for Industry 4.0 and well-known methodologies for LSS is a beneficial starting point for this combination. Some studies have focused on LSS and Industry 4.0 in the current literature. However, there is a gap in the knowledge in terms of the systematic integration of these concepts. This study aims to integrate the LSS DMAIC methodology with the RAMI 4.0 model by proposing LSS 4.0 tools and techniques for each DMAIC stage. This research focuses on the life cycle and the value stream level of RAMI 4.0, where DMAIC can be applied to each life cycle and different LSS 4.0 tools and techniques can be used. To prioritize according to the needs of companies, the FEW method is suggested for evaluating LSS 4.0 tools and techniques for each life cycle level. The proposed structure in this study is flexible and can be generalized. However, the prioritization of the LSS tools and techniques may vary depending on the organizational needs. A study was conducted in a high-technology electronics firm to show the implementations. At the end of the study, general theoretical and managerial implications are presented.

Due to the nature of this research, this study has some limitations. First, decision makers' familiarity with LSS 4.0 tools and techniques might be limited since the proposed approaches are entirely new and require knowledge of both Industry 4.0 and LSS. Second, high investment requirements and employees' unwillingness might be limitations for the implementation. However, practitioners may use the proposed structure for investment decisions and work on integrating it with the current practices and systems.

Future research can test the proposed structure by comparing different sectors' prioritization of LSS 4.0 tools and techniques in the life cycle and value stream level. Another future research idea is to focus on other RAMI 4.0 levels, that is, hierarchy levels and layers, to apply the DMAIC methodology. That would be a more macro study by including external stakeholders and processes.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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