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PhD Thesis

Decision-Support Frameworks for Supply Chain Resilience and Sustainability in SMEs, Enabled by AI, Modelling, and Digital Automation

Supervisor: Prof. Dr. Roberto Revetria

PhD coordinator: Prof. Dr. Daniele Simone

PhD Candidate: Khursheed Ahmad

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ABSTRACT

Nowadays, manufacturing organizations are working in ever increasing volatile and complex environments due to increasing disruption frequencies and sustainability regulations. These challenges come across all organizational supply chains regardless of their size. However, small and medium-sized enterprises (SMEs) are more prone to these risks due to their limited resources in terms of building resilience and achieving sustainability goals.

This thesis addresses the dual challenge, risk mitigation and enhancing sustainability performance, by providing decision-making frameworks through the integration of artificial intelligence, modeling & simulation, and multi-criteria decision-making. In the resilience domain, the thesis contributed with two conceptual frameworks; the first framework enhances supply chain resilience for SMEs by integrating generative artificial intelligence at different stages of standard risk management cycle i.e., risk identification, risk assessment, risk mitigation, and risk control. The second framework aids in choosing best collaboration strategy for SMEs to minimize operational impacts while facing environmental disruptions. The conceptual framework integrates modeling & simulation and artificial intelligence in decision-making. In the sustainability domain, this thesis developed a comprehensive sustainability assessment framework with the integration of structured set of European Sustainability Reporting Standards' (ESRS) indicators and multi-criteria decision-making technique Analytical Hierarchy Process (AHP). The framework has been validated by a case study applied to an Italian manufacturing organization. The results of the case study provided insights for strategic decision-making in improving sustainability performance. Moreover, this thesis also contributed by the digital implementation of the developed sustainability assessment framework which brings transparency and avoids manual handling of the sustainability data.

Overall, this thesis provides a practical guide that supports data-driven decision-making in managing supply chain risks and sustainability challenges especially in the context of SMEs.

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Chapter 1 INTRODUCTION

The first chapter of the thesis comprises of the broader introduction of the thesis topic. The chapter starts by setting the research context and leads to the formation of thesis objectives and research questions. The chapter ends with the description of the overall thesis structure.

1.1 Background and Context

Nowadays, supply chains (SCs) have been exposed to various risks which impact their overall business performance. Modern SCs are widely spread across the globe which increases their complexity. Moreover, human activities such as terrorism, labour strikes, and natural disasters e.g., floods, earthquakes, and pandemics result in severe disruptions due to their global dependencies [1], [2]. Disruptions at one part or at one node of the SC have a significant impact on the overall business of that organization. For example, Toyota's component suppliers were unable to deliver parts at the expected volume and time following the 2011 earthquake and tsunami in Japan. Consequently, Toyota had to halt their production. Similarly, General Motors faced temporary production shutdowns due to the unavailability of essential components from its Japanese suppliers [3]. Therefore, SC disruptions are not localized instead they propagate through the whole SC. This phenomenon is referred as 'ripple effect' which was first described by [4]. According to the 2018 EventWatch Report, SC disruption frequency increased up to 36% which severely affected financial and operational performance of SC partners [5]. The reasons for the increased disruption frequency include global supplier distribution, political instability, adoption of lean & just-in-time principles. These practices work fine under normal conditions but make organizations more vulnerable in turbulent times [6], [7].

Apart from resilience challenges, manufacturing organizations are also being compelled to increase their sustainability performance. Although manufacturing is a key component of economic development of any country but their activites have several negative impacts on sustainability. These impacts include consumption of natural resources, pollution generation, and environmental degradation. These impacts become more severe in densely populated areas where nearly 70% of Europe's population resides [8], [9]. Growing sustainability awareness has also transformed customer preference towards organizations adopting sustainable practices. This reality has prompted growing scrutiny from consumers, regulators, and stakeholders. Moreover, changing government policies now require firms to demonstrate transparency and accountability in relation to their environmental, social, and governance (ESG) impacts [10]. Starting 2024, more than 50,000 organization fell into new sustainability regulations under European Sustainability Reporting Standards (ESRS). ESRS have changed sustainability reporting from voluntarily disclosure to a mandatory compliance [11].

To comply with these regulations, organizations must report their current sustainability performance. In addition, organization must also disclose their strategic sustainability goals. Therefore, they must identify their key areas of sustainability improvement [12], [13], [14]. In this regard, many firms enhanced the use of renewable energy, recycling programmes, and waste-reduction initiatives to reduce environmental footprints and strengthen stakeholder trust [15]. Moreover, approaches like Green Leasn Six Sigma (GLS) also aid in improving efficiency and reducing emissions while keeping economic resilience [16].

Despite these developments, current sustainability assessment methods remain fragmented. Literature lacks in proposing standard Key Performance Indicators (KPIs). Most of the studies use equal weights for all the indicators which does not reflect true importance of individual indicators. Therefore, their practical applicability and regulatory compliance is limited in the manufacturing context [17], [18], [19], [20], [21]. At the same time, advances in Industry 4.0 offer opportunities for automated and data-driven sustainability assessment, though systematic frameworks remain underdeveloped [22], [23].

Therefore, manufacturing organizations are facing dual challenges in today's turbulent business environment. Organizations have to maintain their resiliency as well as comply with sustainability regulations. Recent developments in artificial intelligence (AI) and its sub fields such as machine learning and generative AI are revolutionizing all research fields. Their capabilities of handling large datasets and learning from the historic data is also being used to enhance decision-making across the fields [24], [25], [26]. Therefore, this thesis addresses both dimensions by integrating artificial intelligence, modelling and simulation, and structured decision-making techniques to support resilient and sustainable operations.

1.2 *Small and medium-sized enterprises (SMEs) challenges*

Small and medium-sized enterprises (SMEs) are significant component of global economic growth. However, they are more prone to SC disruptions and have less resources to overcome sustainability challenges. Previous section highlighted increasing frequency of disruptions due to multiple reasons including natural disasters, pandemics, and economic instability [27]. Increasing SC complexity increases this vulnerability as organisations struggle to predict fluctuations in demand, supply, and technology [28]. Strategic factors such as resource depletion, climate change, and strict regulations make SC planning even more complex [29].

Although these risks affect organisations of all sizes, SMEs face unique constraints. They have limited resources and less bargaining leverage. Moreover, inability to build redundancies and limited access to technology make it difficult for SMEs to adopt effective risk-management approaches [30], [31]. Unlike large enterprises, SMEs often operate with narrow margins and tight operational constraints. Consequently, resilience planning becomes a critical challenge, and existing literature offers limited guidance on how SMEs can practically build resilience under such constraints [32]. However, SMEs can overcome the issue of limited resources by collaborating among themselves. Collaboration includes information sharing, resource sharing, and joint contingency planning. In this way, they can adopt advanced risk-management approach to build resilience [33], [34]. Nevertheless, SMEs lack structured tools to evaluate which collaboration strategies best suit their operational context.

As mentioned in previous section, SMEs are also required to disclose their sustainability performance. The introduction of ESRS imposes comprehensive reporting obligations that involve analysing extensive quantitative and qualitative indicators across environmental, social, and governance dimensions [11], [20]. For SMEs with limited technical capabilities, this poses a significant challenge [35]. Conducting a structured sustainability assessment is a laborious job starting from the data collection and ending with the final sustainability disclosure. Traditional methods used unstructured key performance indicators (KPIs) and equal weights of the indicators. These approaches do not provide exact importance of each indicator for the strategic decision-making in order to achieve higher sustainability level [19], [20]. Moreover, manual implementation of methods such as the Analytic Hierarchy Process (AHP) becomes impractical when dealing with the large number of indicators included in ESRS.

Therefore, SMEs face a dual pressure i.e., increasing their sustainability performance as well as building resilient SCs. These challenges highlight the need for decision-support frameworks that are both analytically rigorous and operationally feasible. This thesis responds to this gap by proposing AI-enabled resilience frameworks, simulation-supported collaboration strategies, and an ESRS-AHP sustainability assessment system. All of these frameworks have been proposed in the context of SMEs i.e., keeping in view of their limited resources.

1.3 Research problem

Modern SCs, especially SMEs, face two parallel but distinct challenges. First, efficient decision-making frameworks for SC risk management in the face of increasing disruption frequencies. Existing resilience frameworks offer valuable insights but often assume the availability of redundancies, advanced technologies, or extensive datasets. However, SMEs cannot afford these resources. As a result, there is a need for resilience-oriented decision-support tools that are specifically adapted to the constraints and operational realities of SMEs.

Second, manufacturing organisations now face growing regulatory pressure to report their sustainability performance, especially with the introduction of the European Sustainability Reporting Standards (ESRS). These standards require organisations to assess a large set of environmental, social, and governance indicators, assign relative importance to them, and communicate performance transparently. Previous sustainability evaluation methods reveal several limitations. These limitations include the lack of standard set of sustainability indicators and ranking or weightage of these indicators. Moreover, previous studies lack in implementing an automated approach for the sustainability evaluation of the organizations. These gaps become a significant challenge for SMEs considering their limited resources.

1.4 Research aim and objectives

Aim: This thesis aims to help SMEs increase their resilience and sustainability by developing decision-making frameworks. To achieve the aim, this thesis sets following four objectives:

Objectives:

I. To review existing literature on SC resilience, collaboration, and the role of artificial intelligence in disruption management.

II. To investigate sustainability assessment methodologies and reporting frameworks, with a particular focus on manufacturing organizations.

III. To develop AI-based decision-making frameworks that enhances SC resilience for SMEs.

IV. To design a comprehensive sustainability assessment framework that provides strategic insights in improving sustainability performance.

1.5 Research questions

I. How can data-driven decision-support approaches improve supply chain resilience in small and medium-sized enterprises under conditions of high uncertainty and disruption?

II. How can collaborative decision-making mechanisms be evaluated and strengthened to support resilience and risk mitigation in SME supply chains?

III. How can manufacturing organisations develop a structured and transparent approach to sustainability performance assessment that aligns with emerging regulatory requirements?

IV. How can sustainability assessment frameworks be operationalised through digital systems to enable automation, consistency, and scalability in organisational decision-making?

1.6 Significance of the Study

This research is significant for both theory and practice as it addresses two critical SC domains i.e., resilience and sustainability for SMEs. In the area of resilience, the research is significant as it explores how AI and simulation can be integrated in decision-making for efficient risk management. The research also explores the integration of generative AI for scenario based risk identification which was lacking in traditional risk management techniques as they mostly relied on historic data.

In sustainability domain, the research introduces a structured sustainability assessment methodology by integrating ESRS and multi-criteria decision-making. This part of the thesis addresses the gap of existing approaches i.e., unstructured KPIs and equal weights. The digital implementation of this framework further contributes to practice by automating complex calculations and reducing manual errors.

Academically, this thesis contributes to ongoing discussions on AI-enabled decision support for risk management. It also contributes to resilience building in resource-constrained environments as well as quantitative sustainability assessment. Practically, it provides SMEs and policymakers with structured tools and methodologies that support decision-making to enhance resilience and sustainability.

1.7 Structure of the Thesis

The thesis consists of seven chapters. Chapter 1 of the thesis introduces a broader topic of the thesis and outlines the main research problems and highlights the significance of this research. Chapter 2 presents a comprehensive literature review covering SC resilience, SMEs collaboration, modelling and simulation, and sustainability problem. Chapter 3 develops a generative AI–enabled decision-making framework aimed at enhancing SC resilience for SMEs. Chapter 4 introduces a conceptual modelling and simulation supported collaboration framework that helps SMEs evaluate disruption scenarios and select suitable resilience-building strategies. Chapter 5 presents the ESRS-AHP integrated sustainability assessment framework including a real-world case study application. Chapter 6 details the digital implementation of the ESRS-AHP framework using MySQL including an automated sustainability-processing pipeline. Chapter 7 concludes the thesis by synthesising the key findings, limitations, and several directions for future research.

Chapter 2 LITERATURE REVIEW

This chapter reviews the current state of SC resilience and decision-making frameworks for SC risk management. The chapter also covers the role of collaboration in risk management especially for SMEs. The latter part of the chapter reviews existing sustainability assessment approaches and challenges. In this way, Chapter 2 fulfils first two objectives of the thesis.

2.1 Supply Chain Resilience

In the last ten years, SC resilience has become a growing field of research for SC disruption management. Special issues in the leading journals prove the growing research in this field. For example, International Journal of SC Management issued a special issue “New supply chain Models: Disruptive supply chain Strategies for 2030” in 2019. International Journal of Production Research (IJPR) also issued a special issue “supply chain dynamics, control and disruption management” in 2016 [36] [37]. These issues and the recent research highlight the importance of risk management in today’s turbulent business environment. Moreover, recent disruption events such as COVID-19, political conflicts, and terrorist attacks have exposed the vulnerability of the SCs. Globalization of the SC businesses have added to their complexity as disruption at one part of the SC impacts the whole SC [2], [38], [39], [40], [41].

SC resilience can be defined as its ability to adjust, react, and recover from any disruption while maintaining the normal operational efficiency. It requires planning ahead of the disruption and being prepared before the disruption by building redundancies. Flexibility also aids SC in adapting new operational environment during disruptions [42], [43], [44], [45], [46]. Disruption events are characterized by their intensity and impact [47]. These events can vary significantly in scope. For example, some events are global in nature such as the COVID-19 pandemic which caused widespread interruptions across supply networks. On the other hand, some events are localized such as labor-strike, fire, and political conflicts [48], [49], [50]. It is important to understand the scope of these disruption events in order to effectively mitigate them.

Despite the recent rise in SC resilience field the research still lacks in empirical findings. Organizations are still looking to assess the quantitative impact of [51]. Some studies explored the empirical impact of disruptions but these impacts depend on industry size and context. Although these empirical results aid as secondary source of data for further exploration but lack in broader applicability [4]. Over the years, researchers presented many review articles and theoretical contributions. These works focussed on various themes including risk mitigation methods and strategies to enhance resilience [52],[53]. Some of the articles focussed on rising role of artificial intelligence (AI) in supporting decision-making [54].

In the literature, several capabilities have been identified as a key to achieving resilience. Robustness is often described as a fundamental characteristic that allows SCs to withstand and absorb disruptions. On the other hand, adaptability enables them to transform and recover once disruptions occur. Flexibility and readiness also help organizations in coping with uncertainty and maintaining operational stability [55]. Robustness requires proactive redundancy planning, early risk identification, and preparing contingency plans [56]. On the contrary, adaptability focuses on dynamic responses to changing conditions. Adaptability allows firms to reconfigure operations in response to new challenges. Adaptability benefits in the long-term as it increases organization's responsiveness. However, there might be a short-term decrease in efficiency and extended recovery time [57].

General risk management procedure consists of four phases. These phases include risk identification, risk assessment, risk mitigation, and risk control [58]. The study [59] proposed a general framework for comparison and classification of different types of risks. According to the major literature, resilience strategies are generally classified in two categories including redundancy and responsiveness. Redundancy related strategies are generally preventive in nature and rely on bulk of resources. On the other hand, responsiveness includes flexibility through adaptation. However, combination of both of these approaches has proved to be more effective [60].

In recent years, scholars have increasingly employed quantitative modeling to analyze and enhance SC resilience [1], [40], [61], [62]. Several studies have found that the integration of both proactive and reactive strategies produces the most comprehensive and effective resilience frameworks [63], [64], [65], [66]. However, even with such progress, existing research still does not fully address all dimensions of SCR [56]. Some of the existing frameworks and conceptual models considered only SCR [67], [68]. Some others expand the analysis to include interrelated aspects such as sustainability [69], [70], [71], [72]. Few researchers explored the combination of agility and sustainability [73], or the trade-offs between resilience and efficiency [74], [75], [76]. Scholars also presented various theoretical approaches to enhance SC resilience including risk management frameworks, dynamic capability theory, and control mechanisms [69], [77], [78].

Recent literature highlights the positive impacts of integrating AI in SC risk management [24], [79]. AI has the ability to interpret and analyze large data sets and its sub-fields such as machine learning have the capability of learning from algorithms which can aid in more informed decision-making [80]. Moreover, it can detect anomalies in real-time data patterns which helps in early risk identification to supports informed decision-making [81]. These capabilities make AI applicable across different stages of the risk management process, including risk identification, mitigation, and control [82]. Generative AI can also be used to generate novel disruption scenarios instead of solely relying on historical datasets. Generative AI can be particularly effective during the risk identification and mitigation phases [83]. As a result, the integration of AI and SCR has become a growing research field that aims to provide data-driven solutions to support decision-makers [84].

As summarized in Table 1, the existing body of research demonstrates a steady evolution of SCR studies from conceptual development to advanced quantitative modeling. However, significant gaps remain, particularly in the integration of AI in decision-making for the risk management. These gaps provide motivation for the present research, which seeks to develop an AI-integrated decision-making framework aimed at enhancing SC resilience in SMEs.

Table 1. Summary of literature SC resilience

Theme	Key Insights	Research Gaps	References

Evolution of SCR research	Disruption management; preparedness; adaptability; proactive resilience	Limited SME-oriented frameworks; weak strategic integration	[36], [37], [2], [38], [39], [40], [41]
Nature of disruptions	Global vs. local disruptions; intensity; duration; ripple effects	No standard disruption taxonomy; cascading effects underexplored	[42], [43], [44], [45], [46] [47], [48], [49], [50]
Measurement & empirical challenges	Impact quantification; case-based evidence; context dependency	Lack of standardized metrics; limited longitudinal studies	[51], [4]
Resilience capabilities	Robustness; adaptability; flexibility; readiness	Trade-offs under resource constraints; cost–benefit imbalance	[55],[56], [57]
Risk management approaches	Risk identification; assessment; mitigation; control; redundancy vs. responsiveness	Lack of integrated, holistic models under uncertainty	[58], [59], [60]
Quantitative modeling	Simulation; optimization; proactive & reactive strategies	Limited human decision focus; weak inter-organizational modeling	[1], [40], [61], [62], [63], [64], [65], [66]
AI in SCR	Data-driven risk analysis; anomaly detection; scenario generation	Limited SME applications; poor integration into decision cycles	[24], [79], [83]

2.2 SMEs Collaboration

Collaboration has been defined as an approach in which organizations align their objectives, share resources, and cooperated for their common goals. Collaboration has proved to be an effective approach in increasing SC performance [85], [86], [87]. It allows organizations to enhance decision-making by sharing information under uncertainty. Collaboration is more important for SMEs considering their limited resources. It enhances both strategic as well as operational performance. Coordination is another closely linked concept with collaboration. Coordination facilitate joint response to disruptions and promotes synchronization of supply and demand. It helps in minimizing redundant resources and increasing profitability and competitiveness [88], [89].

Despite the proven benefits of coordination or collaboration, organizations still lack in maintaining their collaborative relationships. Various barriers related to organizational culture and structure hinder effective collaboration. Literature categorizes these barriers into four primary groups [90], [91]. The first and perhaps most persistent category includes information-related barriers. Organizations hesitate to share sensitive information with their partners which hinders joint contingency planning. Effective information sharing can help in mutual problem-solving and trust building [92].

The second barrier is related to communication, reasons for this barrier includes lack of necessary infrastructure to process consistent communication with SC partners. Most of the SMEs are equipped with outdated communication tools which makes it difficult to exchange data. Poor communication not only disrupts operational synchronization but also leads to trust issues [93] . Over time, this communication gap amplifies other challenges such as uncertainty in forecasting which weaken the resilience of the SC.

The third barrier is related to the internal dynamics of the organization and referred as intra-organizational barrier. This results from the weak relationships within the SC departments, strict hierarchy, and resistance to change. Some organizational cultures discourage knowledge sharing and innovation. Hierarchy may also resist in adopting new technologies by considering them as a disruption to the established routines. These internal challenges hinder effective collaboration with external SC partners. The fourth and final barrier pertains to inter-organizational relationships which involve weak or unstable connections between different SC partners. This barriers comes from the lack of trust and limited commitment to long term partnerships [94], [95]. For the organizations working in different territorial regions some other barriers such as regulatory frameworks and difference in cultural values also hinder collaboration. In addition, short-term contractual relationships also discourage investment in deeper partnerships and knowledge sharing. However, organizations can overcome these challenges by investing in clear communication channels and technology.

SMEs should also accept that not all organizations have the equal resources and communication capabilities, therefore, they must be flexible in collaboration [96]. Collaborative frameworks should therefore be designed to accommodate varying capabilities while ensuring that mutual goals remain aligned. Ultimately, overcoming these barriers enables SMEs to strengthen their resilience and enhance their capacity to respond effectively.

2.3 Modeling & Simulation as a tool for SC risk management

As mentioned in the previous section, research shows that collaborative practices increases SCs performance and efficiency [97]. Therefore, organizations should visualize potential impact of their chosen collaboration strategy and quantify its impact on organizational performance. Modeling and simulation techniques offer significant benefits by enabling managers and researchers to replicate and analyze real-world SC systems [98]. These methods provide a virtual environment in which complex interactions can be visualized and tested without disturbing the actual system [99]. Organizations can conduct "what-if" analyses to predict the effects of different disruption events with these visual representations. This helps managers evaluate potential outcomes, compare alternative strategies, and make informed decision-making [100].

Over the past two decades, modeling and simulation have become essential tools in SC risk management research. Numerous studies emphasize the value of M&S for quantifying disruption impacts and evaluating the effectiveness of resilience strategies. For example, the study [101] utilized simulation to assess the consequences of cybersecurity disruptions on physical infrastructure. Another study [102] used micro-agent simulation to analyse transport-related disturbances, illustrating how system-wide dependencies influence performance outcomes during disruption events. M&S supported decision-makers in developing risk mitigation policies and maintaining operational continuity during crises [103]. Furthermore, several specialized software tools have been developed to facilitate M&S in SC contexts. Among these, *AnyLogistix* has gained widespread acceptance due to its ability to model complex SC structures [104], [105], [106], [107]. Other simulation platforms, such as Arena, Simio, and FlexSim, are also used to evaluate network performance, assess demand variability, and identify bottlenecks [108], [109], [110], [111]. These tools assist managers in visualizing trade-offs between efficiency and resilience, thereby improving long-term strategic planning.

Table 2 show the summary of literature review. It highlights the benefits of collaboration as well as M&S tools for risk management. However, the literature reveals limited integration between these two areas. Most existing studies address collaboration and modeling separately, leaving a gap in frameworks that combine real-time simulation and data sharing. Addressing these limitations, this thesis aims to integrate collaborative mechanisms with modeling and simulation tools to enhance the resilience and decision-making capability of SME SCs.

Table 2. Summary of literature collaboration and M&S

Theme	Key Insights	Research Gaps	References
SME collaboration & coordination	Goal alignment; resource sharing; joint risk management; performance improvement	Sustainability of collaboration under resource constraints	[85], [86], [88], [89]
Information-related barriers	Limited transparency; data-sharing reluctance; trust deficits	Secure data exchange mechanisms; standardized platforms	[90], [91], [92]

Communication-related barriers	Fragmented systems; outdated tools; weak real-time interaction	Digital communication infrastructure for SMEs	[93]
Intra-organizational barriers	Resistance to change; weak internal coordination; rigid structures	Organizational readiness; collaborative culture development	[90], [91]
Inter-organizational barriers	Low trust; short-term partnerships; cultural differences	Trust-building frameworks; long-term collaboration models	[94], [95]
Collaboration improvement strategies	Training; digital platforms; communication protocols	Limited SME adoption; lack of implementation evidence	[96]
M&S in supply chain management	Scenario testing; disruption analysis; virtual experimentation	Integration with real-time decision systems	[87], [98], [99]
M&S in risk assessment	KPI impact analysis; proactive & reactive strategy evaluation	SME-scalable, industry-validated models	[101], [102], [103]
M&S software tools	AnyLogistix; Arena; Simio; FlexSim	Limited benchmarking for SME applications	[104], [105], [106], [107]
Collaboration–M&S linkage	Joint risk evaluation; strategy testing; network resilience	Lack of AI–M&S–collaboration integration	[87], [97]

2.4 Manufacturing sustainability

An extensive literature review has been performed in this section which highlights the previous efforts made in the manufacturing sustainability assessment. The following sub-sections will encompass the past multi-criteria decision-making approaches and set of indicators that have been used by the researchers.

Sustainability has been one of the most frequently discussed and evolving concepts in both academic research and industrial practice over the past few decades. The literature reflects a wide range of interpretations of the term, each emphasizing different priorities depending on disciplinary perspectives and contextual applications. Some authors consider sustainability only an environmental initiative to reduce ecological degradation and responsible use of resources. Others consider it as a more holistic approach under three dimensions i.e., environment, economy, and society [112]. The study [113] defined sustainable manufacturing as "Sustainable manufacturing is a new paradigm in which manufacturing industries produce products in a sustainable manner while maintaining global competitiveness and coping with recent challenges and problems." This definition emphasizes that sustainability in manufacturing enables firms to remain competitive while minimizing their negative environmental and social footprints. The first step to make strategic decision to enhance sustainability performance is to assess current sustainability performance of the organization. It helps organizations to identify weak areas of sustainability performance.

A considerable body of research has explored various methods for assessing the sustainability performance of organizations. During the early 2000s, German companies pioneered the use of sustainability indices, surveys, metrics, and accreditation processes to evaluate their sustainability performance [114]. Over time, the development of quantitative and semi-quantitative tools has allowed for more structured and objective evaluations. The study [115] applied a fuzzy logic-based approach to assess the sustainability performance of a Saudi manufacturing organization. Similarly, the study [19] proposed an index-based sustainability assessment model at both the production line and plant levels. Another study [13] employed the distance-to-target method which calculates the difference of actual performance from predefined sustainability targets. In a related study, [14] introduced a matrix-evaluation approach to compare the sustainability level of manufacturing organizations before and after implementing alternatives. Further, [116] developed a composite sustainability index for assessing corporate sustainability performance. All of the approaches discussed show the gradual transformation of sustainability assessment from simple descriptive metrics to analytical systems. However, sustainability assessment still faces challenges in terms of its standardisation across industries.

A critical component of sustainability assessment involves defining key performance indicators (KPIs) that enable organizations to measure their performance systematically. In the context of sustainable manufacturing KPIs serve as quantifiable metrics under three dimensions. The literature indicates that economic and environmental indicators have been extensively studied and standardized. However, the social dimension has received relatively less attention due to their qualitative nature. For instance, [117] categorized 23 sustainability indicators within the framework of the triple bottom line (TBL) i.e., economic, environmental, and social aspects for evaluating the performance of the automotive manufacturing sector. In contrast, [118] used only 19 indicators. These differences underline the absence of a standardized indicator set as sustainability objectives tend to vary based on industry characteristics, stakeholder priorities, and regional regulations. However, European Sustainability Reporting Standards (ESRS) framework provides an opportunity to address these limitations by providing a structured set of guidelines under three dimensions i.e., environmental, social, and governance [119].

Among the various decision-making tools used in sustainability assessment, the Analytical Hierarchy Process (AHP) has emerged as one of the most widely applied multi-criteria decision-making (MCDM) methods. AHP [120] provides a structured and systematic framework for evaluating complex problems involving multiple, and often overlapping criteria. The approach starts with a hierarchical structure that decomposing a complex decision problem into smaller and more manageable components. It also accommodates both qualitative and quantitative factors, which makes it particularly suitable for sustainability evaluation. The logical consistency of AHP have led to its adoption across diverse domains, including engineering, economics, and policy analysis [121].

The study [122] applied AHP for employee selection, incorporating multiple evaluation criteria to ensure objective decision outcomes. Similarly, [123] employed AHP to determine the optimal hydropower development scale in Nepal, aiding strategic decision-making in infrastructure planning. The methodology has also been used in software selection and prioritization, where complex trade-offs between technical and economic factors must be managed efficiently [124]. In industrial and manufacturing contexts, [125] utilized AHP for supplier selection, allowing firms to assess potential partners based on cost, quality, and environmental performance. AHP has proven to be an effective decision-support tool in sustainability assessment by assisting organizations in prioritizing sustainability indicators for performance improvement [8], [126]. These applications illustrate the method's adaptability and robustness, particularly when used to support complex sustainability evaluations that span multiple organizational dimensions.

Although AHP has been widely used in multi-criteria decision-making, its implementation becomes increasingly complex when applied to large-scale frameworks such as ESRS. The traditional AHP method requires numerous pairwise comparisons among indicators, which can become time-consuming especially when the indicator set is extensive [121]. Most of the existing studies have employed AHP in contexts where the number of indicators was relatively small [117], [118]. Consequently, there remains a significant research gap in the literature regarding the application of AHP within large, structured frameworks like ESRS. This thesis addresses both of these gaps by developing a structured sustainability assessment method through the integration of ESRS and AHP and its automation.

Chapter 3 AI- based decision making framework to enhance SC resilience

This chapter builds on the author's peer-reviewed publication [127] " Supply chain resilience in SMEs: integration of generative AI in decision-making framework. In 2024 International Conference on Machine Intelligence and Smart Innovation (ICMISI) (pp. 295-299). IEEE" and answers first research question of the thesis; How can data-driven decision-support approaches improve supply chain resilience in small and medium-sized enterprises under conditions of high uncertainty and disruption?

3.1 Introduction and Background

As mentioned in Chapter 1, SC resilience (SCR) is the SC's ability to anticipate, absorb, and recover from disruptions while maintaining an acceptable operational performance. However, small and medium sized enterprises (SMEs) have limited technical and financial resources. Therefore, these disruptions have a greater impact on SMEs' performance. Due to their limited resources, traditional risk management approaches such as building redundancies and static decision making do not provide expected outcomes for SMEs. Therefore, SC managers are still looking for real-time decision making frameworks to identify, evaluate, and mitigate disruption risks in today's volatile environment.

Recently, artificial intelligence (AI) and its sub-fields have emerged as powerful tools to analyze and interpret large data sets. These capabilities of AI can be used for an accelerated and more informed decision-making. Moreover, generative AI has the capability of learning from historical data and creating novel disruption scenarios. Contrary to many predictive models, which provide predictions based on historical data sets, generative AI can create new future disruption scenarios and candidate response options. Integrating these capabilities with decision-making framework enables testing of 'what-if' scenarios and helps in choosing optimum risk mitigation strategies.

Based on these developments, this chapter presents AI-integrated decision-making framework to increase SC resilience for SMEs. The proposed framework integrates AI's capabilities at different stages of decision-making. Starting from the initial stage of the framework, AI-generated novel scenarios aid in risk identification. Later, the decision-making framework can get insights from AI in order to trigger optimal mitigation strategies. The AI integrated framework aims to speed up the decision-making process by identifying, analysing, and evaluating optimal mitigation strategies to overcome disruption risks and to achieve the objective of SC resilience. The framework provides a practical tool for SMEs to achieve resiliency for their SCs.

The remainder of this chapter is structured as follows. Section 3.2 introduces the proposed AI-integrated decision-making framework and explains its main components and operational logic. Section 3.3 discusses the theoretical and practical implications of the framework, highlighting its contribution to SC resilience theory and its relevance for SMEs. Finally, Section 3.4 provides a summary of the chapter and outlines how the findings presented here connect to the next chapter, which focuses on modeling, simulation, and collaborative frameworks for resilience enhancement.

3.2 AI-Integrated Decision-Making Framework

SMEs face challenges in achieving resilience for their SCs. Despite having a major contribution to the economy scholarly work is limited in guiding SME to achieve resilience [128]. These organizations cannot build excessive inventories due to their limited resources. Hence, they are severely impacted by increasing low-frequency and high-impact disruptions. These organizations need well-structured decision-making frameworks to efficiently navigate in the disruption events. The proposed decision-making framework is shown in Figure 1.

AI integrated decision-making framework is an integration of generative AI at different stages of the decision-making framework. The proposed framework aims to identify optimum proactive strategy to build SCR by minimizing the effects of potential SC disruptions. Proposed framework adheres to the standard risk management procedures followed in the literature which entails, risk identification and assessment, risk mitigation, risk monitoring, and control [129].

The framework starts with integration of generative-AI in the first step, named as risk identification. Generative AI has the capability to generate various scenarios based on large data [83]. Both internal and external factors contribute to potential risks for SCs [130]. Generative-AI uses three input data sets to generate novel disruption scenarios. First data set is related to internal risks associated with design of the organization and its structure. Second data set comprises of external factors such as geographic and political conditions of the SC partners, environmental factors, and regulations. Historic data regarding disruptions and environmental conditions also aids generative-AI to create more possible disruption scenarios.

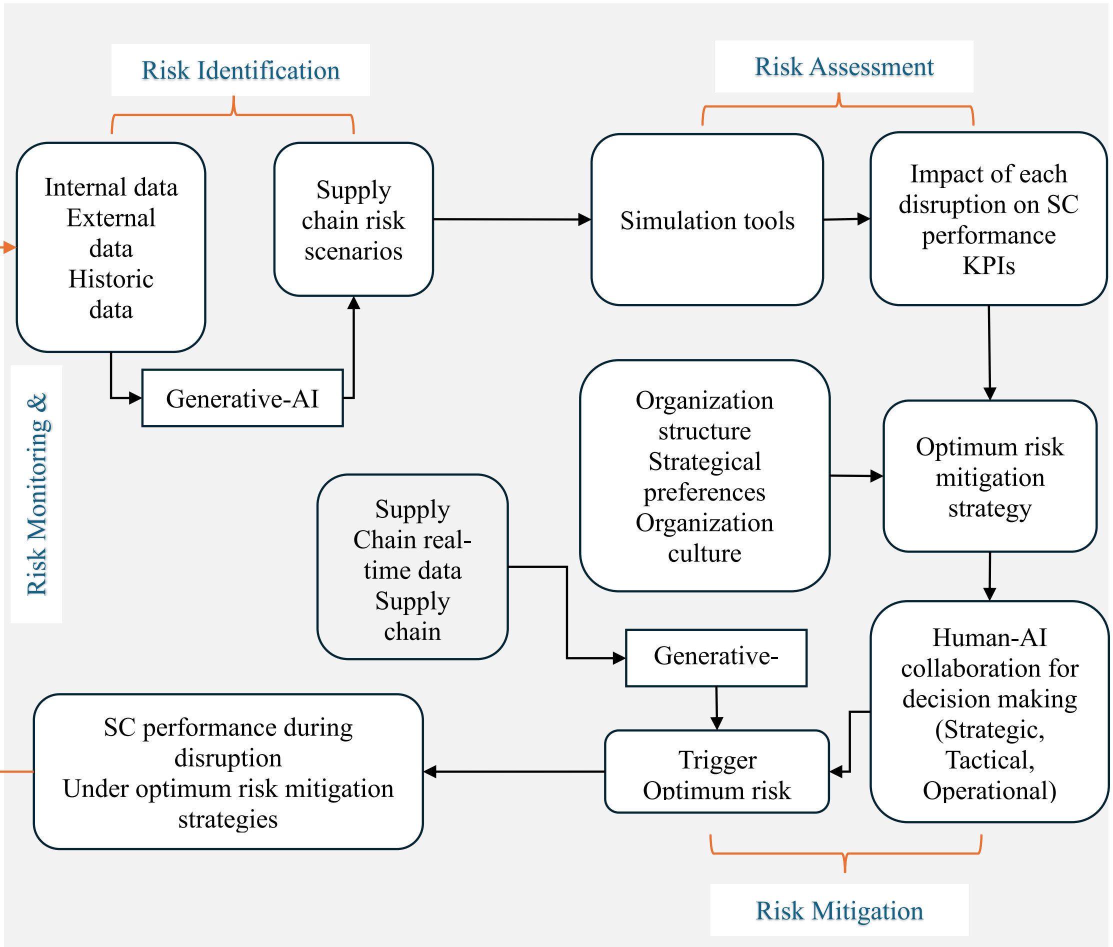

Figure 1. AI-integrated Decision-making framework

Following the detailed risk identification process, we quantify impact of each disruption scenario on SC performance with respect to cost, lead time, and service level. Simulation and optimization software AnyLogistix has been used for this cause [131]. Evaluating the best mitigation strategy is also beneficial. The organization's structure, strategic preferences, and culture all influence the best risk mitigation strategy. By offering visuals and empirical results for the chosen risk mitigation strategies, simulation and optimization tools eliminate the need for guesswork.

Based on this step's results, frameworks explore its most crucial component i.e., making decisions. The proposed framework suggests using human-AI cooperation to make tactical and strategic choices. In the event of a disruption, these choices serve as a guide for making daily operational decisions. Businesses become proactive in the event of a disruption and expedite the decision-making process, ultimately reducing the impact of the disruption, by having potential disruption scenarios and mitigation strategies against each disruption.

Next vital stage is the triggering of risk mitigation strategies at optimum time in case of disruption strike. AI with its capability of reasoning and learning can support timely trigger of risk mitigation strategies [132]. Or it can provide insights to the decision-makers who lack in this expertise. It requires end-to-end SC visibility with real time data in order to employ AI in this stage. Overall, the framework proposes human-AI collaboration for the selection of the final strategy. The last stage involves the assessment of SC's performance with respect to resilience. AI's capability to detect irregularities in data is utilized in risk monitoring and control. It can provide novel risk identification scenarios based on real time data. The framework provides practical guide for SMEs to tackle disruptions and enhance SCR.

3.3 Theoretical and practical implications

The proposed framework contributes in the growing literature of SC resilience management. Firstly, the integration of AI in decision-making treats resilience as a continuous learning process rather than a fixed set of capabilities. This framework aligns with the dynamic capability theory, which is defined by organizational ability to sense, seize and reconfigure in response to changes [133], [134]. In the sensing phase, generative AI helps in early risk identification by generating novel disruption scenarios. The seizing phase aligns with the risk mitigation phase where generative AI provides optimum risk mitigation strategy by comparing alternative strategies. The feedback loop of the proposed framework contributes towards the reconfiguration phase by continuous learning.

The proposed framework also contributes to risk management theory by embedding generative AI within the standard risk management cycle i.e., identification, mitigation, monitoring, and control. Previous frameworks heavily relied on the historic data for the potential risk identification. The use of generative AI allows the system to explore a broader number of potential disruption scenarios, including those not previously observed. In this way, organization's approach changes from risk prediction to risk exploration.

From a managerial perspective, the framework offers a practical tool that helps SMEs enhance resilience despite their limited resources. It allows SMEs to adopt AI gradually, organizations can start from the generation of risk scenarios and later extend it to risk mitigation and risk control stages. The framework also accelerates decision-making by early risk identification and prioritization of risk mitigation strategies. The integration of feedback loops allows SMEs to capture knowledge from each disruption event and embed it into future planning.

Lastly, the framework advances the digital transformation agenda for SMEs. Implementing AI-based tools encourages digitization of processes, and integration of real-time information systems. These technological advancements extend benefits beyond resilience, improving operational efficiency and enabling alignment with broader sustainability and Industry 4.0 objectives.

3.4 Chapter Summary

This chapter presented an AI–integrated decision-making framework aimed at enhancing SC resilience (SCR) in small and medium-sized enterprises (SMEs). The framework was developed to offer a structured, data-driven approach to disruption management. By embedding generative AI across the traditional risk management stages, the model enables dynamic and adaptive decision-making under uncertainty.

While this chapter focused on individual firm-level decision-making, chapter 4 extends the discussion to network-level collaboration among SMEs. Chapter 4 introduces a complementary framework that integrates modeling, simulation, and AI to support decision-making and joint risk mitigation strategies.

Chapter 4 Modeling & Simulation and AI for Collaborative Framework

This chapter builds on my co-authored peer-reviewed publication [135] “Use of Modeling & Simulation and AI for Collaborative Framework: SMEs SC Disruptions. In *New Trends in Intelligent Software Methodologies, Tools and Techniques* (pp. 392-397). IOS Press.” And answers second research question : How can collaborative decision-making mechanisms be evaluated and strengthened to support resilience and risk mitigation in SME supply chains?

4.1 Introduction and Background

As mentioned in Chapter 1, SMEs have limited financial and technical resources to navigate during disruption events. Therefore, collaboration and resource sharing are a one way to effectively navigate during turbulent times. SMEs can work in partnership by sharing information and making joint contingency plans for effective risk mitigation despite their limited resources. However, effective collaboration is hindered by various barriers such as lack of trust and weak communication. That is why SMEs are looking for structured and data-driven frameworks for impactful collaboration.

In this regard, modeling and simulation (M&S) with its ability of replicating real-world systems, provides an opportunity for decision-makers. They can perform ‘what-if’ analysis before choosing the effective collaboration strategy. Decision-makers can visualize the impact of disruption as well as collaboration strategy before their real-world implementation. Moreover, AI with its ability of analysing large data sets can provide prescriptive insights and aid in choosing best collaboration strategies.

Therefore, this chapter introduces a framework for how modeling simulation and artificial intelligence can aid in collaboration to support SMEs in risk mitigation. The proposed framework guides SMEs for effective collaboration by resource sharing, creating contingency plans, and building resilience. It identifies key benefits of collaboration for SMEs and different strategies that SMEs can use to mitigate the disruptions due to environmental issues. The proposed framework contributes to both the theoretical understanding and practical implementation of collaboration for resilience in SME networks.

The remainder of this chapter is structured as follows. Section 4.2 details the proposed collaborative framework, explaining how modeling and AI tools are integrated to facilitate decision-making and coordination among SMEs. Section 4.3 discusses the theoretical and practical implications of the framework, highlighting its contribution to SC collaboration and resilience theory. Finally, Section 4.4 summarizes the chapter and outlines its connection to the subsequent discussion on sustainability assessment presented in Chapter 5.

4.2 Conceptual framework

SMEs have limited resources to negotiate in the face of escalating disruptions and are more vulnerable to SC disruptions. SMEs are more susceptible to environmental disruptions because they are less established than large organizations. To support the cause, this chapter offers a conceptual framework (Figure 2) that looks at how artificial intelligence and modeling simulation can work together to help SMEs lessen the operational effects of environmental SC disruptions. Climate change, resource scarcity, and natural disasters are the three primary environmental disruptions that can affect SMEs, according to the framework's analysis of the literature. For SME SCs, these disruptions have detrimental operational effects like longer lead times, higher expenses, and decreased revenue.

The framework starts with identifying different disruption scenarios for the SC. The identification of disruption scenarios is the most critical stage of this framework as it leads to the quantification of the disruption impact. The prior identification of potential disruptions provokes proactive approaches among decision-makers. We use generative AI for risk identification. Generative AI has the capability of generating new risk scenarios based on large data. This large data is comprised of both internal and external data of the SC. Organizational structure and SC design are the key components of this phase of the framework due to the risks associated with them. In addition to these data sets, historical data has also been used as input to generative AI for the creation of novel disruption scenarios.

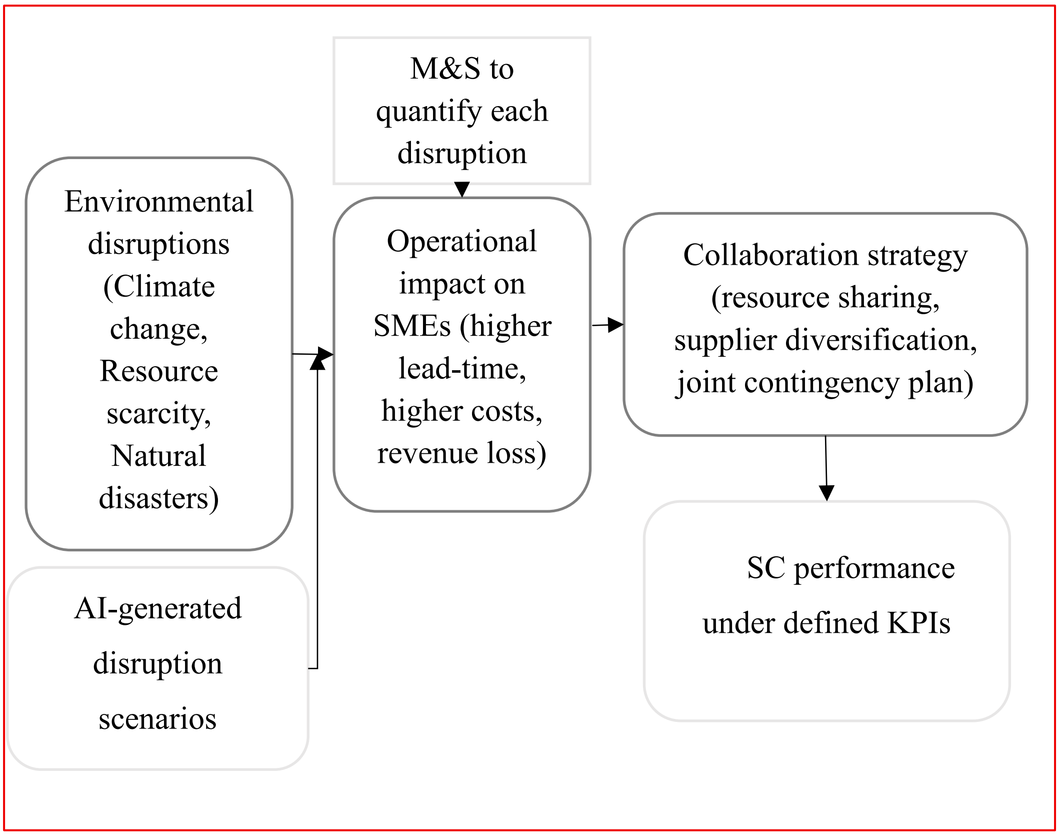

Figure 2. Collaboration Framework

The second phase of the framework involves the assessment and quantification of the operational impacts of each scenario on the SME SC. For example, possible disruption may lead to partial or complete unavailability of one or multiple nodes of the SC. Which can result in increased lead time, higher costs, and decreased revenue. Simulation software Anylogistix has been utilized for the assessment of risk associated with each disruption scenario. Based on the assessment of potential disruptions to the SC, organizations may choose a feasible collaboration strategy against each risk scope. Selection of collaboration strategy depends on organizational culture, its preference, and organizational structure. Organizations can opt for resource sharing among SC partners in order to navigate in turbulent times, or may diversify their suppliers, can build joint contingency plans to mitigate potential disruptions [136], [137]. Employment of simulation eliminates guesswork and managers can already visualize the impact of their selected strategy on the performance of SC. Lastly, the framework evaluates how the chosen collaboration strategy affects SC performance using predetermined KPIs. Proactive disruption management is the result of the suggested framework. For every possible disruption, the SC managers can create more effective backup plans. The conceptual framework seeks to reduce the amount of time needed to make decisions during disruptive events.

4.3 Theoretical and practical implications

The proposed framework contributes both theoretically and practically to the growing literature of risk mitigation frameworks. Theoretically, this framework presents collaboration as a key approach for SMEs to navigate during environmental disruptions considering their limitations in terms of building redundancies. Traditional risk management approaches are often insufficient for SMEs, which operate in partnerships where the risk mitigation capability of one partner directly influences the others. The framework extends the scope of resilience from individual firms to the inter-organizational level.

In addition, the framework offers a theoretical extension to collaborative decision-making and AI integration in SC contexts. Previous studies have highlighted the role of AI in predictive analytics and optimization. This study extends that integration by using AI capabilities for the mutual decision-making among multiple SC partners.

The proposed framework also provides three managerial implications. The first managerial implication includes the integration of M&S as a risk quantification tool. Through simulation, managers can view the potential ripple effects of disruptions and identify the most vulnerable nodes. Moreover, M&S results guides SC managers to select the best possible strategy to minimize operational impacts of disruption. Secondly, it offers a structured approach for the collaboration strategy selection by quantifying the impact of each strategy. For example, simulation results may reveal that shared warehousing or pooled logistics yield better performance under specific disruption scenarios than unilateral strategies. Thirdly, the integration of AI-driven scenario generation speeds up the decision-making process.

4.4 Chapter Summary

The chapter presented a collaborative framework for the SMEs to maintain their operational performance during the environmental disruptions. The framework integrated AI for the disruption scenario generation and M&S for the quantification of disruption impact as well as risk mitigation strategy. Overall, the proposed framework provided a practical tool for SMEs to accelerate the decision-making process during turbulent times.

The previous chapters (chapter 3 & 4) focused on resilience and collaboration as mechanisms for disruption management. The next Chapter 5 discusses another challenge faced by SMEs i.e., compliance with sustainability regulations. It introduces a comprehensive sustainability assessment framework aligned with the European Sustainability Reporting Standards (ESRS) using multi-criteria decision-making. This transition reflects the thesis's broader objective of addressing resilience, collaboration, and sustainability for strategic decision-making in SMEs.

Chapter 5 ESRS-AHP integrated Sustainability Assessment Framework for Manufacturing Organisations

This chapter builds on the author's peer-reviewed publication [138] "Development of a European Sustainability Reporting Standards Compliant Sustainability Assessment Framework for Manufacturing Organisations Using Analytic Hierarchy Process. *Sustainability*, *17*(11), 4772." and directly answers the third research question i.e., How can manufacturing organisations develop a structured and transparent approach to sustainability performance assessment that aligns with emerging regulatory requirements?

5.1 Introduction and Background

As mentioned in Chapter 1, sustainability has become a significant challenge for manufacturing organizations. Although manufacturing industries are backbones of each economy but their activities have great impacts on natural resources and environmental pollution. Worldwide changing regulations and customer preferences have also compelled manufacturers to be more socially responsible. Therefore, manufacturing organizations are looking to adopt more sustainable practices to minimize their impact on three sustainability dimensions i.e., environment, society, and governance. In Europe, this transformation has been accelerated by the introduction of the European Sustainability Reporting Standards (ESRS), which establish a comprehensive and mandatory framework for environmental, social, and governance (ESG) disclosure.

According to ESRS, organizations have to disclose their current sustainability performance along with their strategic goals in improving sustainability performance. Assessing current sustainability performance is a primary step in achieving strategic sustainability goals. Because assessment of current sustainability performance provides insight into key areas of improvement. Therefore, organizations are looking structured sustainability assessment frameworks not only to disclose their sustainability level but also to make better strategic decisions. The ESRS include a large number of qualitative and quantitative indicators under

ESG which makes assessment procedure a complex task. Therefore, a systematic approach is needed to evaluate sustainability performance in a manner consistent with ESRS guidelines.

In this regard, this chapter aims to develop a sustainability assessment framework for the manufacturing organizations which is in line with ESRS. The key aspect of this framework includes the integration of ESRS guidelines with multi-criteria decision-making to rank the importance of the indicators. This study used analytical hierarchy process (AHP) for multi-criteria decision-making in ranking the importance of different overlapping elements. This combination of AHP and ESRS provides a standard sustainability assessment framework for the manufacturing organizations. Based on the insights provided by this framework, the organizations can identify their areas of improvement and make strategic decisions for the sustainability improvement.

The remainder of this chapter is organised into five main sections. Section 5.2 provides a methodological foundation of the proposed framework. Section 5.3 introduces the proposed ESRS–AHP sustainability assessment framework, outlining its conceptual foundations and explaining how the ESRS structure is integrated with multi-criteria decision-making. Section 5.4 presents a case study by applying the framework to a real manufacturing organisation. Section 5.5 shows the resulting sustainability scores and performs the robustness check. Section 5.6 provides in-depth discussion of the key findings. Finally, Section 5.7 summarises the chapter and establishes a transition toward the digital implementation of the framework, which is addressed in the subsequent Chapter 6.

5.2 Methodological foundation

It is important to understand the current sustainability regulations and sustainability evaluation methods before developing a comprehensive sustainability framework. Therefore, this section discusses two key components that provide the foundation of the proposed framework. In the first part, the research examine the sustainability regulations in EU i.e., European Sustainability Reporting Standards (ESRS). In the second part, we evaluate the role of multi-criteria decision-making approaches specifically analytical hierarchy process (AHP) in prioritizing the sustainability indicators. Integration of these elements establish the theoretical and practical basis for the ESRS-AHP sustainability assessment framework.

The ESRS were developed by the European Financial Reporting Advisory Group (EFRAG) and approved by the European Commission to create a unified and mandatory framework for sustainability reporting across EU. These standards apply to both large and SMEs, reflecting the European Union's broader objective of achieving climate neutrality by 2050 [20]. ESRS are designed to enhance transparency, accountability, and comparability of sustainability disclosures among organizations. This approach aligns ESRS with the goals of European Green Deal [139]. Their primary objective is to ensure that environmental, social, and governance (ESG) considerations are fully integrated into corporate strategy and decision-making. This integration shifts organizations from conventional profit-based models towards more sustainable practices. These shifts guide organizations to assess their ESG impacts and look for the opportunities for sustainability improvement as well as address challenges such as climate change and resource depletion.

In addition to setting reporting requirements, the ESRS also strengthen the credibility and comparability of sustainability information across industries. ESRS provides harmonized metrics that facilitate compliance with EU regulations and stakeholders to access reliable and comparable data. This harmonization supports informed decision-making and enhances the integration of sustainability into financial and strategic planning.

Among international sustainability frameworks, ESRS share several similarities with the Global Reporting Initiative (GRI) in terms of principles and indicator structure [140]. However, ESRS have been structured solely in EU context as a mandatory legal requirement. It has been developed in collaboration with diverse EU stakeholders, industry representatives, and non-governmental organizations. On the other hand, GRI considers reporting as a volunteer activity and scopes around the globe.

The ESRS framework covers both measurable and non-measurable KPIs and requires organizations to report on existing performance as well as future objectives and strategies for the short, medium, and long term. The structure of ESRS is organized into four main categories: General, Environmental, Social, and Governance [119]. Figure 3 shows the overall ESRS structure under these dimensions. A brief description of each dimension and its subfields is explained below.

The General category includes the generic disclosures and requirements applicable to all organizations. Therefore, this study focuses on three dimensions i.e., environment, social, and governance. The Environmental category is subdivided into five topics: climate change (E1), pollution (E2), water and marine resources (E3), biodiversity and ecosystems (E4), and resource use and circular economy (E5). The Social dimension comprises of four sub-topics: own workforce (S1), workers in the value chain (S2), affected communities (S3), and consumers and end users (S4). The Governance category focuses on business conduct (G1), addressing issues such as ethics, corporate culture, and compliance.

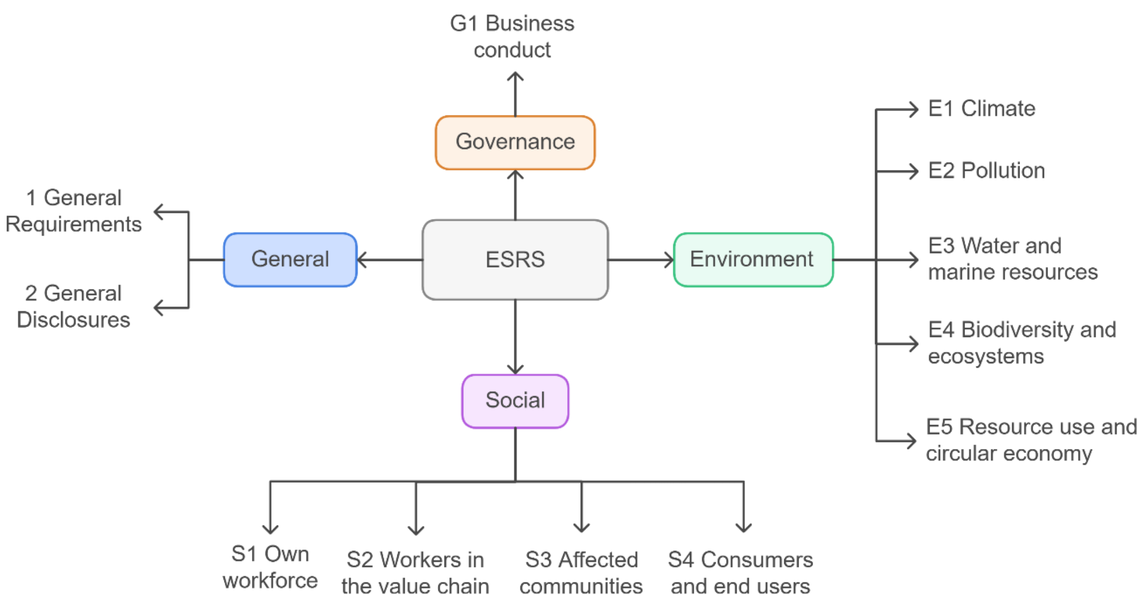

Figure 3. ESRS structure [119]

The ESRS structure is further subdivided into sub-topics and sub-sub-topics or indicators in order to apply AHP, which is based on hierarchical structure. The five subtopics (E1–E5) that make up the environmental dimension are further broken down into 43 KPIs that cover topics like waste reduction, water management, pollution, and greenhouse gas emissions [141]. The social dimension includes four sub-topics (S1–S4) and 21 sub-indicators focusing on labor conditions, human rights, community relations, and consumer welfare. The governance dimension contains one subtopic and four indicators, covering ethical behavior, anti-corruption, and whistleblower protection. Altogether, the ESRS framework incorporates ten sub-topics and 68 indicators, offering a comprehensive structure for sustainability assessment. Table 3 summarizes this hierarchical breakdown.

Table 3. ESRS sustainability structure

ESRS dimensions	Sub-topics	Number of indicators
Environmental information	Climate change (E1)	18
	Pollution (E2)	06
	Water and marine resources (E3)	03
	Biodiversity and ecosystems (E4)	04
	Resource usage and circular economy (E5)	12
Social information	Own workforce (S1)	12
	Workers in value chain (S2)	03
	Affected communities (S3)	03

	Consumers and end users (S4)	03
Governance	Business conduct (G1)	04
	Total indicators	**68**

The Analytical Hierarchy Process (AHP) complements the ESRS by providing a systematic method to assign weights and priorities to the sustainability indicators. Developed by Thomas Saaty [120], AHP organizes complex decision problems into a hierarchical structure, enabling decision-makers to compare criteria pairwise [142]. This approach is particularly valuable when trade-offs are required, such as balancing economic gains with environmental protection or short-term financial performance with long-term sustainability. Figure 4 shows hierarchical framework structure of ESRS. For one subtopic, resource use and circular economy (E5), Figure 5 illustrates the establishment of a hierarchical structure from the goal to the indicator level.

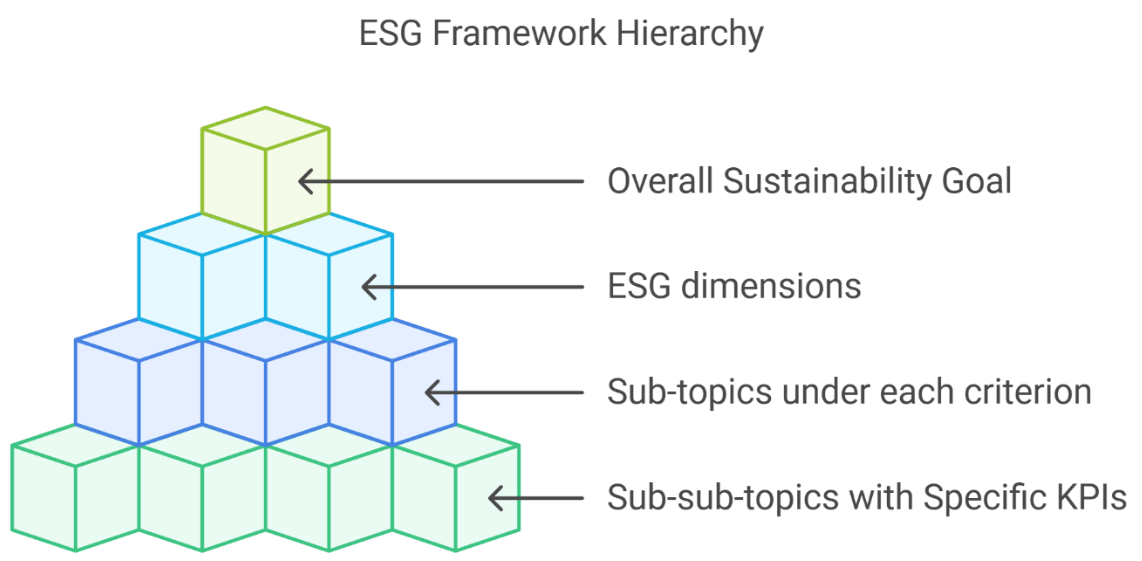

Figure 4. ESG framework hierarchy

AHP has risen as a key approach for incorporating sustainability principles into business strategies in recent years, especially in environmental, social, and governance analyses [143]. It supports comprehensive evaluation by allowing both quantitative data and qualitative judgments to be incorporated into a single analytical framework. Previous studies have applied AHP to a wide range of sustainability-related decisions including prioritizing renewable energy solutions by considering criteria such as cost, efficiency, and environmental impacts [144]. Similarly, [145] employed AHP to evaluate circular economy initiatives aimed at improving resource efficiency and minimizing waste. Other researchers have combined quantitative metrics and qualitative assessments to use AHP to evaluate suppliers' sustainability [146].

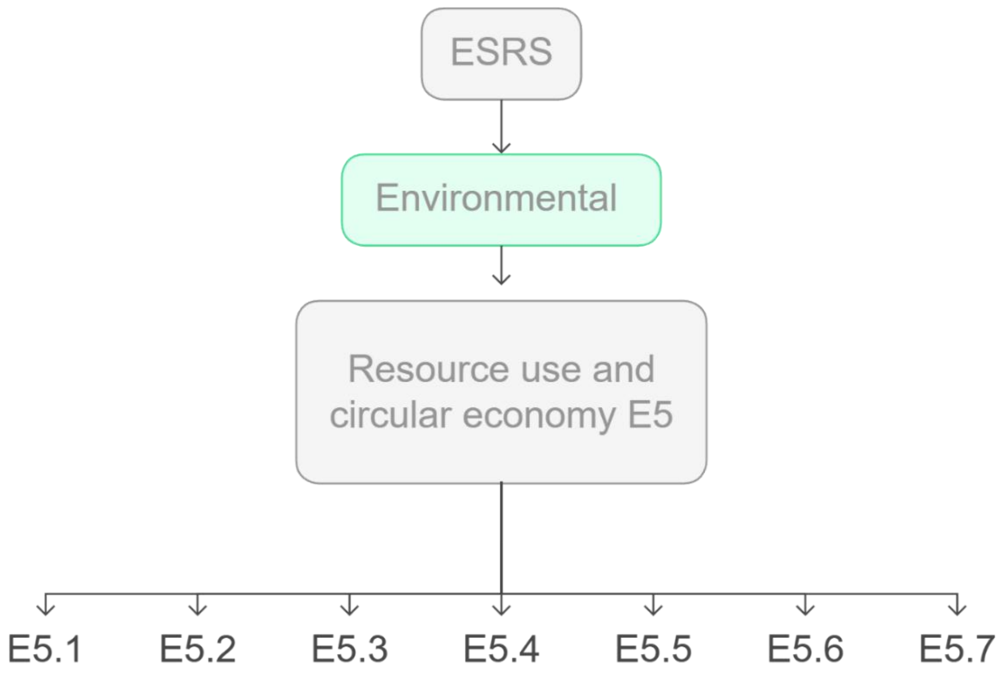

Figure 5. Example hierarchical structure for subtopic E5

Despite its advantages, AHP is not without limitations. The approach depends on expert judgments, which can introduce subjectivity and potential inconsistencies. When the number of indicators increases, the number of pairwise comparisons grows rapidly, making the process time-consuming and difficult to manage. Recent studies have attempted to address these challenges by integrating fuzzy logic and other uncertainty-handling techniques into AHP to enhance the reliability and robustness of results [147], [148].

To summarise the discussion, Table 4 provides a comparative overview of the two methodological pillars that underpin this study: the European Sustainability Reporting Standards (ESRS) and the Analytical Hierarchy Process (AHP). The table highlights their respective purposes, structures, strengths, and limitations, as well as the complementary relationship between them. While ESRS establishes the regulatory and structural framework for sustainability reporting, AHP offers an analytical tool for prioritising and integrating sustainability indicators within that framework. The integration of both approaches forms the foundation of the proposed sustainability assessment model developed in this research, ensuring that it is both compliant with established reporting standards and methodologically robust for decision-making.

Table 4. Overview of ESRS-AHP

Aspect	**European Sustainability Reporting Standards (ESRS)**	**Analytical Hierarchy Process (AHP)**
Purpose	Establishes a standardized and mandatory framework for sustainability reporting and disclosure within the European Union.	Provides a systematic, multi-criteria decision-making approach to prioritize and weight sustainability indicators.
Scope	Focuses on environmental, social, and governance (ESG) dimensions of organizational performance.	Applicable across diverse decision-making contexts involving both quantitative and qualitative criteria.
Structure / Framework	Four main categories: General, Environmental (E1–E5), Social (S1–S4), and Governance (G1). Contains 10 subtopics and 68 measurable indicators.	Hierarchical structure enabling pairwise comparisons of criteria and sub-criteria to derive relative importance weights.

Key Features	Promotes harmonized, transparent, and comparable sustainability reporting aligned with EU policy goals and the European Green Deal.	Converts subjective judgments into quantitative weights; facilitates consistency and transparency in complex evaluations.
Strengths	Enhances data comparability and regulatory compliance; integrates ESG considerations into strategic decision-making; encourages innovation and corporate responsibility.	Allows integration of diverse data types; supports structured decision-making under uncertainty; adaptable to various sustainability contexts.
Limitations	Focused mainly on reporting; does not specify weighting or prioritization methods for indicators.	Relies heavily on expert judgment; becomes complex and time-consuming with large indicator sets.
Integration Potential	Defines the "what" of sustainability assessment — the indicators and dimensions to be reported.	Defines the "how" — the method to analyze, prioritize, and integrate ESRS indicators into a unified sustainability index.
Role in This Study	Provides the regulatory and structural foundation for indicator selection and categorization.	Provides the analytical mechanism for weighting and integrating ESRS indicators into a comprehensive assessment model.

5.3 Proposed framework

This section highlights the importance of structured sustainability evaluation method for manufacturing organizations and examines the benefits offered by the integration of ESRS and AHP. AHP offers a systematic tool to prioritize sustainability indicators provided by the ESRS. Therefore, integration of both ESRS and AHP provides a sustainability score which meets the regulatory requirements as well as provides strategic insights for the sustainability improvements.

There are two reasons for this integration. First, all three aspects of sustainability i.e., environment, social, and governance are covered by ESRS, which serves as a regulatory reference point. Secondly, AHP assigns meaningful weights at all hierarchical levels which can be used for more informed decision-making. Previous studies mostly used equal weights for the prioritization which diminishes the real essence of multi-criteria decision-making. As a result, our framework recognizes that, depending on corporate priorities, industry-specific factors, and performance benchmarks, some indicators may be more relevant than others. An outline of the proposed methodology is shown in Figure 6. A detailed description of each step of the framework is explained in the sub-sections.

The framework starts with the definition of a goal i.e., sustainability assessment of manufacturing organizations. The goal is further divided into subfields of dimensions and sub-topics and structured as an hierarchy. To assure homogeneity, the data from the measurable and non-measurable KPIs is then gathered and normalized. Experts can perform pairwise comparisons and allocate relative importance to various elements at each hierarchy level using the AHP-based weight determination process. Before combining weighted KPIs into a single SI, consistency checks are performed to confirm the validity of expert judgments. The achieved SI provides a comprehensive picture of organisational sustainability performance.

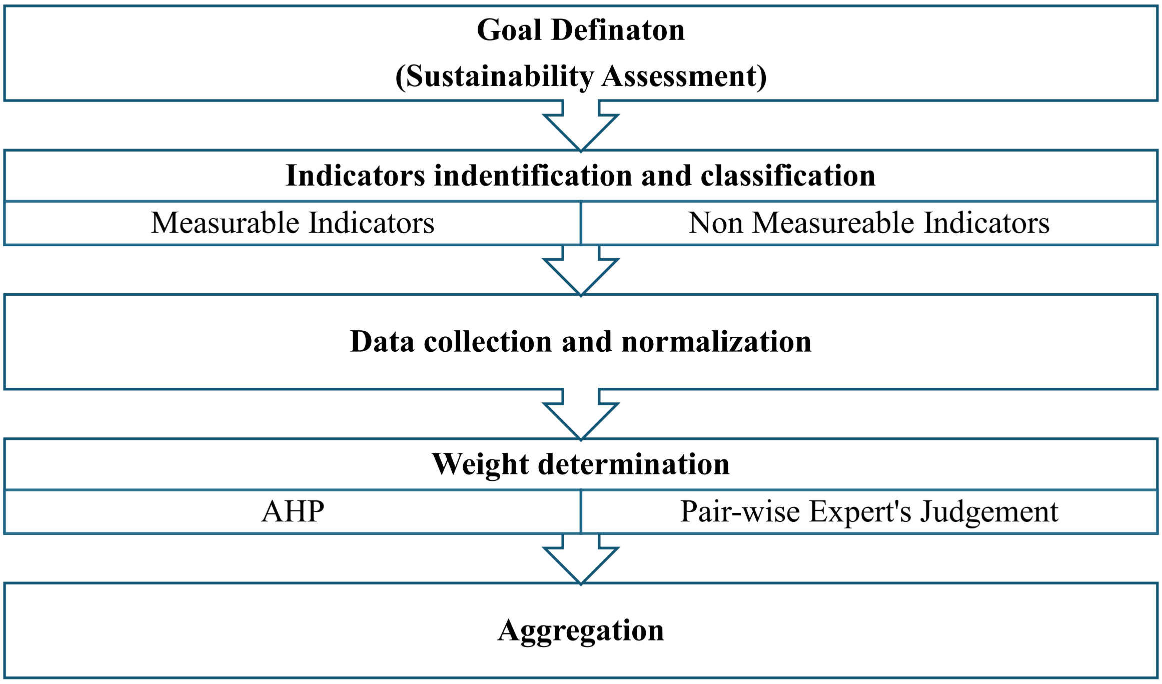

Figure 6. Proposed ESRS-AHP assessment framework

5.3.1 Indicators identification and classification

Despite the fact that ESRS offers a structured set of sustainability KPIs under three categories environment, social, and governance[119], the final selection of KPIs depends on industry relevance, actionability, and stakeholder's assessment. Managers should receive strategic insights from a chosen KPI. [149]. A KPIs should help organization in strategic decision-making by providing insights about its current and future impacts. The study [119] summarised 68 KPIs (Table 3) under three dimensions of sustainability, i.e., environment, society, and governance, as structured by ESRS guidelines [150].

After finalizing the KPIs to be included, they have been categorized into two groups: measurable and non-measurable KPIs:

- Measurable KPIs refer to those KPIs which can be easily quantified and measured. These KPIs can be collected from organizational database and provide objective, numerical insights into performance. For example, energy usage and percentage of renewable energy.

- Non-measurable KPIs consists of those sustainability aspects which cannot be easily quantified. Most of these indicators are qualitative in nature and mostly rely on managerial assessments such as ethical considerations in marketing.

5.3.2 Data collection and Normalization

Measurable indicators are directly obtained from organization records and ERP systems. However, non-measurable indicators are assessed by organizational managers on the provided scales. Normally a scale of 0 to 10 is used and it allows the inclusion of those KPIs which cannot be easily measured.

After measurement of KPIs, the next challenge lies in the conversion of all the indicators into homogenous scale. KPIs are measured in different units and in order to use these values for a structured sustainability index, it is essential to normalize these values into a common scale. Various normalization techniques have been discussed in the literature [141], including expert judgment, benchmark normalization, and worst-best case. Nevertheless, a single normalization cannot be used for every KPI; instead, it must be chosen based on the type of data and the features of each indicator, such as the indicator's unit and data range. The worst-best case and benchmark normalization techniques were chosen for this study based on how well they fit the indicators in question.

By identifying the worst and best scenarios for every KPI, the worst-best case normalization technique creates the scale. For instance, the worst-case scenario for the percentage of energy that comes from renewable sources is 0%, which represents a normalized score of 0. However, utilizing 100% renewable energy is the best option and receives the highest normalized score of 10. Benchmark normalization involves comparing an organization's performance to an external benchmark or standard and assigning a value at a predetermined scale. These benchmarks can be derived from regulatory thresholds, industry average performance, or international industry standards. The approach guarantees that the assessment takes into account relative as well as absolute performance, providing a detailed view of how each KPI compares to current standards.

5.3.3 Weight determination

Pairwise comparisons of elements at each hierarchical level are the first step in the AHP weight assignment process. The large number of studies used equal weights for the initial sustainability assessment when allocating the weights to the multiple elements. Equal weights, however, do not accurately reflect the contexts. The AHP has been widely used in Multi-Criteria Decision Making (MCDM) and the assignment of weights to various elements. Field experts provide the relative weight of elements according to the Saaty [120] scale, where values ranging from 1 to 9 indicate how important a particular element is compared to others. For instance, a value of 9 denotes an absolute preference for one element over another, while a value of 1 indicates equal importance of the elements. The results of pairwise comparison form a square matrix of order n:

$$A = [a_{ij}], \quad A \in R^{n\times n}$$

Where,

$$a_{ij} = \begin{cases} 1, & i = j, \\ \dfrac{1}{a_{ij}}, & i \neq j, \end{cases} \qquad i,j = 1,2,3 \dots n.$$

Where, n is the number of elements under the same parent node.

The pairwise judgment is based on the parent node, for example, in case of 'Environment (E)' dimension as a parent node, we have five (n = 5) children elements or sub-topics. Therefore, it results into a 5×5 matrix (Table 5). This pairwise comparison is done for all the hierarchical levels and all the parent nodes. Table 6 shows the description of each scale value.

Table 5. Comparison matrix example for environment dimension

ENVIRONMENT	E1	E2	E3	E4	E5

E1	1				
E2		1			
E3			1		
E4				1	
E5					1

The weights for each element are determined once the pairwise square matrix has been constructed. Each element is divided by the sum of its corresponding column after the matrix's column sum has been determined. The weight of each element in the updated matrix is determined by taking the average value for each row. In order to obtain the final SI, this process converts the qualitative expert judgments into quantitative data that are utilized in the subsequent stages of the analysis.

Table 6. Pairwise comparison scale

Scale value	Description
1	Both elements are equally important
3	First element is moderately more important
5	First element has a strong importance
7	First element has a very strong importance
9	It shows the absolute importance of first element over second element
2,4,6,8	In between values of the preferred odd values

In real life scenarios, the errors in the judgements are unavoidable which lead to inconsistencies in the ranking of the elements. Therefore, we use a metric called Consistency Ratio (CR) to measure the error in the judgments. This ratio is calculated as:

$$CR = \frac{CI}{RI}$$

The average Consistency Index (CI) for a randomly filled matrix is represented by the Random Index (RI). The pairwise matrix's order determines the RI values. These values are listed in Table 7 according to the matrix's order. A CR of less than 0.1 is widely recognized as a consistency threshold to guarantee reliable result [151].

CI can be calculated as:

$$CI = \frac{\lambda_{max} - n}{n - 1}$$

Where, n is the order of the matrix, and λmax is the maximum eigenvalue of the comparison matrix. The consistency ratio (CR) aid in understanding and enhancing the reliability of the expert's judgments.

Table 7. Random index (RI) table

N	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*
R.I.	0	0	.52	.89	1.11	1.25	1.35	1.40	1.45	1.49

5.3.4 Aggregation

The final step of the sustainability assessment framework is the aggregation of overall SI. The process of aggregation begins with KPIs at the lowest level and progresses to the final SI at the organizational level. The following formula is used to determine the sustainability score for the parent subtopic, beginning at the KPIs level:

$$ST_{\ i} = \sum_{i=1}^{n} M_i \times w_i$$

where n is the total number of indicators connected to that parent element, M_i is the normalized KPI value, w_i is the KPI weight, and $ST_{\ i}$ is the subtopic score. By weighing each KPI based on its relative importance, this formula guarantees that each KPI's contribution is accurately accounted for.

Next, these scores are aggregated towards the hierarchical level i.e., dimensions (ESG) as follows:

Environmental (E):

$$E = \sum_{i=1}^{n} w_{Ei} \times ST_{Ei}$$

Social (S):

$$S = \sum_{i=1}^{n} w_{Si} \times ST_{Si}$$

Governance (G):

$$G = \sum_{i=1}^{n} w_{Gi} \times ST_{Gi}$$

The subtopic weights for the environmental, social, and governance dimensions are represented by w_{Ei}, w_{Si}, and w_{Gi} in these formulas, while the subtopic-level sustainability scores for each dimension are represented by ST_{Ei}, ST_{Si}, and ST_{Gi}. Therefore, all dimension-specific subtopic information can be combined into summary indices E, S, and G using the formulas.

In the final stage, the values of E, S, and G are combined according to their relative importance to the organization to determine the final SI. The following is the final formula:

$$SI = w_E \cdot E + w_S \cdot S + w_G \cdot G$$

The weights of the three primary dimensions (ESG) are represented here by w_E, w_S, and w_G. This formula enables us to create a single metric that represents the organization's overall level of sustainability by combining all levels of the hierarchy.

The following qualitative thresholds can be used to interpret sustainability index values since this study used 5 as a baseline value during normalization: values below 5 are considered ‘poor’; values; between 5.00 and 7.99 are considered ‘satisfactory’; and values between 8.00 and 10.00 are considered ‘good’. The threshold value of 5 was chosen based on the company’s historical performance and validated through discussions with domain experts. Additionally, the mid-range reference values and the 0–10 scale are in line with methods frequently used in the literature on sustainability evaluation [19], [141].

A reliable and methodical way to compute the SI is offered by the developed sustainability assessment framework. The relationship between the normalized KPI values, their weights, and their total contribution to the final SI are provided by the formulas at each hierarchical level. This method enables the inclusion of both quantitative and qualitative data, offering a credible tool for strategic decision-making on reaching long-term sustainability objectives.

5.4 Application of the proposed framework: case study

The developed framework was applied to an Italian manufacturing company as a case study. The selected organization specializes in the development of flooring solutions. As the case study organization is based in EU, therefore, facing a strict sustainability compliance. Due to the EU context, the organization provided a favourable opportunity for the integration of ESRS to evaluate its current performance and identify opportunities to improve its sustainability.

The next sub-sections step-wise applies the developed methodology to this manufacturing industry's sustainability assessment.

5.4.1 Indicators identification and classification

As mentioned in the previous section, the framework used the ESRS guidelines for the selection of the sustainability KPIs under ESG. The final inclusion and exclusion of KPIs used the criteria explained in Section 5.3.1 , i.e., relevance and actionability. For example, the indicators related to radioactive waste have not been included because of their irrelevance in this case. A total of 38 KPIs were selected, and a hierarchical structure was developed, as shown in Table 8. This arrangement provided base for the next stages i.e., assigning weights by pairwise comparisons and aggregation. These 38 KPIs have been grouped into 9 non-measurable KPIs (S1.3, S2.1, S3.2, S4.1, S4.2, S4.3, S4.4, G1.3, and G1.4) and 29 measurable KPIs.

Table 8. Summary of indicators and measured values

Dimension	Sub-topic	Indicator	Measured value	Unit
Environment (E)	Climate change (E1)	% of renewable energy use (E1.1)	20	%
		Total energy usage (E1.2)	2600	kWh/unit
		Energy usage efficiency (E1.3)	75	%

		Hazardous gas emission (E1.4)	0	kg/unit
		Total GHG emissions (E1.5)	3	kg/unit
	Pollution (E2)	Total solid waste (E2.1)	2.5	lb/unit
		Total liquid waste (E2.2)	55	gallon/unit
		Cost of water treatment (E2.3)	50	$/unit
	Water & marine resources (E3)	Water consumption (E3.1)	300	gallon/unit
		Recycling of water (E3.2)	10	%
		Water usage efficiency (E3.3)	80	%
	Biodiversity & ecosystem (E4)	Total land used (E4.1)	1200	m^2
		Total sealed area (E4.2)	800	m^2

	Resource use & circular economy (E5)	Raw material cost (E5.1)	60	$/unit
		Packaging cost (E5.2)	50	$/unit
		Processing cost (E5.3)	40	$/unit
		Cost of waste disposal (E5.4)	35	$/unit
		Productivity (E5.5)	78	$/unit
		Leadtime (E5.6)	12	$/unit
		Labor efficiency (E5.7)	95	%
Society (S)	Own workforce (S1)	Exposure to toxic substance (S1.1)	2	Dimensionless
		Exposure to high voltage (S1.2)	1	Dimensionless
		Adequate wages (S1.3)	-	Dimensionless

		Injury incidents (S1.4)	1	#
	Workers in value chain (S2)	Equal opportunities for all (S2.1)	-	Dimensionless
		Child labor incidents (S2.2)	0	#
		Access to remedies (S2.3)	95	%
	Affected communities (S3)	Civil right violation (S3.1)	1	#
		Freedom of expression (S3.2)	-	Dimensionless
		Social rights violation (S3.3)	2	#
	Consumers & end-users (S4)	Access to information (S4.1)	-	Dimensionless
		Privacy provisions (S4.2)	-	Dimensionless
		Social inclusion (S4.3)	-	Dimensionless

		Ethical marketing (S4.4)	-	Dimensionless
Governance (G)	Business conduct (G1)	Incidents of corruption (G1.1)	0	#
		Incidents of bribery (G1.2)	0	#
		Prevention of corruption & bribery (G1.3)	-	Dimensionless
		Secure payment methods (G1.4)	-	Dimensionless

5.4.2 Data collection and Normalization

There were two stages to the data collection process. The values for the quantifiable KPIs, like total solid waste (E2.1), were taken straight from the organization's database. However, the values of non-measurable KPIs have been provided by the managers based on their judgements. The managers assessed these KPIs' performance on a scale of 0 to 10 and assigned a value that was subsequently utilized in the total SI; for example, prevention of corruption and bribery (G1.3) and equal opportunities for all (S2.1). As the non-measurable KPIs do not have numerical numbers at this stage, they are written as'-' in the "measured value" column of Table 8.

Stakeholder engagement received special attention. As a result, the data collection process involved suppliers, production workers, sustainability specialists, and regulatory experts. The manager level staff assigned non-measurable KPIS values, and the production staff supplemented operational data. Sustainability specialists made sure the dataset accurately reflected social, governance, and environmental elements. The accuracy and legal compliance of the supplied data figures were assured by regulatory compliance officers.

In order to remove heterogeneity of the data, all the values were normalized on a scale 0-10. As non-measurable KPIs were already assigned a score on this scale i.e., already normalized. Two normalization techniques, worst-best case and benchmark normalization, were used for the measurable indicators. The worst-best case normalization technique was used for the indicators lying in a certain range such as efficiency. For the benchmark normalization, this study derived benchmarks from the historical data of the organization as a starting point for sustainability assessment. This approach provided contextual relevance for the initial application of ESRS-AHP sustainability assessment framework. However, these benchmarks can be selected from industrial references and international standards as explained in section 5.3.2.

The base value for normalization in relation to the benchmark was set at 5. The following formula is used to determine the normalized value:

$$Normalised\ value\ = \frac{5 \cdot Actual\ value}{Benchmark\ value}$$

If any KPI impacts sustainability in a negative way (e.g., a lower value is better for sustainability), the normalised value is calculated as follows:

$$Normalised\ value\ = 10 - \frac{5 \cdot Actual\ value}{Benchmark\ value}$$

For KPIs whose values fall within a certain range, the "best–worst case" approach is applied. For instance, the labor efficiency share falls between 0% and 100%, with 10 representing the best scenario and 0 representing the worst. Table 9 shows the respective normalised values against all the KPIs.

Table 9. Sustainability scores at the sub-topic level

Sub-topic	Aggregated score $ST = \sum M_i * w_i$	Indicator	Sustainability score $(M_i * w_i)$	Normalized value (M_i)	Weight (w_i)
Climate change (E1)	6.04	% of renewable energy use (E1.1)	0.52	02	0.2601
		Total energy usage (E1.2)	0.82	5.98	0.1377
		Energy usage efficiency (E1.3)	2.56	7.50	0.3416
		Hazardous gas emission (E1.4)	1.03	10	0.1029
		Total GHG emissions (E1.5)	1.10	7.00	0.1577

Pollution (E2)	7.45	Total solid waste (E2.1)	3.77	6.88	0.5485
		Total liquid waste (E2.2)	1.95	8.10	0.2409
		Cost of water treatment (E2.3)	1.73	8.21	0.2106
Water & marine resources (E3)	3.67	Water consumption (E3.1)	1.20	5.71	0.2098
		Recycling of water (E3.2)	0.55	01	0.5499
		Water usage efficiency (E3.3)	1.92	08	0.2402
Biodiversity & ecosystem (E4)	6.44	Total land used (E4.1)	4.00	06	0.6667
		Total sealed area (E4.2)	2.44	7.33	0.3333
Resource use & circular economy (E5)	7.90	Raw material cost (E5.1)	2.40	7.86	0.3051
		Packaging cost (E5.2)	1.75	8.21	0.2137
		Processing cost (E5.3)	1.07	8.57	0.1244
		Cost of waste	0.99	8.75	0.1131

		disposal (E5.4)			
		Productivity (E5.5)	0.61	5.57	0.1088
		Leadtime (E5.6)	0.34	06	0.0570
		Labor efficiency (E5.7)	0.74	9.5	0.0779
Own workforce (S1)	7.38	Exposure to toxic substance (S1.1)	1.87	6.67	0.2810
		Exposure to high voltage (S1.2)	1.00	8.33	0.1197
		Adequate wages (S1.3)	2.55	7	0.3645
		Injury incidents (S1.4)	1.96	8.33	0.2348
Workers in value chain (S2)	9.27	Equal opportunities for all (S2.1)	1.18	7	0.1692
		Child labor incidents (S2.2)	3.87	10	0.3874
		Access to remedies (S2.3)	4.21	9.5	0.4434

Affected communities (S3)	6.980	Civil right violation (S3.1)	3.43	7.5	0.4577
		Freedom of expression (S3.2)	2.91	7	0.4160
		Social rights violation (S3.3)	0.63	5	0.1263
Consumers & end-users (S4)	7.28	Access to information (S4.1)	2.77	7	0.3952
		Privacy provisions (S4.2)	2.22	8	0.2781
		Social inclusion (S4.3)	1.14	7	0.1634
		Ethical marketing (S4.4)	1.14	7	0.1634
Business conduct (G1)	9.58	Incidents of corruption (G1.1)	1.44	10	0.1443
		Incidents of bribery (G1.2)	4.38	10	0.4380
		Prevention of corruption	2.61	9	0.2904

	& bribery (G1.3)			
	Secure payment methods (G1.4)	1.15	9	0.1274

5.4.3 Weight determination

The sample of experts for AHP pairwise comparisons included both industry professionals and researchers. Specifically, a total of 39 experts were involved: 15 experts from academia including professors and researchers and 24 industry professionals having experience as managers and deputy managers. The experts were chosen from both academic institutions and manufacturing-related businesses. Each of the specialists had previously shown proficiency in regulatory compliance, ESG integration, and sustainability. To cover both technical and managerial aspects of the evaluation process, academic participants were chosen from engineering and economics. To lessen individual bias, the opinions of all these experts were combined into a single group. The consistency ratio has been used to monitor the AHP coefficients' steadiness. The same section provides more details on this consistency check.

The pairwise comparison judgments were obtained through a consensus-based group evaluation process involving the 39 experts. During the assessment sessions, the experts discussed the relative importance of the ESG dimensions, sub-topics, and indicators until a common judgment was reached for each pairwise comparison. Therefore, the matrices reported in this study represent aggregated group judgments rather than independently calculated individual matrices. The consistency ratio (CR) was subsequently used as a basic measure of agreement and reliability among the expert evaluations. All reported matrices satisfied the commonly accepted consistency threshold of $CR < 0.1$.

Numerous KPIs in the social and governance dimensions were based on the subjective opinions of experts and were not measurable. As a result, the data's verification received special attention. The case company complies with the ESRS, which requires external audits of sustainability disclosures, and has its headquarters in the European Union. Businesses are encouraged by this regulatory environment to refrain from selective reporting or deception. In actuality, businesses frequently take a cautious, self-critical stance when conducting internal evaluations due to worries about potential legal or reputational repercussions during audits. The subjective weights employed are more credible as a result of this internal pressure.

If pairwise comparisons were inconsistent, the experts were asked to reconsider their conclusions. As an example, Table 10 displays a pairwise comparison with consistency ratio computation for the elements under sub-topic climate change (E1).

Table 10. Pair wise comparison under sub-topic climate change(E1)

Climate change (E1)	**E1.1**	**E1.2**	**E1.3**	**E1.4**	**E1.5**
E1.1	1	2	½	3	2
E1.2	½	1	½	1	1
E1.3	2	2	1	3	2
E1.4	1/3	1	1/3	1	½
E1.5	½	1	½	2	1

The KPIs' weights can be obtained by calculating the mean values of the rows and normalizing the matrix's columns. The final indicator weights for the Climate Change subtopic are displayed in Table 11.

Table 11. Weights of the indicators under the sub-topic of climate change(E1)

Climate change (E1)	**E1.1**	**E1.2**	**E1.3**	**E1.4**	**E1.5**	**weight**
E1.1	0.2308	0.2857	0.1765	0.3000	0.3077	0.2601
E1.2	0.1154	0.1429	0.1765	0.1000	0.1538	0.1377
E1.3	0.4615	0.2857	0.3529	0.3000	0.3077	0.3416
E1.4	0.0769	0.1429	0.1176	0.1000	0.0769	0.1029
E1.5	0.1154	0.1429	0.1765	0.2000	0.1538	0.1577
Sum	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

The maximum eigen value λ_{max} and the calculated consistency indices are used to evaluate the consistency of the pairwise comparison matrix. The maximum eigenvalue λmax is defined as the value satisfying the following equation:

$$Aw = \lambda_{max}$$

where A is the matrix of pairwise comparisons and w is the normalised vector of weights. For this example:

$$\lambda_{max} = 5.098 \qquad order\ of\ matrix = n = 5$$

Based on λ_{max}, the CI is calculated using the following formula:

$$CI = \frac{\lambda_{max} - n}{n - 1} = 0.0245$$

The final consistency check uses CR, which is defined as the ratio of CI to the RI:

$$CR = \frac{CI}{RI} = \frac{0.0245}{1.11} = 0.022$$

The matrix of pairwise comparisons is deemed consistent since the CR value is less than 0.1. In a similar vein, every metric at the indicator level has undergone pairwise comparison for the corresponding weight assignment (Table 9). The complete pairwise comparison matrices and corresponding consistency ratios for all hierarchical levels are provided in APPENDIX A.

5.4.4 Aggregation

For the aggregation of SI, starting at the level of KPIs and working up to the level of dimensions, the calculations were performed in compliance with the developed framework. Data were combined at each level while accounting for the weights and normalized indicator values.

For the lowest level i.e., KPIs the sub-topic scores were obtained by the product sum of normalized values of KPIs and their respective weights as shown in Table 9.

Moving to the dimensions (E, S, G) level, the scores were calculated by using their subtopic scores and respective weights:

$$E = \sum_{i=1}^{n} w_{Ei} \times ST_{Ei}\,; \qquad S = \sum_{i=1}^{n} w_{Si} \times ST_{Si}\,; \qquad G = \sum_{i=1}^{n} w_{Gi} \times ST_{Gi}$$

The following formula was used in the last stage to combine the three dimensions and determine the company's overall SI:

$$SI = w_E \cdot E + w_S \cdot S + w_G \cdot G$$

Table 12 displays the totals for each dimension (E, S, and G) as well as the total SI. These findings offer a thorough understanding of the organization's sustainability level and serve as a foundation for additional analysis.

Table 12. Sustainability index breakdown

Sustainability Index (SI)	**Dimension**	**Aggregated score at dimension level (E,S,G)**	**Sub-topic**	**Sub-topic score ST_i**	**Sub-topic weight (w_{STi})**
8.13	Environment (E)	6.52	Climate change (E1)	6.04	0.3118
			Pollution (E2)	7.45	0.1779
			Water & marine resources (E3)	3.67	0.1277
			Biodiversity & ecosystem (E4)	6.44	0.126
			Resource use & circular economy (E5)	7.90	0.2565
	Society (S)	7.73	Own workforce (S1)	7.38	0.3403
			Workers in value chain (S2)	9.27	0.2431

		Affected communities (S3)	6.98	0.2431
		Consumers & end-users (S4)	7.28	0.1736
Governance (G)	9.58	Business conduct (G1)	9.58	1

5.5 *Results and Analysis*

A radar chart (Figure 7) shows the organisational sustainability performance at the sub-topic and dimension levels. The organisational sustainability performance seems satisfactory in the dimensions of social (7.73) and governance (9.58). The environmental performance (6.52) needs to be improved, though, as it is near the baseline value of five. The organization's sustainability score (3.67) is below the established benchmark for water and marine resources (E3), necessitating immediate improvements at the subtopic level. The organization may have made modest progress in the subtopics of biodiversity and ecosystem (E4) and climate change (E1), which are likewise only marginally higher than the benchmark value (6.04 and 6.44, respectively). In a similar manner, even at the indicator level, the compiled Table 9 and Table 12 offer insights into the areas that require improvement. Overall, the organizational SI of 8.13 indicates that the organization is performing satisfactorily because it is higher than the benchmark value.

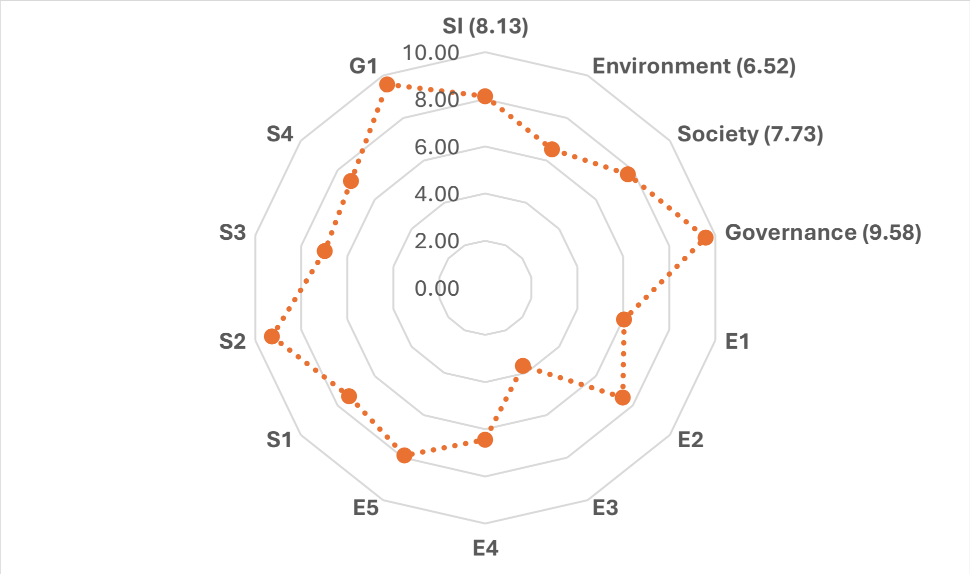

Figure 7. Radar chart of Sustainability index

5.5.1 Local robustness and sensitivity analysis

The study performed an analysis where each weight is perturbed by ±10% and then renormalized ($w_E + w_S + w_G = 1$) in order to confirm that the Sustainability Index (SI = 8.13) is robust against minor changes in the top-level ESG dimension weights. The original weights are:

$$w_E = 0.30, \qquad w_S = 0.29, \qquad w_G = 0.41,$$

with dimension scores:

$$E = 6.52, \qquad S = 7.73, \qquad G = 9.58,$$

Yielding

$$SI = 0.30 \cdot 6.52 + 0.29 \cdot 7.73 + 0.41 \cdot 9.58 \approx 8.13.$$

The following SI values are obtained after renormalizing and varying each weight by ±10% (Table 13). The stability of the index against small weighting uncertainties is confirmed by the fact that even a 10% shift in any one dimension weight only modifies the SI by ±0.07 (less than 1% of its value).

Table 13. Sensitivity of the overall SI to ±10% perturbations in top-level ESG weights

Weight Perturbed	NewWeights	New SI	Δ SI
$\boldsymbol{w_E}$ **±10%**	(0.33, 0.29, 0.38)	8.08/8.18	−0.05 /+0.05
$\boldsymbol{w_S}$ **±10%**	(0.30, 0.32, 0.38)	8.12/8.15	−0.01/+0.02
$\boldsymbol{w_G}$ **±10%**	(0.27, 0.26, 0.47)	8.06/8.20	−0.07/+0.07

The overall SI's stability against modest changes in the top-level dimension weights is confirmed by this analysis. Further research could examine the model's robustness throughout the entire hierarchy by conducting a more thorough multi-level sensitivity analysis that examines the effects of weight variations at the sub-topic and indicator levels.

5.5.2 Monte Carlo robustness analysis

To further evaluate the robustness of the Sustainability Index (SI), a Monte Carlo sensitivity analysis was implemented in Python using 10,000 simulation runs. In each simulation, the top-level ESG weights were randomly perturbed within ±10% of their original values and subsequently renormalized to ensure that the total weight remained equal to one. The perturbed weights were then used to recalculate the overall SI, and the simulation results are summarized in Table 14.

The Monte Carlo analysis produced a mean SI value of 8.1248 with a standard deviation of 0.0446. The simulated SI values remained within a narrow interval ranging from 8.0104 to 8.2406, while the 95% confidence interval ranged from 8.0407 to 8.2085. These findings further confirm the stability and robustness of the proposed ESRS–AHP framework against moderate uncertainty in the top-level ESG weighting structure.

Although the present Monte Carlo analysis focused on the ESG dimension weights, future research may extend the perturbation analysis to sub-topic and indicator-level weights to evaluate robustness across the full hierarchical structure.

Table 14. Monte Carlo robustness analysis of SI (10,000 simulations)

Metric	Original SI	Mean simulated SI	Standard deviation	Minimum SI	Maximum SI	2.5th percentile	97.5th percentile
Value	8.13	8.1248	0.0446	8.0104	8.2406	8.0407	8.2085

5.6 Discussions

This section interprets the results of the case study in order to provide managerial insights and also highlights the adaptability of the developed framework,

The AHP was found to be the most appropriate for three primary reasons, despite the possibility of using other multi-criteria decision-making techniques like TOPSIS, Fuzzy-AHP, or DEA The first was that ESRS's hierarchical structure complemented AHP's hierarchical structure [152], [153], [154]. The second reason was based on the simplification in understanding of pairwise comparisons especially for the stakeholders. Additionally, it avoided calibration complexity which is required in case of Fuzzy-AHP's linguistic variables. Thirdly, AHP quantitatively integrates regulatory priorities which ensures strategic sustainability goals carry the correct emphasis. Because of this, DEA, which is excellent at relative efficiency analysis but does not have clear and specific weighting pathways, was not employed.

The results of the study demonstrated the proficiency of the presented ESRS-AHP sustainability assessment framework. The results present a well-organized and clear picture of the organization's sustainability performance. Overall sustainability index value of 8.13 shows above average sustainability performance but an in depth analysis provides better insights. For example, Environmental dimension achieved only 6.52 which is close to the baseline value of 5. Therefore, organization need to invest more in the environmental dimension. Especially, in the sub-topic of water & marine resources (E3) which only achieved a score of 3.67. Taking the analysis to the KPI's level, the reason for the low performance in water & marine resources is due to the low percentage of water recycling i.e., 10 %. These findings guide decision-makers to reconsider their investment plans and focus on low performing KPIs to achieve long-term sustainability goals.

Conversely, the social (7.73) and governance (9.58) dimensions showed significantly higher scores, indicating a better dedication to ethical business practices and personnel management. However, since both of these dimensions include a lot of non-measurable KPIs, the strong performance seen in these areas needs to be carefully considered. High scores in both of these dimensions may have been a result of biasedness instead of a true picture. Because of social desirability or reputational factors, these biases may have unintentionally raised scores. Even though these findings are encouraging, they should ideally be confirmed by additional impartial evaluations or independent audits to guarantee dependability and credibility.

When these results are critically examined, the ESRS-AHP framework shows its ability to identify areas that need immediate intervention as well as the necessity of carefully verifying seemingly excellent results. For example, excellent scores in social and governance may have been a result of biased judgement by the organization's experts.

In light of these observations, it is crucial to determine whether the framework's outcomes hold up to variations in expert weighting assessments. The study performed a local sensitivity analysis by changing each top-level ESRS weight by ±10% in order to test the stability of our findings. The overall change in SI was less than 1%, such low change highlights the robustness of the framework. This robustness proves that our results are not dependent on the exact weight settings.

The ESRS-AHP framework's adaptability allows it to be used by any manufacturing company located across the globe. Organizations can use their local benchmark and expert’s judgments to replicate this sustainability assessment across continents.

5.7 Chapter Summary

A new ESRS-AHP sustainability assessment framework has been presented in this chapter, providing organizations with an organized and transparent way to assess their adherence to new mandatory reporting requirements. The suggested framework used AHP to assess sustainability and converted the structured indicators supplied by ESRS into a hierarchical structure. The case study's findings guided management for strategic investments in sustainable practices and offered opportunities for improvement, particularly in the environmental dimension.

The findings offer researchers and practitioners a promising approach. The framework may be extended across different organizational scales and industrial sectors in future research. In order to eliminate managerial bias, future research might also concentrate on a more organized and quantitative method of evaluating the non-measurable indicators.

Although ESRS-AHP framework provided a comprehensive sustainability assessment framework but it involved laborious calculations especially in AHP where a large number of pairwise comparisons are involved. Therefore, the next chapter (Chapter 6) presents implementation of digital automation of ESRS-AHP framework. This implementation avoids manual handling of sustainability data and provides periodic sustainability reports. Through this transition from conceptual methodology to automated execution, the thesis provides a complete and scalable solution for real-world sustainability assessment.

Chapter 6 Digital Implementation and Automation of the ESRS–AHP Sustainability Assessment Framework

This chapter is based on the author's peer-reviewed publication [155] "Analytical Hierarchy Process Based Sustainability Assessment Framework Implementation in MySQL. In New Trends in Intelligent Software Methodologies, Tools and Techniques (pp. 219-227). IOS Press." And answers the last research question of the thesis i.e., How can sustainability assessment frameworks be operationalised through digital systems to enable automation, consistency, and scalability in organisational decision-making?

6.1 Introduction and Background

As discussed in Chapter 1 and Chapter 5, sustainability reporting has become a mandatory requirement for all the organization working in European Union (EU). While Chapter 5 presented ESRS compliant sustainability assessment framework, its manual implementation requires a laborious calculation procedure starting from pairwise comparisons and weight assignment leading to the aggregation of organizational sustainability index (SI) calculation. Manual calculation process is prone to human errors especially when ESRS requires a large number of indicators. Therefore, organizations require an automated calculation system where they can see their sustainability reports on their dashboards while avoiding any calculation errors.

To address these operational challenges, this chapter introduces a comprehensive digital implementation of the ESRS–AHP framework using a relational database system. MySQL was selected as the computational engine because of its ability to store hierarchical data, support complex mathematical operations through stored procedures, and maintain strong data integrity constraints. Moreover, the system does not solely rely on the static mySQL database and incorporates a whole end-to-end automation pipeline. It starts with fetching and validation of the pending sustainability assessment requests from the client's endpoint. In the second phase, the database calculates the results and then posts the required tables to the client's endpoint. In parallel, the automation pipelines also updates the status requests such as inprocess, processed, and error at respective endpoints. In order to avoid manual effort, the pipeline has been enabled to periodically executable using ‘cron’. Together, the MySQL implementation and the automated processing pipeline transform the ESRS–AHP framework from a conceptual decision-support tool into an operational digital system.

The remainder of the chapter is organized as follows: section 6.2 provides database level implementation of ESRS-AHP framework including validation of results at the same level. The section 6.3 describes the upper layers of end-to-end automation. Finaly, the section 6.4 concludes the chapter by providing overall summary of the automated ESRS-AHP framework.

6.2 Database design and functionality

This section focuses on the database level implementation of ESRS-AHP framework including hierarchical modeling, calculation by stored procedures, and results validation at database level. Following the definition of KPIs, the sustainability assessment process explores a structured hierarchy of these KPIs that is necessary for the MCDM technique, AHP. After automating pairwise comparisons and weight calculations at every level of the hierarchy, the application aggregates the organization's SI. Figure 8 illustrates the entire framework's pipeline. Below is an explanation of each pipeline phase's specifics:

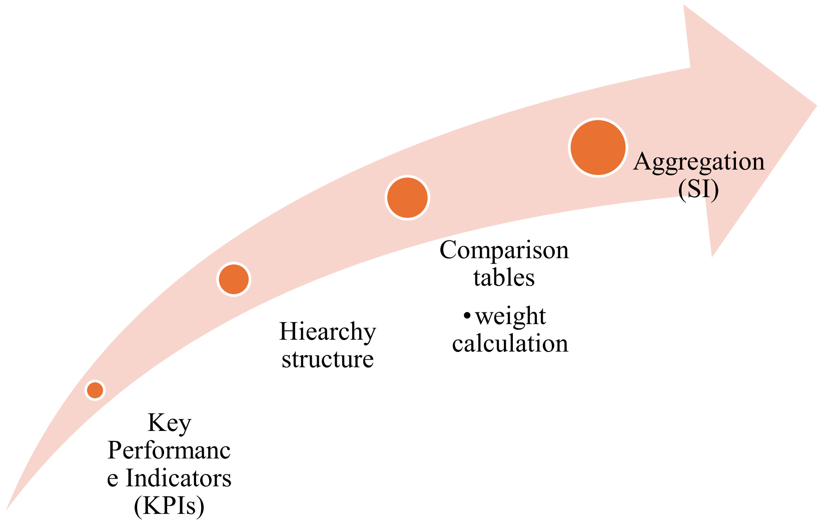

Figure 8.Database pipeline

Key performance indicators (KPIs): The organization's nature and strategic preferences determine which indicators are used for sustainability assessment. But under three dimensions i.e., environment, social, and governance, the new ESRS offers an extensive set of indicators. Due to the context of the target organizations, specifically the European Union (EU), and a structured set of indicators, the study utilizes the indicators proposed in the ESRS.

Hierarchy structure: the next phase of the procedure involves defining the hierarchical structure of these indicators. A hierarchical structure is required to apply MCDM techniques for calculating weights and aggregating the sustainability score [156]. The hierarchical structure in the developed application is defined by creating tables at each hierarchical level. Four levels of tables have been created in the application: dimension, sub-topic, sub-sub-topic, and indicator.

Comparison tables: Following the creation of a hierarchical structure table, we produced pairwise comparison tables at each level of the hierarchy in which experts assigned a pairwise comparison score based on how important each element was in relation to other elements. In order to assign relative weights to each element using the MCDM technique, AHP, pairwise comparisons are necessary. A scale of 1 to 9 is used to assign the pairwise score, with 1 denoting equal importance and 9 denoting the absolute importance of the first element over the second. A sample pairwise comparison scale for the sub-topics under the social dimension has been shown in Table 15. Stored procedures have been created in MySQL workbench to automate the weight calculations using standard AHP methodology. The stored procedure also calculates the consistency ratio (CR), which ensures consistent judgments by the experts. If the CR is above 0.1, the experts are advised to revisit their judgments [157].

Table 15. Pairwise comparison table for social dimension

Social (S)	**9**	**8**	**7**	**6**	**5**	**4**	**3**	**2**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**Social (S)**
S1	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	S1

S1	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	S2
S1	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	S3
S1	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	S4

Aggregation sustainability index (SI): the final stage of the developed application involves aggregating the sustainability score of the organization, starting from the indicator level and then moving to the dimension level, to ultimately aggregate the overall SI of the organization [19]. For this, stored procedures have been created in the MySQL database to automate the calculation of the sustainability score at each level, following the product sum logic as shown in the equation below:

$$sustainability\_score_i = \sum_{ij} (weight_{ij} \times score_{ij})$$

Where 'i' represents the hierarchical level and 'j' represents the 'jth' element of that level. For the indicator level, the score of the element is the normalized value of that indicator. The user provides the normalized value of the indicator on the scale of 0 to 10 [141]. The product sum of normalized values and corresponding weights of elements provides an aggregated score for their parent sub-sub-topic. The stored procedures follow the same logic until the calculation of the overall SI. Example database schema definitions and stored procedures used in the implementation are provided in APPENDIX B.

For the initial assessment of the functionality of the developed application, the pairwise comparison tables for the indicator level have been populated with a score of 1, i.e., equal weightage of all the indicators. The comparison scores for other hierarchical levels have been varied randomly. The indicator scores have also been inserted as normalized values on a scale of 0 to 10. All procedures for automating calculations for SI have been called successfully. These initial steps were essential to verify whether the system could handle the complete assessment pipeline without errors and whether it could correctly interpret both uniform and variable pairwise inputs.

A sample pairwise comparisons table in MySQL workbench at the dimension level is shown in Figure 9. It is important to note that for a 3 by 3 matrix, only 3 comparison values are required from the experts. The first row comparison score of 1 means that the two dimensions, environment and social, are equally important for the sustainability score. These observations confirm that the database accurately stores and retrieves expert judgments while maintaining the structural requirements of the AHP methodology.

Result Grid | Filter Rows: | Edit:

id	first_element_name	second_element_name	comparison_score
1	Environment	Social	1
2	Environment	Governance	1
3	Social	Governance	2
NULL	NULL	NULL	NULL

Figure 9. Pairwise comparison at dimension level

After populating the comparison tables, the application then used the already created stored procedure to develop a square matrix and calculate weights and consistency ratio. According to the standard AHP methodology, the diagonal values of the square matrix should be 1 (as it shows the self-comparison between elements), and symmetrical values across the diagonal should be reciprocal, i.e., if social vs governance has a comparison score of 2, then governance vs social must have a score of 1/2. In the application, we named this table as AHP-matrix. The automatically developed AHP-matrix for the dimension level is shown in Figure 10. The procedure successfully reciprocates the symmetrical values and calculates the weight of each element. The consistency ratio also provides validation for the expert judgments. For this study, the acceptable consistency ratio limit has been defined as 0.1. If the consistency ratio is higher than 0.1, the experts are advised to readjust their comparison scores. This automated consistency check demonstrates that the application not only performs mathematical operations correctly but also supports quality control of expert inputs, which is critical for reliable sustainability assessment.

dimension	Environment	Social	Governance	Weight	CR
Environment	1	1	1	0.32778	0.04626
Social	1	1	2	0.41111	NULL
Governance	1	0.5	1	0.26111	NULL

Figure 10. AHP-matrix at dimension level

The developed application also successfully aggregated the sustainability scores starting from the indicator level. As described in section 6.2 the aggregated score for any parent element is obtained by the product sum of the weights and scores of all its child elements. For the indicator level, this 'score' is the normalized value of that indicator. Figure 11 and Figure 12 show the sustainability score at the dimension level and overall SI of the organization, respectively. These outputs indicate that the system is fully capable of handling multi-level aggregation and of reflecting changes in weights or indicator values throughout the hierarchy.

id	dimension_id	weight	score	aggregated_d_score
1	1	0.32778	4.04434	1.32565
2	2	0.41111	1.25001	0.513892
3	3	0.26111	5.80304	1.51523
NULL	NULL	NULL	NULL	NULL

Figure 11. Sustainability score at dimension level

id	worst_SI	actual_SI	best_SI	created_at
1	0	3.35478	10	2025-05-27 14:03:26
NULL	NULL	NULL	NULL	NULL

Figure 12. Sustainability Index (SI)

Particularly in the context of ESRS, where a lot of indicators are involved, the application demonstrated the easy calculation of SI and eliminated the tedious work for pairwise comparisons and weight calculations. Therefore, the test run shows that automation can minimize human error that would otherwise occur during repetitive matrix calculations and greatly reduce computational burden.

6.3 Automated sustainability processing pipeline

To operationalise the SQL-based implementation of the ESRS–AHP framework and ensure continuous, reliable sustainability assessment, the system incorporates an automated processing pipeline. This automation layer manages the complete workflow starting with the retrieving pending requests from the organization and ending with the final posting of the results.

The pipeline (shown in Figure 13) is built around a scheduled execution mechanism that triggers the system at periodic intervals. The whole automation scripts have been written in 'python' as a programming language. The pipeline begins with the retrieval of pending assessment requests submitted from an API endpoint. These requests include JSON payloads containing the measurable and non-measurable indicator values (named as completion in the JSON payload) as well as their parent hierarchical sub-topics and ESRS for a given reporting period. An example payload is shown below:


```
{
"Entity": "Entity A",
"Esrs": "E1",
"Sub_topic": "E1-6",
"Sub_sub_topic": "47",
"Completion": "4",
}
```


It must be noted that indicator's values (named *completion* in JSON payload) are already normalized. Once the payload is received, whole data is validated to check if there is any missing or out of format value. For example, if parent value i.e., sub-topic or ESRS is missing the request is marked as *'error'* and the status is updated at API endpoint. These foreign key checks ensure data integrity and prevent partial or inconsistent records from entering the system. If all the data is complete and valid, the data is fetched into mySQL database for the calculations and request status is updated as *'inprocess'* at the API endpoint. All the data is inserted in 'entity_score' table built in mySQL.

In the second stage, the automation pipeline activates stored procedures for population of sustainability score tables at sub-topic, dimension, and overall sustainability index. After the calculation of the results, three tables i.e., overall sustainability index, sustainability score at dimension level, and sustainability score at sub-topic level are posted to the API endpoint. If there is any issue in posting the results, the request status is again marked as *'error'* otherwise it is marked as *'processed'*. An anonymized version of the Python automation pipeline script is provided in APPENDIX C.

Automation is maintained through a system scheduler, which runs the pipeline at fixed time intervals. This scheduling ensures that new requests are processed promptly and that results remain current even as organisations update their sustainability inputs. A comprehensive logging mechanism records the status of each processing step, including successful operations, validation outcomes, database transactions, calculation execution, and result posting. These logs support system monitoring, enable fault diagnosis, and provide full traceability for audit or verification processes.

This automation pipeline, ensures scalability, reduces the risk of manual errors, and enables organisations to obtain up-to-date sustainability results at regular intervals.

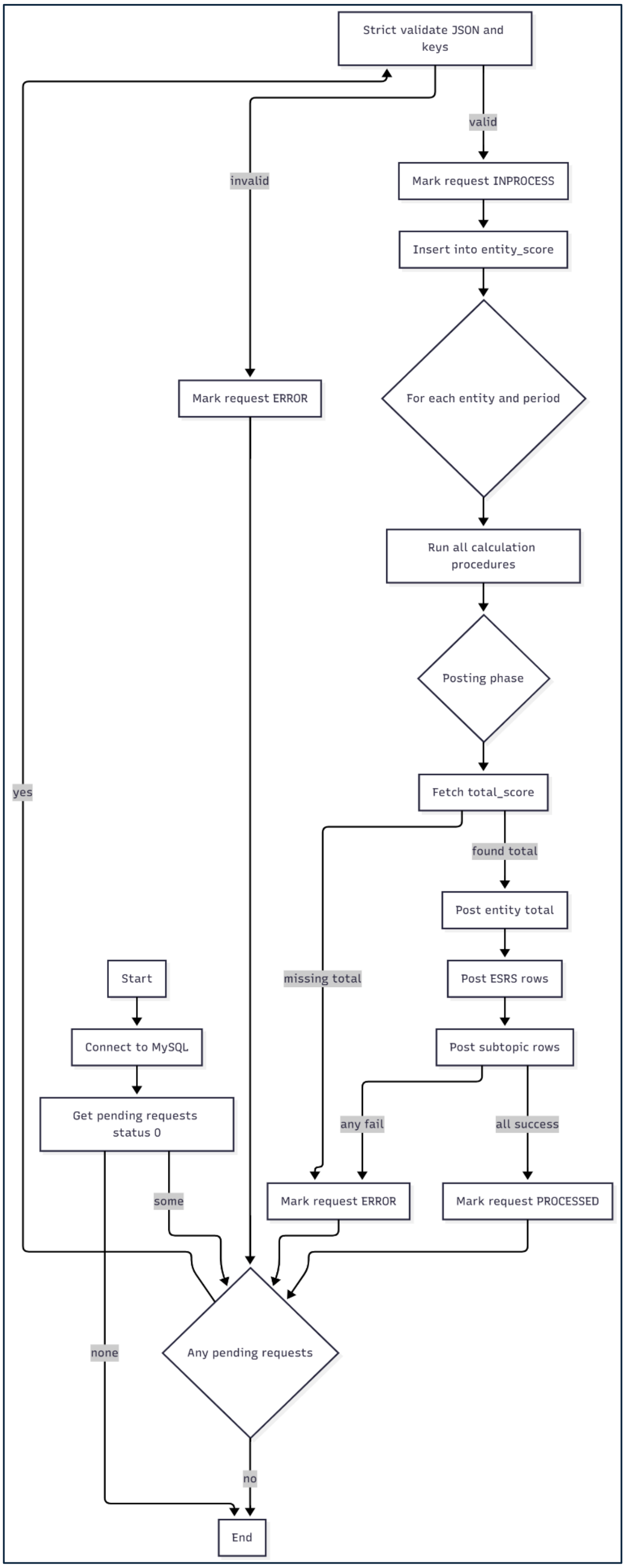

Figure 13. Automation pipeline

6.4 Chapter Summary

This chapter presented the digital implementation of the ESRS–AHP sustainability assessment framework, demonstrating how a structured relational database and automated processing pipeline can transform a complex methodological model into an operational decision-support system. The system eliminates the laborious manual computations traditionally associated with sustainability assessment. The automated pipeline further ensures robustness by managing the complete end-to-end workflow. Overall, this chapter highlights how digitalisation and automation can meaningfully support organisations in meeting emerging regulatory requirements.

Chapter 7 Conclusion

7.1 Summary of contributions

This thesis addressed the two challenges faced by manufacturing organizations especially SMEs i.e., the need for effective SC risk management and compliance with sustainability regulations. Overall, this research helped SMEs to make strategic decisions in improving SC resilience and sustainability despite their limited resources. Modern SCs are more exposed to natural and man-made disruptions due to their global dependencies and volatile business environments. Moreover, organizations are facing strict sustainability regulations to decrease the impact of their activities on environment and society. The thesis addressed these challenges in four parts.

Firstly, this research developed an AI-integrated decision-making framework to enhance SC resilience. The framework explained how AI can provide effective insights at different stages of standard risk mitigation framework. The use of generative AI strengthened risk identification stage by providing novel disruption scenarios and accelerated risk mitigation process by human-AI collaboration. Secondly, research introduced a collaborative framework to identify the best collaboration strategies while navigating through disruptions. The framework integrated AI and simulation tools such as Anylogistix to quantify the impact of environmental disruptions and selected collaborative strategies to strengthen decision-making for SMEs.

Thirdly, the thesis developed a comprehensive sustainability assessment framework by integrating ESRS and multi-criteria decision-making technique i.e., AHP. The framework not only evaluates the current state of sustainability performance but also identifies areas of improvement to achieve strategic goals. The framework was validated through a case study applied to an Italian manufacturing organization. Lastly, this thesis contributed by the digital automation of the sustainability assessment framework. This automation not only eliminated the manual handling of the sustainability data but also provided a dashboard insights about the sustainability performance of the organizations.

7.2 Limitations

7.2.1 AI-Integrated SC Resilience Framework

The developed framework for SC resilience is conceptual in nature and lacks empirical validation. The framework explained how AI can support different stages of the risk mitigation process, however, the practical effectiveness of AI-generated insights may vary across organizations and industries. SMEs also vary greatly in structure, resources, and industry characteristics, therefore industrial case study validation is needed to assess the practical relevance of the framework.

7.2.2 Collaboration and Simulation Framework

The collaboration framework developed for SMEs is also conceptual in nature and lacks empirical validation. Although the framework identified collaboration strategies and the role of simulation and AI tools in supporting decision-making, the framework was not validated through a complete industrial implementation. Practical collaboration between SMEs may also be limited by lack of trust, weak communication, and limited data sharing.

7.2.3 ESRS–AHP Sustainability Assessment Framework

Although the sustainability assessment framework was validated through a case study, it also carries some limitations. The ESRS–AHP framework relies partly on expert judgement for pairwise comparisons, which introduces an inherent degree of subjectivity. In addition, several KPIs in the social and governance dimensions are qualitative in nature and depend on managerial assessments, which may introduce response bias.

7.2.4 Digital Automation Framework

The digital automation framework eliminated the manual handling of sustainability data and provided dashboard-based sustainability insights. However, the implementation was tested within a limited organizational setting. Further industrial validation and integration with ERP systems and real-time organizational databases may improve scalability and practical applicability.

7.3 Future Research Directions

Future research may focus on empirical validation of the developed resilience and collaboration frameworks through industrial case studies. Advances in AI and uncertainty modelling also offer opportunities for refining the proposed frameworks. Future studies may employ fuzzy AHP to handle vagueness in expert judgement more effectively and may extend robustness analysis to sub-topic and indicator-level perturbations. Reinforcement learning could also be explored to support adaptive risk mitigation policies that improve over time with additional data.

Finally, although the thesis addressed two domains of SC i.e., resilience and sustainability, it did not explore the integration of these two domains. Future research may explore how advancement in resilience impacts sustainability performance and vice versa. Additional research may also investigate the integration of the developed digital sustainability framework with ERP systems, IoT infrastructures, and external industrial benchmark databases to improve scalability and cross-sector comparability.

List of contributions

I. Development of a European Sustainability Reporting Standards Compliant Sustainability Assessment Framework for Manufacturing Organisations Using Analytic Hierarchy Process

K Ahmad, MG Marchesano, V Popolo, R Revetria, A Rozhok

Sustainability 17 (11), 4772

II. Supply chain resilience in SMEs: integration of generative AI in decision-making framework

K Ahmad, A Rozhok, R Revetria

2024 International Conference on Machine Intelligence and Smart Innovation

III. Use of Modeling & Simulation and AI for Collaborative Framework: SMEs Supply Chain Disruptions

R Revetria, L Damiani, A Rozhok, K Ahmad

New Trends in Intelligent Software Methodologies, Tools and Techniques, 392-39

IV. INTEGRATING SIMULATION AND OPTIMIZATION FOR SUSTAINABILITY ASSESSMENT IN COMPLEX SUPPLY CHAINS: A UNIFIED FRAMEWORK WITH AI

A Rozhok, K Ahmad, R Revetria

International Maritime Transport and Logistic Journal 14, 459-467

V. Integrating Value Chain Analysis and System Dynamics for EPC Project Optimization

A Rozhok, R Revetria, K Ahmad, R Pedemonte

2025 International Conference on Machine Intelligence and Smart Innovation

VI. Strategic decision-making for the job shop layout: AI-trained metamodel using modelling and simulation results

K Ahmad, A Rozhok, L Bonorino, R Revetria, L Damiani

XXX SUMMER SCHOOL “Francesco Turco”, 1-9

VII. Analytical Hierarchy Process Based Sustainability Assessment Framework Implementation in MySQL

K Ahmad, A Rozhok, R Revetria

New Trends in Intelligent Software Methodologies, Tools and Techniques, 219-227

VIII. MARITIME ENGINEERING EDUCATION. A CRUISE SCHOOL ACTIVITY ON BOARD CASE

A Rozhok, R Revetria, A Khursheed, T Miroglio

MARITIME ENGINEERING 3, 5

IX. Use of modeling and simulation for training students: warehouse operations management

K Ahmad, A Rozhok, R Revetria, L Damiani

XXIX SUMMER SCHOOL “Francesco Turco”–Industrial Systems Engineering, 1-7

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APPENDIX A

Pairwise Comparison Matrices and Consistency Ratios

A- Pairwise comparison at indicators level

1. Pairwise comparison under the sub-topic climate change (E1).

Climate change (E1)	E1.1	E1.2	E1.3	E1.4	E1.5	Weight
E1.1	1	2	½	3	2	0.2601
E1.2	½	1	½	1	1	0.1377
E1.3	2	2	1	3	2	0.3416
E1.4	1/3	1	1/3	1	½	0.1029
E1.5	½	1	½	2	1	0.1577
CR = 0.022						

2. Pairwise comparison under the sub-topic pollution (E2).

Pollution (E2)	E2.1	E2.2	E2.3	Weight
E2.1	1	2	3	0.5485
E2.2	½	1	1	0.2409
E2.3	1/3	1	1	0.2106
CR = 0.017				

3. Pairwise comparison under the sub-topic water & marine resources (E3)

Water & marine resources (E3)	E3.1	E3.2	E3.3	Weight
E3.1	1	1/3	1	0.2098

E3.2	3	1	2	0.5499
E3.3	1	1/2	1	0.2402
CR = 0.019				

4. Pairwise comparison under the sub-topic Biodiversity & ecosystem (E4)

Biodiversity & ecosystem (E4)	E4.1	E4.2	Weight
E4.1	1	2	0.6667
E4.2	½	1	0.3333
CR = 0.000			

5. Pairwise comparison under the sub-topic Resource use & circular economy (E5)

Resource use & circular economy (E5)	E5.1	E5.2	E5.3	E5.4	E5.5	E5.6	E5.7	Weight
E5.1	1	2	3	2	4	5	3	0.3051
E5.2	1/2	1	2	4	2	3	2	0.2137
E5.3	1/3	½	1	1	2	2	2	0.1244
E5.4	1/2	¼	1	1	2	2	1	0.1131
E5.5	1/4	½	1/2	1/2	1	4	2	0.1088
E5.6	1/5	1/3	1/2	1/2	1/4	1	1	0.0570
E5.7	1/3	½	1/2	1	1/2	1	1	0.0779
CR = 0.053								

6. Pairwise comparison under the sub-topic Own workforce (S1)

Own workforce (S1)	S1.1	S1.2	S1.3	S1.4	Weight
S1.1	1	2	1/2	2	0.2810
S1.2	½	1	1/3	1/2	0.1197
S1.3	2	3	1	1	0.3645
S1.4	½	2	1	1	0.2348
CR = 0.063					

7. Pairwise comparison under the sub-topic Workers in value chain (S2)

Workers in value chain (S2)	S2.1	S2.2	S2.3	Weight
S2.1	1	1/2	1/3	0.1692
S2.2	2	1	1	0.3874
S2.3	3	1	1	0.4434
CR = 0.019				

8. Pairwise comparison under the sub-topic Affected communities (S3)

Affected communities (S3)	S3.1	S3.2	S3.3	Weight
S3.1	1	1	4	0.4577
S3.2	1	1	3	0.4160
S3.3	1/4	1/3	1	0.1263
CR = 0.01				

9. Pairwise comparison under the sub-topic Consumers & end-users (S4)

Consumers & end-users (S4)	S4.1	S4.2	S4.3	S4.4	Weight
S4.1	1	2	2	2	0.3952
S4.2	1/2	1	2	2	0.2781
S4.3	1/2	1/2	1	1	0.1634
S4.4	1/2	1/2	1	1	0.1634
CR = 0.022					

10. Pairwise comparison under the sub-topic Business conduct (G1)

Business conduct (G1)	G1.1	G1.2	G1.3	G1.4	Weight
G1.1	1	1/2	1/3	1	0.1443
G1.2	2	1	2	4	0.4380
G1.3	3	1/2	1	2	0.2904
G1.4	1	1/4	1/2	1	0.1274
CR = 0.043					

B. Pairwise comparison at sub-topic level

1. pairwise comparison under the environmental dimension (E)

Environment (E)	E1	E2	E3	E4	E5	Weight
E1	1	2	3	1	2	0.3118
E2	½	1	2	2	1/2	0.1779
E3	1/3	1/2	1	2	1/2	0.1277
E4	1	1/2	1/2	1	1/3	0.126
E5	½	2	2	3	1	0.2565
CR = 0.097						

2. pairwise comparison under the society dimension (S)

Society (S)	S1	S2	S3	S4	Weight
S1	1	2	1	2	0.3403
S2	½	1	1	2	0.2431
S3	1	1	1	1	0.2431
S4	½	1/2	1	1	0.1736
CR = 0.044					

C. Pairwise comparison at dimension level

Goal	E	S	G	Weight
E	1	1	1	0.327
S	1	1	1/2	0.260
G	1	2	1	0.413
CR = 0.056				

APPENDIX B

MySQL DDL

1. Example table schema

```
CREATE TABLE entity_score (
    id INT NOT NULL AUTO_INCREMENT,
    entity_id VARCHAR(255) NOT NULL,
    period DATE NOT NULL,
    sub_sub_topic_id VARCHAR(50) NOT NULL,
    sub_topic_id VARCHAR(20) NOT NULL,
    esrs_id VARCHAR(10) NOT NULL,
    weight INT DEFAULT NULL,
    completion INT DEFAULT NULL,
    effort INT DEFAULT NULL,

    PRIMARY KEY (id),

    UNIQUE KEY ux_entity_period_topic
    (entity_id, period, sub_sub_topic_id, sub_topic_id, esrs_id),

    FOREIGN KEY (sub_topic_id)
    REFERENCES sub_topic(sub_topic_id),

    FOREIGN KEY (esrs_id)
    REFERENCES esrs(esrs_id),

    FOREIGN KEY (sub_sub_topic_id, sub_topic_id, esrs_id)
    REFERENCES sub_sub_topic(sub_sub_topic_id, sub_topic_id, esrs_id),

    CHECK (weight BETWEEN 1 AND 8),
    CHECK (completion BETWEEN 1 AND 5),
    CHECK (effort BETWEEN 1 AND 5)
);
```

2. Example stored procedure

```
DELIMITER $$

CREATE PROCEDURE calc_score_sub_sub_topic (
```

```
    IN input_entity VARCHAR(255),
    IN input_period DATE
)
BEGIN
    DELETE FROM score_sub_sub_topic
    WHERE entity_id = input_entity
      AND period = input_period;

    INSERT INTO score_sub_sub_topic (
        entity_id,
        period,
        sub_sub_topic_id,
        sub_topic_id,
        esrs_id,
        normalized_weight,
        completion,
        score
    )
    SELECT
        e.entity_id,
        e.period,
        e.sub_sub_topic_id,
        e.sub_topic_id,
        e.esrs_id,
        e.weight / total.total_weight AS normalized_weight,
        e.completion,
        (e.weight / total.total_weight) * e.completion AS score
    FROM entity_score e
    JOIN (
        SELECT
            entity_id,
            period,
            sub_topic_id,
            SUM(weight) AS total_weight
        FROM entity_score
        WHERE entity_id = input_entity
          AND period = input_period
        GROUP BY entity_id, period, sub_topic_id
    ) total
        ON e.entity_id = total.entity_id
```

```
        AND e.period = total.period
        AND e.sub_topic_id = total.sub_topic_id
    WHERE e.entity_id = input_entity
      AND e.period = input_period;
END $$

DELIMITER ;
```

Note: This stored procedure calculates indicator-level weighted scores by normalizing indicator weights within each sub-topic and inserting the resulting scores into the score_sub_sub_topic table. Similar stored procedures were used for sub-topic, ESG-dimension, and total SI aggregation levels.

APPENDIX C

Python Automation Pipeline Script

pipeline.py
Python automation pipeline for ESRS-AHP sustainability assessment
Note: API endpoints, authentication tokens, and database credentials have been anonymized for confidentiality.

```
import sys
import json
from datetime import datetime, date
from typing import Any, Dict, List, Tuple, Optional

import requests
import mysql.connector
from mysql.connector import Error


# =======================
# CONFIGURATION
# =======================

BASE = "<API_BASE_URL>"
URL_GET_PENDING = f"{BASE}/getrequests/0"

URL_STATUS = {
    "inprocess": f"{BASE}/updatereqinprocess",
    "processed": f"{BASE}/updatereqprocessed",
    "error": f"{BASE}/updatereqerror",
}

URL_POST = {
    "entity": f"{BASE}/insresentity",
    "esrs": f"{BASE}/insresesrs",
    "subtopic": f"{BASE}/insressubtopic",
}

TOKEN = "<AUTHENTICATION_TOKEN>"

DB = dict(
    host="<DB_HOST>",
    database="<DB_NAME>",
    user="<DB_USER>",
    password="<DB_PASSWORD>",
)

HTTP_TIMEOUT = 20


# =======================
# HTTP HELPERS
# =======================

def auth_headers(accept_json: bool = True) -> Dict[str, str]:
    headers = {"Accept": "application/json" if accept_json else "*/*"}
    if TOKEN:
        headers["Authorization"] = f"Bearer {TOKEN}"
    return headers
```

```
def is_truthy_ok(status_code: int, body: Any) -> bool:
    if status_code != 200:
        return False

    if body in (1, "1", True):
        return True

    if isinstance(body, dict):
        if str(body.get("RESP", "")).lower() in ("1", "true"):
            return True
        if str(body.get("status", "")).lower() == "success":
            return True
        if str(body.get("ok", "")).lower() == "true":
            return True

    if isinstance(body, str) and "success" in body.lower():
        return True

    return False


def post_status(kind: str, reqid: int) -> Tuple[bool, int, Any]:
    url = URL_STATUS[kind]

    if kind == "inprocess":
        payload = {"reqtid": str(reqid)}
        response = requests.post(
            url,
            headers={**auth_headers(), "Content-Type": "application/json"},
            data=json.dumps(payload),
            timeout=HTTP_TIMEOUT,
        )

    elif kind in ("processed", "error"):
        payload = {"reqid": str(reqid)}
        response = requests.post(
            url,
            headers={**auth_headers(), "Content-Type": "application/x-www-form-
urlencoded"},
            data=payload,
            timeout=HTTP_TIMEOUT,
        )

    else:
        raise ValueError(f"Unknown status type: {kind}")

    try:
        body = response.json()
    except Exception:
        body = response.text

    ok = is_truthy_ok(response.status_code, body)
    print(f"[{kind.upper()}] REQ={reqid} HTTP={response.status_code} OK={ok}
RESP={body}")

    return ok, response.status_code, body
```

```
def get_pending_requests() -> List[Dict[str, Any]]:
    response = requests.get(
        URL_GET_PENDING,
        headers=auth_headers(),
        timeout=HTTP_TIMEOUT,
    )

    if response.status_code != 200:
        print(f"Failed to fetch pending requests. HTTP={response.status_code}")
        print(response.text)
        return []

    try:
        return response.json()
    except Exception:
        print("Failed to parse pending requests JSON.")
        return []


# ======================
# PARSING AND VALIDATION
# ======================

def parse_reqjson(raw: str) -> Optional[List[Dict[str, Any]]]:
    try:
        parsed = json.loads(raw)
        if not isinstance(parsed, list) or not parsed:
            return None
        return parsed
    except Exception:
        return None


def resolve_entity(item: Dict[str, Any], request_entity: str, reqorigin: str) ->
Optional[str]:
    raw_entity = str(item.get("Entity") or "").strip()
    entity = raw_entity or (request_entity or "").strip() or (reqorigin or
"").strip()
    return entity if entity else None


def as_int_in_range(value: Any, lo: int, hi: int) -> Optional[int]:
    value_str = str(value).strip() if value is not None else ""

    if value_str == "" or value_str.lower() == "null":
        return None

    try:
        numeric_value = int(float(value_str))
        return numeric_value if lo <= numeric_value <= hi else None
    except Exception:
        return None


def fk_exists(cur, sub_sub_topic: str, sub_topic: str, esrs: str) -> bool:
    cur.execute(
        """
        SELECT 1
```

```python
        FROM sub_sub_topic
        WHERE sub_sub_topic_id = %s
          AND sub_topic_id = %s
          AND esrs_id = %s
        LIMIT 1
        """,
        (sub_sub_topic, sub_topic, esrs),
    )
    return cur.fetchone() is not None


def strict_validate_rows(
    cur,
    req: Dict[str, Any],
) -> Tuple[bool, List[Dict[str, Any]], str, date]:
    reqid = str(req.get("REQID"))
    reqdate = (req.get("REQDATE") or "")[:10]

    try:
        period = datetime.strptime(reqdate, "%Y-%m-%d").date()
    except Exception:
        period = datetime.today().date()

    request_entity = str(req.get("Entity") or "").strip()
    reqorigin = str(req.get("REQORIGIN") or "").strip()

    raw = req.get("REQJSONRAW") or ""
    parsed = parse_reqjson(raw)

    if not parsed:
        print(f"REQID {reqid}: invalid JSON format. Request skipped.")
        return False, [], reqid, period

    filtered = [
        item for item in parsed
        if str(item.get("Sub_sub_topic") or "").strip()
        and str(item.get("Sub_topic") or "").strip()
        and str(item.get("Esrs") or "").strip()
    ]

    if not filtered:
        print(f"REQID {reqid}: no valid indicator blocks after filtering.")
        return False, [], reqid, period

    strict_rows = []

    for item in filtered:
        entity = resolve_entity(item, request_entity, reqorigin)

        if not entity:
            print(f"Invalid row in REQ {reqid}: missing entity. Request aborted.")
            return False, [], reqid, period

        sub_sub_topic = str(item.get("Sub_sub_topic")).strip()
        sub_topic = str(item.get("Sub_topic")).strip()
        esrs = str(item.get("Esrs")).strip()

        if not fk_exists(cur, sub_sub_topic, sub_topic, esrs):
            print(
```

```
                f"Foreign key mismatch in REQ {reqid}: "
                f"{sub_sub_topic} ({sub_topic} > {esrs}), entity={entity}. Request
aborted."
            )
            return False, [], reqid, period

        weight = as_int_in_range(item.get("Weight"), 1, 8)
        completion = as_int_in_range(item.get("Completion"), 1, 5)
        effort = as_int_in_range(item.get("Effort"), 1, 5)

        if weight is None or completion is None or effort is None:
            print(
                f"Invalid value in REQ {reqid}, entity={entity}: "
                f"weight={item.get('Weight')},
completion={item.get('Completion')}, effort={item.get('Effort')}."
            )
            return False, [], reqid, period

        strict_rows.append(
            dict(
                REQID=reqid,
                entity_id=entity,
                period=period,
                sub_sub_topic_id=sub_sub_topic,
                sub_topic_id=sub_topic,
                esrs_id=esrs,
                weight=weight,
                completion=completion,
                effort=effort,
            )
        )

    return True, strict_rows, reqid, period


# =======================
# DATABASE HELPERS
# =======================

def connect_db():
    connection = mysql.connector.connect(**DB)

    if not connection or not connection.is_connected():
        raise RuntimeError("Could not connect to MySQL.")

    return connection


def insert_and_calculate_one_req(
    connection,
    rows: List[Dict[str, Any]],
) -> Tuple[bool, List[Tuple[str, str]]]:
    if not rows:
        return False, []

    insert_sql = """
        INSERT INTO entity_score
            (REQID, entity_id, period, sub_sub_topic_id, sub_topic_id,
             esrs_id, weight, completion, effort)
```

```
        VALUES
            (%s, %s, %s, %s, %s, %s, %s, %s, %s)
        ON DUPLICATE KEY UPDATE
            weight = VALUES(weight),
            completion = VALUES(completion),
            effort = VALUES(effort)
    """

    pairs = sorted(
        {(row["entity_id"], row["period"]) for row in rows},
        key=lambda item: (item[1], item[0]),
    )

    try:
        cursor = connection.cursor()
        cursor.execute("START TRANSACTION")

        inserted_rows = 0

        for row in rows:
            cursor.execute(
                insert_sql,
                (
                    row["REQID"],
                    row["entity_id"],
                    row["period"],
                    row["sub_sub_topic_id"],
                    row["sub_topic_id"],
                    row["esrs_id"],
                    row["weight"],
                    row["completion"],
                    row["effort"],
                ),
            )
            inserted_rows += 1

        for entity_id, period in pairs:
            period_str = str(period)

            for procedure in (
                "calc_score_sub_sub_topic",
                "calc_score_sub_topic",
                "calc_score_esrs",
                "calc_sustainability_index_total",
            ):
                print(f"Calling procedure {procedure}('{entity_id}',
'{period_str}')")
                cursor.callproc(procedure, [entity_id, period_str])

        connection.commit()
        print(f"Database phase completed. Rows inserted or updated:
{inserted_rows}")

        return True, [(entity_id, str(period)) for entity_id, period in pairs]

    except Error as error:
        try:
            connection.rollback()
        except Exception:
```

```
            pass

        print(f"Database phase failed: {error}")
        return False, []

    finally:
        try:
            cursor.close()
        except Exception:
            pass


# =======================
# RESULT FETCHING
# =======================

def fetch_total(connection, entity_id: str, period: str) -> Optional[float]:
    cursor = connection.cursor()
    cursor.execute(
        """
        SELECT total_score
        FROM sustainability_index_total
        WHERE entity_id = %s AND period = %s
        LIMIT 1
        """,
        (entity_id, period),
    )

    row = cursor.fetchone()
    cursor.close()

    return None if row is None else float(row[0])


def fetch_esrs_rows(connection, entity_id: str, period: str) -> List[Tuple[str,
float, float]]:
    cursor = connection.cursor()
    cursor.execute(
        """
        SELECT esrs_id, normalized_weight, esrs_score
        FROM score_esrs
        WHERE entity_id = %s AND period = %s
        ORDER BY esrs_id
        """,
        (entity_id, period),
    )

    rows = cursor.fetchall()
    cursor.close()

    return [
        (
            str(esrs_id),
            float(normalized_weight) if normalized_weight is not None else None,
            float(esrs_score) if esrs_score is not None else None,
        )
        for esrs_id, normalized_weight, esrs_score in rows
    ]
```

```python
def fetch_subtopic_rows(connection, entity_id: str, period: str) ->
List[Tuple[str, str, float, float]]:
    cursor = connection.cursor()
    cursor.execute(
        """
        SELECT esrs_id, sub_topic_id, normalized_weight, sub_topic_score
        FROM score_sub_topic
        WHERE entity_id = %s AND period = %s
        ORDER BY esrs_id, sub_topic_id
        """,
        (entity_id, period),
    )

    rows = cursor.fetchall()
    cursor.close()

    return [
        (
            str(esrs_id),
            str(sub_topic_id),
            float(normalized_weight) if normalized_weight is not None else None,
            float(sub_topic_score) if sub_topic_score is not None else None,
        )
        for esrs_id, sub_topic_id, normalized_weight, sub_topic_score in rows
    ]


# ======================
# POSTING RESULTS
# ======================

def post_entity_total(reqid: str, entity_id: str, score: float) -> bool:
    payload_form = {
        "reqid_fk": str(reqid),
        "entityvalue": entity_id,
        "score": str(score),
    }

    response = requests.post(
        URL_POST["entity"],
        headers={**auth_headers(), "Content-Type": "application/x-www-form-
urlencoded"},
        data=payload_form,
        timeout=HTTP_TIMEOUT,
    )

    try:
        body = response.json()
    except Exception:
        body = response.text

    ok = is_truthy_ok(response.status_code, body)
    print(f"[ENTITY] REQ={reqid}, ENTITY={entity_id}, HTTP={response.status_code},
OK={ok}")

    if ok:
        return True
```

```
    payload_json = {
        "reqid_fk": str(reqid),
        "entityvalue": entity_id,
        "score": score,
    }

    response = requests.post(
        URL_POST["entity"],
        headers={**auth_headers(), "Content-Type": "application/json"},
        data=json.dumps(payload_json),
        timeout=HTTP_TIMEOUT,
    )

    try:
        body = response.json()
    except Exception:
        body = response.text

    ok = is_truthy_ok(response.status_code, body)
    print(f"[ENTITY JSON] REQ={reqid}, ENTITY={entity_id},
HTTP={response.status_code}, OK={ok}")

    return ok


def post_esrs_rows(reqid: str, entity_id: str, rows: List[Tuple[str, float,
float]]) -> bool:
    all_ok = True

    for esrs_id, normalized_weight, esrs_score in rows:
        payload = {
            "reqid_fk": str(reqid),
            "entityvalue": entity_id,
            "esrsvalue": esrs_id,
            "norm_weight": normalized_weight,
            "score": esrs_score,
        }

        response = requests.post(
            URL_POST["esrs"],
            headers={**auth_headers(), "Content-Type": "application/json"},
            data=json.dumps(payload),
            timeout=HTTP_TIMEOUT,
        )

        try:
            body = response.json()
        except Exception:
            body = response.text

        ok = is_truthy_ok(response.status_code, body)
        print(f"[ESRS] REQ={reqid}, ENTITY={entity_id}, ESRS={esrs_id},
HTTP={response.status_code}, OK={ok}")

        if not ok:
            all_ok = False

    return all_ok
```

```python
def post_subtopic_rows(reqid: str, entity_id: str, rows: List[Tuple[str, str,
float, float]]) -> bool:
    all_ok = True

    for esrs_id, sub_topic_id, normalized_weight, sub_topic_score in rows:
        payload = {
            "reqid_fk": str(reqid),
            "entityvalue": entity_id,
            "esrsvalue": esrs_id,
            "subtopic2value": sub_topic_id,
            "norm_weight": normalized_weight,
            "score": sub_topic_score,
        }

        response = requests.post(
            URL_POST["subtopic"],
            headers={**auth_headers(), "Content-Type": "application/json"},
            data=json.dumps(payload),
            timeout=HTTP_TIMEOUT,
        )

        try:
            body = response.json()
        except Exception:
            body = response.text

        ok = is_truthy_ok(response.status_code, body)
        print(
            f"[SUBTOPIC] REQ={reqid}, ENTITY={entity_id}, "
            f"ESRS={esrs_id}, SUBTOPIC={sub_topic_id},
HTTP={response.status_code}, OK={ok}"
        )

        if not ok:
            all_ok = False

    return all_ok


# =======================
# ORCHESTRATION
# =======================

def process_one_req(connection, req: Dict[str, Any]) -> None:
    cursor = connection.cursor()
    is_valid, rows, reqid_str, period = strict_validate_rows(cursor, req)
    cursor.close()

    reqid = int(reqid_str) if reqid_str and reqid_str.isdigit() else None

    if reqid is None:
        print("Missing or invalid REQID. Request skipped.")
        return

    if not is_valid:
        ok, status_code, body = post_status("error", reqid)
        if not ok:
```

```
            print(f"Failed to mark REQ={reqid} as error after validation
failure.")
        return

    ok, status_code, body = post_status("inprocess", reqid)

    if not ok:
        print(f"REQ={reqid} was not accepted as in process. Request skipped.")
        return

    ok_db, entities_periods = insert_and_calculate_one_req(connection, rows)

    if not ok_db:
        ok_error, status_code_error, body_error = post_status("error", reqid)
        if not ok_error:
            print(f"Failed to mark REQ={reqid} as error after database failure.")
        return

    all_ok = True

    for entity_id, period_value in entities_periods:
        total_score = fetch_total(connection, entity_id, period_value)

        if total_score is None:
            print(f"Missing total score for entity={entity_id},
period={period_value}, REQ={reqid}.")
            all_ok = False
            continue

        ok_entity = post_entity_total(reqid_str, entity_id, total_score)

        esrs_rows = fetch_esrs_rows(connection, entity_id, period_value)
        ok_esrs = post_esrs_rows(reqid_str, entity_id, esrs_rows) if esrs_rows
else False

        subtopic_rows = fetch_subtopic_rows(connection, entity_id, period_value)
        ok_subtopic = post_subtopic_rows(reqid_str, entity_id, subtopic_rows) if
subtopic_rows else False

        if not (ok_entity and ok_esrs and ok_subtopic):
            all_ok = False

    if all_ok:
        ok_processed, status_code_processed, body_processed =
post_status("processed", reqid)
        if not ok_processed:
            print(f"Results posted, but final processed status was not accepted
for REQ={reqid}.")
    else:
        ok_error, status_code_error, body_error = post_status("error", reqid)
        if not ok_error:
            print(f"Failed to mark REQ={reqid} as error after posting failure.")


def main():
    filter_ids = []

    for argument in sys.argv[1:]:
        try:
```

```
                filter_ids.append(int(str(argument)))
            except ValueError:
                print(f"Skipping non-numeric REQID argument: {argument}")

    try:
        connection = connect_db()
        print("Connected to MySQL.")
    except Exception as error:
        print(f"Database connection failed: {error}")
        sys.exit(2)

    pending_requests = get_pending_requests()

    if not pending_requests:
        print("No pending requests found.")
        connection.close()
        return

    if filter_ids:
        filter_id_set = {str(item) for item in filter_ids}
        pending_requests = [
            request for request in pending_requests
            if str(request.get("REQID")) in filter_id_set
        ]

        if not pending_requests:
            print("No matching REQIDs found among pending requests.")
            connection.close()
            return

    for request in pending_requests:
        reqid = request.get("REQID")
        print(f"\nProcessing REQ={reqid}")

        try:
            process_one_req(connection, request)
        except Exception as error:
            print(f"Unexpected error while processing REQ={reqid}: {error}")

            try:
                if reqid is not None and str(reqid).isdigit():
                    post_status("error", int(reqid))
            except Exception as status_error:
                print(f"Failed to mark REQ={reqid} as error: {status_error}")

    connection.close()
    print("\nPipeline run complete.")


if __name__ == "__main__":
    main()
```