



Research article

Evaluation of barriers toward data-driven supply chain sustainability via Single-Valued Pythagorean PIPRECIA

Hakan Turan^{1,*} and Elif Çaloğlu Büyükselçuk²

¹ OPEX Consultant, OPEX Academy Turkey, Kocaeli, TURKEY

² Department of Industrial Engineering, Fenerbahçe University, Ataşehir, Istanbul, TURKEY

* **Correspondence:** Email: hakansigma@gmail.com.

Abstract: Sustainable supply chain management (SSCM) is a holistic approach that encompasses economic, social, and environmental dimensions, enabling firms to enhance their long-term competitiveness by meeting legal requirements and strengthening brand equity. The effective implementation of this approach necessitates a strong emphasis on data-driven decision-making. Accordingly, we aimed to identify the key barriers hindering the implementation of data-driven sustainable supply chain practices and to explore potential strategies to overcome these challenges. In the initial phase of the study, a comprehensive literature review was conducted to identify the major barriers to implementing data-driven sustainable supply chains. Subsequently, the relative importance of these barriers was assessed with input from top and mid-level managers working in manufacturing sector enterprises. The identified barriers were then prioritized using the Pivot Pairwise Relative Criteria Importance Assessment (PIPRECIA) method based on Pythagorean fuzzy numbers. Finally, solution proposals were developed to address the most critical barriers. The study revealed that organizational barriers constitute the most prominent category, representing 29.86% of the total identified obstacles. Closely following are technical barriers, which account for 26.41% and reflect the difficulties associated with implementing and integrating digital technologies. Internal and external environmental barriers are similarly substantial, comprising 25.87% of the total. In comparison, economic barriers make up the smallest share, with a relative weight of 17.86%. The number of researchers analyzing the importance weights of barriers in the context of SSCM 4.0 remains limited. The utilization of a more contemporary and robust method compared to previously applied techniques for determining these weights enhances the originality of this study.

Keywords: supply chain sustainability; barrier; data-driven; Pythagorean fuzzy set; PIPRECIA

1. Introduction

Individuals must engage in industrial activities to sustain their livelihoods and meet basic needs. In response to increasing population growth, businesses are facing heightened demand and intensified competitive pressures. Consequently, they are compelled to manage their supply chains, production processes, and operational activities with greater efficiency and strategic focus to ensure long-term viability and competitiveness [1–4]. Businesses that provide services, especially in the field of manufacturing, are under the economical, environmental and social pressure [5,6]. In this context, they have adopted the concept of sustainability as a guiding principle across their supply chain. The primary objective of sustainable supply chain management (SSCM) is to conduct activities that enhance economic efficiency, promote social responsibility, and minimize environmental impacts in an integrated and balanced manner [7,8]. By adopting a SSCM approach, companies are provided with the opportunity to establish more robust and resilient structures against climate change, scarcity of natural resources and global risks. It has been concluded that with the SSCM approach equipped with digital technologies, waste is reduced, resources are used more efficiently, and performance is increased even in small and medium-sized enterprises (SMEs) [9].

For successful SSCM, many factors such as waste management, water use, energy consumption, carbon emissions, ethical supplier selection, and consideration of social factors need to be monitored. A large amount of data is needed to monitor, evaluate, analyze, and interpret the results of these factors [10]. Sustainability assessments can be made using data-driven methods. For example, suppliers can be evaluated in terms of economic, social and environmental criteria using multi-criteria decision-making (MCDM) methods [11], risks can be identified using data obtained from sensors, cameras, and automatic devices, and appropriate measures can be taken to reduce carbon emissions and similar activities can be carried out [10,12,13]. Technologies used within the scope of Supply Chain Management 4.0 (SCM 4.0), such as IoT, big data, artificial intelligence, blockchain, and cloud computing, make achieving environmental, social and economic sustainability goals throughout the supply chain data-driven and measurable [14].

In addition to researchers investigating how digitalization enhances operational efficiency and sustainability, researchers also examine the barriers and driving forces behind the implementation of SSCM. While these researchers comprehensively analyze the technical aspects, they also find shortcomings in policy alignment and cultural adaptation. Although significant research has been conducted on the technological and operational dimensions of SSCM, certain aspects remain underexplored. It has been identified that there is a limited number of studies examining the alignment between digital transformation and organizational culture, as well as a lack of sufficient empirical research that integrates multiple Industry 4.0 technologies within a single analytical framework. Moreover, the interactions among policy frameworks, financial incentives, and sustainability outcomes have not been adequately addressed.

To bridge these gaps, we propose an integrated model that combines Industry 4.0 technologies, SSCM, and big data analytics in order to provide actionable recommendations for policymakers and practitioners. We seek to answer the questions: “What are the barriers to data-driven sustainable supply chain practices, and how can these barriers be prioritized using the Pythagorean fuzzy Pivot Pairwise

Relative Criteria Importance Assessment (PIPRECIA) method?” Accordingly, our aim of this study is to systematically identify the barriers to data-driven sustainable supply chain practices, analyze their relative importance levels using the proposed MCDM method, and offer strategic solutions to guide decision-makers and implementers in eliminating the most critical barriers. Furthermore, a sensitivity analysis is conducted to test how the proposed model performs under different scenarios, and the findings will be supported by policy and implementation recommendations for SSCM 4.0 applications. We aim to fill the methodological gap in the literature and provide original contributions in this field.

In this study, the Pythagorean PIPRECIA method was selected because it enables a more effective evaluation of uncertainty, hesitation, and information gaps inherent in expert assessments. Compared to other methods, it manages ambiguity more precisely, provides greater reliability in subjective judgments, and enables clearer differentiation among criteria. Moreover, due to its sequential comparison structure inherent in the PIPRECIA framework, the method reduces the risk of inconsistency and offers significant advantages in terms of ease of application, time efficiency, and minimizing potential errors, particularly in decision problems involving numerous criteria.

In addition to the advantages that a data-based sustainable supply chain approach provides to businesses, there are also barriers encountered during the adoption of this approach. Our aim of this study is to determine what these barriers are and their level of importance, and to develop strategies to be used to eliminate these barriers. In the second part of the study, literature review will be included, while in the third part, the barriers in the study and the PIPRECIA method based on Pythagorean fuzzy numbers that are used to determine the weights of these barriers will be introduced. In the fourth part, the application will be included, and the obtained results will be discussed in detail. In addition, a sensitivity analysis will be performed to determine how the problem will work for different scenarios. In the conclusion section, the importance and findings of the study will be included, and the limitations of the study and future studies will be mentioned.

2. Literature Review

In this section, we present a systematic literature review on the topic, summarizing research and exploring what more can be done. In this context, the research findings will be evaluated under different thematic groups such as technological integration and digital infrastructure, organizational/cultural adaptation, policy and governance barriers, and methodological approaches, and the results will be synthesized.

In their study, Chalmeta and Santos-deLeón comprehensively examined 87 articles published between 2009 and 2019 in the fields of Industry 4.0, big data, supply chain management, and sustainability, and determined six research categories that demonstrate how Industry 4.0 and big data integrate with sustainable supply chains, creating research areas for the future. They contributed to the literature on supply chain sustainability in the Industry 4.0 era. The study highlights that technological barriers (data processing, analysis) are a significant shortcoming for integration into sustainable practices [15]. Businesses need more operational data to effectively manage stochastic and dynamic supply chain operations. Therefore, the integration of monitoring and tracking devices into the system has become inevitable. Similarly, Koot and his colleagues examined 79 publications from different disciplines in the literature in their study, and most researchers integrate new measurement devices with traditional information technology infrastructure. In order for decision support processes to work more efficiently, it will be possible to collect more and more different data from operational processes.

Therefore, it is necessary to integrate more different devices into the system, invest in wireless communication networks, and enrich pattern recognition models [16]. These studies highlight the increasing recognition of technology as a driver of sustainability, but they show limited attention to the organizational readiness required for digital transformation, with a persistent lack of cultural adaptation and managerial awareness.

Rahman and his colleagues, who think that big data analytics has positive effects on supply chain sustainability, have investigated the effects of green supply chain applications on sustainability. As a result of the statistical analysis, sustainability is positively affected in environmental, economic, and social aspects, and green supply chain applications significantly moderate the relationship between supply chain sustainability and big data analytics [17]. Likewise, Fayyaz and his colleagues investigated the effects of big data analytics, green lean six sigma, and SSCM on economic performance in SMEs using structural equation model and artificial neural networks. According to the research results, although the combination of big data analytics, green lean six sigma, and SSCM strengthens the economic performance of the organization, it has been determined that while SSCM practices can be implemented technologically, cultural adaptation has not been achieved in organizations [18]. These findings demonstrate that the integration of big data analytics and green practices is critical for sustainability and economic performance, but that cultural transformation plays a decisive role in the success of this process.

Although it is accepted that big data analytics is very important in supply chain management, since there is a limited number of studies in the literature on how big data analytics affects environmental sustainability in the supply chain, Agrawal and his colleagues conducted a bibliometric analysis study in which 155 articles were examined to examine the studies on this subject. They concluded that big data analytics reduces the carbon footprint, increases product life cycles, and minimizes transportation costs. Additionally, an environmentally friendly supply chain method was implemented. It was also emphasized that it is necessary to create policies that support big data analytics [19]. Similarly, Zayed and Yaseen conducted a study to determine the barriers to SSCM in the Egyptian industry and to determine the relationships between these barriers. They developed solutions to overcome these barriers. As a result of interviews with experts, barriers were determined and an interpretive structural model representing the interrelationships was established. This study will help managers working in the Egyptian industry to determine the internal and external barriers to SSCM and to develop solutions that will be effective in eliminating these barriers [20]. As a result of the analysis of 249 academic studies with the PRISMA systematic research protocol, the relationship, barriers, and drivers between SSCM and Industry 4.0 were determined. However, inadequate organizational culture and policies, such as lack of awareness of employees and actors in the chain, low transparency in the use of data, security and cooperation level, high research and development costs, limited organizational resources, inadequate public policies, and lack of financial support are the factors that prevent their proper implementation [21]. These studies show that big data analytics offers significant opportunities for environmental sustainability, but overcoming cultural and political barriers, in addition to technological advancements, is critical for the effective implementation of SSCM.

Building on this line of research, Menon and Ravi conducted a study to determine the barriers encountered in SSCM. They determined the barriers encountered in SSCM for the electronics industry. Causal factors, impact factors, and the degree of significance of the barriers were found using the Grey the Decision-Making Trial and Evaluation Laboratory (DEMATEL) method. Sensitivity analysis was conducted to test the robustness of the results. Lack of regulation and guidance from authorities was

determined as the first causal barrier, while complexity in measurement and monitoring had the largest net impact value. The barrier with the highest correlation with other barriers was obtained as the high cost of disposal of hazardous waste. Moreover, 11 barriers hindering the sustainable supply chain in the electronics industry in India were analyzed and as a result of this analysis, and recommendations were made that could guide managers and policy makers to resolve these barriers [22]. Likewise, Kumar et al. also identified 12 barriers to Industry 4.0 applications required for a sustainable food supply chain. Cause-effect analysis and significance ranking of the barriers were performed using the Rough-DEMATEL techniques: “Technological immaturity”, “high investment”, “lack of awareness and customer acceptance”, “technological limitations and lack of eco-innovation” were determined as the most significant barriers [23]. Different researchers have conducted research to identify barriers encountered during the implementation of SSCM in different sectors [2,24,25]. These findings reveal that the barriers encountered in SSCM and Industry 4.0 applications vary across sectors, but key factors such as regulatory gaps, technological maturity, and high costs stand out as common challenges.

Waste management is also an important issue for a sustainable supply chain. In their study conducted in 2023, Liang and his colleagues conducted research to determine the barriers in the waste supply chain. They used the fuzzy DEMATEL method to determine the weight and centre of each barrier. They designed a waste supply chain coordination scheme based on a closed-loop supply chain around critical barriers by drawing causality diagrams of the barriers [26]. One of the important concepts in terms of sustainability is the concept of circular supply chain. It is a concept that has become the focus of researchers worldwide in recent years. The reason for this is the huge amount of waste generated, deteriorating environmental conditions, damage, and decrease in natural resources. Some studies are being conducted to determine the barriers to circular supply chain management, especially in developing countries. In parallel, Lahane and Kant determined the weights of the barriers and the causal dependency between them using the Analytical Hierarchy Process (AHP) and DEMATEL methods based on Pythagorean fuzzy numbers [27]. While the most important barrier was determined as “the lack of top management support”, the least important one was determined as “low acceptability to adopt remanufactured, recycled, and renewed products”. This study can help managers, practitioners, and policy makers in preparing business strategies. These findings demonstrate that waste management and circular supply chain practices are critical to sustainability, but factors such as top management support and cultural acceptance play a decisive role in the success of these processes.

Barua and his friends drew attention not only to sustainability but also to lean, agile, and durability concepts in supply chain management. Therefore, they analyzed the barriers encountered in the implementation of the Lean, Agile, Resilient, and Sustainable (LARS) supply chain. The barriers were identified using the fuzzy Delphi method, and the relationships among the barriers were analyzed using the fuzzy DEMATEL method [28]. This study reveals that the barriers encountered are significant in terms of diversity and complexity, and that overcoming them plays a critical role in achieving sustainability, resilience, and robustness goals.

Blockchain applications are also an important phenomenon for supply chain transparency and sustainability. Singh and his colleagues identified the barriers encountered in the implementation of blockchain applications, especially in the construction sector. In the first stage of the study, 37 potential barriers were identified as a result of a comprehensive literature review. Later, as a result of expert discussions, 15 extremely important barriers were identified. In the second stage of the study, data was collected from 17 experts, and in the third stage, the importance levels of these barriers were determined using the Pythagorean AHP methodology. The most important barrier was determined as

“security environment”. This study has the quality of shedding light for managers and policy makers in the construction sector [29]. Moreover, this study reveals that blockchain technology offers significant opportunities for supply chain transparency and sustainability, but overcoming critical hurdles such as the security environment is essential to the implementation’s success.

In addition to studies exploring how technologies like Industry 4.0 and the Internet of Things improve operational efficiency and sustainability, researchers also explore the barriers and drivers to SSCM implementation. While these researchers comprehensively analyze the technical aspects, they also reveal shortcomings in policy alignment and cultural adaptation. While the literature contains significant work on the technological and operational aspects of SSCM, some aspects remain lacking. It is found that there are limited researchers examining the fit between digital transformation and corporate culture, and there are insufficient empirical studies combining multiple Industry 4.0 technologies within a single analytical framework. Finally, the interaction between policy frameworks, financial incentives, and sustainability outcomes has not been adequately addressed. To address these shortcomings, we propose an integrated model that bridges Industry 4.0 technologies, SSCM, and big data analytics to provide actionable recommendations for policymakers and practitioners. The literature provides insights into the role of Industry 4.0 technologies in enhancing supply chain visibility, operational efficiency, and sustainability. These studies have not addressed technological, organizational, and policy aspects together, but rather examined them separately. Many studies, from a technology-focused perspective, assume that digital tools improve sustainability, but organizational capabilities, cultural readiness, and human factors are not sufficiently considered for successful implementation. While technologies such as big data analytics, IoT, or blockchain are often analyzed independently, few researchers have investigated how multiple Industry 4.0 technologies work together to influence SSCM performance.

Moreover, while environmental factors have received significant attention in sustainability studies, economic and social dimensions have been relatively under-researched. In this context, the literature provides an incomplete understanding of how digitalization drives sustainable supply chain outcomes. In future research, researchers should adopt approaches that integrate technological, organizational, and policy perspectives and utilize multi-technology analytical frameworks to capture the complex and interconnected nature of data-driven SSCM.

3. Materials and methods

In this section of the study, the barriers to data-driven supply chain sustainability are given, and their definitions are provided. In addition, the PIPRECIA method, which is based on Single-Valued Pythagorean fuzzy numbers and used to determine the importance levels and weights of these barriers, is introduced.

Barriers toward data-driven supply chain sustainability

In this section, information on barriers is provided. In line with a comprehensive literature review and expert opinions, a total of 24 barriers were identified under four major barriers and sub-barriers under each main barrier. The definitions of the barriers are given in Table 1.

Table 1. Barriers toward data-driven supply chain sustainability.

Barrier Code	Main Barrier	Sub-Barrier
TB1	Technological	Challenges in data quality and accessibility
TB2	Barriers	Difficulties encountered in integrating new systems
TB3		Lack of advanced software and technical infrastructure
TB4		Cybersecurity threats
TB5		Lack of activities such as recovery, reuse, recycling, waste management etc.
OB1	Organizational	Lack of support from top management
OB2	Barriers	Personnel resistance to new systems
OB3		Technical knowledge level and competence of personnel
OB4		Lack of communication between stakeholders within the chain
OB5		Lack of performance measurement and incentive system
OB6		Lack of R&D and innovation
OB7		Challenges in transforming traditional operations into data-driven ones
EB1		Economical Barriers
EB2	High operational cost	
EB3	Return on Investment	
EB4	Difficulty accessing financial resources	
IEB1	Internal and External	Legal challenges
IEB2	Environmental Barriers	Social environmental pressure
IEB3		The difficulty of international operations
IEB4		Supply chain complexity
IEB5		Digital maturity level of suppliers
IEB6		Lack of sustainable suppliers
IEB7		Negative perspective on the concept of sustainability
IEB8		Long, complicated bureaucracy and documentation process

Barriers are examined under the major barriers of technological, organizational, economic, and internal/external environmental barriers. Five sub-barriers are defined under technological barriers. These are:

Challenges in data quality and accessibility (TB1): In data-driven and digital supply chain applications, data quality and accessibility are critical. Incomplete, inaccurate or outdated, inconsistent and unstructured data, and inability to access required data due to authorization, confidentiality, and security will negatively affect the success of a data-driven sustainable supply chain [25,30,31].

Difficulties encountered in integrating new systems (TB2): Real-time monitoring, automated decision making and measurability are important concepts for a data-driven sustainable supply chain. Therefore, the integration of new systems such as IoT, enterprise resource planning (ERP), cloud systems, artificial intelligence, and big data infrastructures into systems is important [2,32].

Lack of advanced software and technical infrastructure (TB3): This is one of the critical barriers for data-based SSCM. The lack of software systems and technical equipment negatively affects SSCM in environmental, economic, and social terms [33,34].

Cybersecurity threats (TB4): During the cybersecurity threat process, production, logistics, and stock processes may be damaged. Accurate data may not be collected for carbon footprint and social

practices. A cyber-attack on any link in the chain will negatively affect the system. The trust of stakeholders in the chain is shaken, and transparent reporting cannot be done [35,36].

Lack of activities such as recovery, reuse, recycling, and waste management (TB5): As a result of the lack of these activities (recovery, reuse, recycling, waste management), natural resource use, carbon footprint, and waste amount increase. This increases raw material cost and energy consumption while green marketing advantage is lost. Public health is negatively affected due to hazardous waste [2,26].

Seven sub-barriers are defined under organizational barriers. These are:

Lack of support from top management (OB1): Lack of support from top management results in inadequate resource allocation and investment required for SSCM. It also creates cultural resistance and causes a loss of motivation within the company [2,37].

Personnel resistance to new systems (OB2): Personnel resistance to new systems is a significant barrier to digitalization and data-driven transformation in SSCM. The effects of this obstacle directly affect sustainability performance both technically and culturally [2,38].

Technical knowledge level and competence of personnel (OB3): The technical knowledge and competence of personnel is crucial for successful SSCM. Inadequacy of this element creates serious obstacles, especially in terms of the integration of digital systems and environmental/social performance monitoring [2,39].

Lack of communication between stakeholders within the chain (OB4): Inadequate communication between supply chain stakeholders (manufacturer, supplier, logistics company, distributor, retailer, and customer) directly impacts issues such as data sharing, coordination, and strategic alignment, making it difficult to achieve sustainability goals [38,40].

Lack of performance measurement and incentive system (OB5): Measuring the performance of employees, suppliers, or managers in sustainable behaviors and having a system that rewards employees according to this performance will positively affect the success of sustainable activities [2,41].

Lack of R&D and innovation (OB6): This will also negatively affect the management of a data-driven sustainable supply chain. Sustainability will be possible not only with the optimization of existing systems but also with the integration of innovative activities into the system [2,42].

Challenges in transforming traditional operations into data-driven ones (OB7): The transition from experience-based decision-making systems based on manual processes to digital and automated systems based on data is a painful process for every business. Different challenges arise, such as infrastructure problems, data quality issues, organizational resistance, and talent gaps [43,44].

Four sub-barriers are defined under economical barriers. These are:

Lack of capital (EB1): Creating a data-driven SSCM requires high-investment strategies, and insufficient financing directly threatens the foundation of this transformation [2,37].

High operational cost (EB2): The increasing costs of energy, raw materials, logistics, and production processes, the additional maintenance, training, and management expenses resulting from the integration of new sustainable and digital systems, the software and infrastructure burden of data collection, analysis, and reporting systems are economic pressures that directly limit the adoption of both sustainability practices and digital systems in businesses [2,41].

Return on Investment (EB3): This expresses the ratio between the financial return an investment will provide and the investment cost [2,40].

Difficulty accessing financial resources (EB4): Access to financial resources is a significant problem, especially for SMEs, developing countries, and capital-intensive transformation projects [2].

Eight sub-barriers are defined under internal and external environmental barriers. These are:

Legal challenges (IEB1): Legal challenges affect data sharing, transparency, and compliance processes in data-driven SSCM, so they need to be managed effectively [2].

Social environmental pressure (IEB2): Social environmental pressure requires companies to be more transparent and accountable in the area of sustainability. Data-driven management increases this transparency and efficiency. Increasing environmental and social awareness among consumers, investors, civil society organizations, and society in general puts pressure on businesses to increase sustainable practices. This pressure leads companies to collect and analyzed data to improve their sustainability performance [2,41].

The difficulty of international operations (IEB3): The difficulty of operations carried out on a global scale also affects data-based sustainable supply chain performance [2].

Supply chain complexity (IEB4): As supply chain complexity increases, data management becomes more difficult, sustainability visibility decreases, risk management becomes more difficult, coordination and integration problems increase, and the need for artificial intelligence and analytical systems increases [2].

Digital maturity level of suppliers (IEB5): The digital maturity level of suppliers is vital for the integrity, efficiency, and sustainability goals of the system because data-based decision-making and sustainability practices depend on the digital capacity of not only the main company but also all stakeholders in the supply chain [2].

Lack of sustainable suppliers (IEB6): The lack of sustainable suppliers in data-driven SSCM is a barrier that seriously undermines the overall sustainability of the system. This lack negatively affects not only environmental and social performance, but also data quality, transparency, and reliability [2].

Negative perspective on the concept of sustainability (IEB7): The negative view of the concept of sustainability is an important cultural and behavioral barrier that hinders the development of the system. This negative perspective directly affects not only technological investments but also the process of collecting, analysing, and implementing data sustainability policies [39,41].

Long, complicated bureaucracy and documentation process (IEB8): The process of obtaining permits and documentation for the implementation of new technologies is quite complex and difficult [2].

3.1. Single-Valued Pythagorean PIPRECIA

The Pythagorean Fuzzy PIPRECIA method aims to reduce errors in decision-making by leveraging linguistic terms. It characterizes uncertainty in expert judgments through membership (μ), non-membership (ν), and indeterminacy (π) degrees. A known limitation arises when the sum of these values exceeds 1, a challenge partially addressed by Intuitionistic Fuzzy Sets (IFS). To mitigate this, the Pythagorean Fuzzy Sets (PFS) framework calculates indeterminacy by squaring the relevant degrees, offering a more robust representation of uncertainty. This approach remains a prevalent and modern technique in contemporary research.

In contrast, the PIPRECIA method ranks criteria based on their relative importance without the use of pairwise comparisons or the calculation of consistency ratios, distinguishing it from methods like the Analytic Hierarchy Process (AHP).

An advantage of the Pythagorean Fuzzy PIPRECIA approach is its capacity to model hesitation—a limitation inherent in traditional PIPRECIA. Although IFS incorporates membership and non-membership degrees, it becomes inadequate when their total, including hesitation, exceeds one. In such cases, Pythagorean Fuzzy Sets (PFS) offer a more flexible modeling alternative. Moreover, in

multi-criteria decision-making scenarios with numerous criteria, pairwise comparisons, such as those required in AHP, can become highly time-consuming and susceptible to inconsistency. Although AHP includes a consistency mechanism for matrices up to 15 elements, its practicality diminishes as the number of criteria increases. As a result, PIPRECIA is considered more efficient and scalable for weighting purposes in complex decision-making problems. SWARA is based on the ranking of criteria and is considered more practical when the number of criteria increases. On the other hand, PIPRECIA tends to produce more precise results compared to SWARA, as it is a reference-based method similar to AHP. Therefore, it is recommended to apply PIPRECIA in cases where the number of criteria is relatively limited.

PFS, initially introduced by Yager in 2013, extend the classical and intuitionistic fuzzy set frameworks. They enable greater flexibility in modeling the uncertainty of expert evaluations by using the squared sum of membership and non-membership degrees. As this sum can exceed 1 in conventional models, PFS overcome this constraint, offering a more generalized and expressive approach. The formal structure of PFS is provided in Eq.1 [45,46].

$$(\mu_A(x))^2 + (\vartheta_A(x))^2 \leq 1 \quad (1)$$

The foundational structure of PFS is formulated in Eq. 2, while the corresponding hesitation degree is delineated in Eq. 3 [47].

$$P = \{ \langle x, (\mu_p(x), \nu_p(x)) \rangle : x \in X \} \quad (2)$$

This hesitation quantifies the ambiguous portion not captured by the degrees of membership and non-membership. As the quality and definitiveness of expert evaluations improve, the level of hesitation naturally diminishes.

$$\pi_p(x) = \sqrt{1 - (\mu_A(x))^2 - (\vartheta_A(x))^2}, x \in X \quad (3)$$

The score and accuracy functions of α are defined in Eq. 4. Given that $S(\alpha)$ lies within the interval $[-1, 1]$, an enhanced score function for the PFN is subsequently proposed. The score function determines the direction of the evaluation by calculating the difference between the degrees of positive and negative assessments. The accuracy function quantifies the overall reliability of the evaluation by providing a numerical measure of certainty.

$$S(\alpha) = (\mu_\alpha)^2 - (\vartheta_\alpha)^2, K(\alpha) = (\mu_\alpha)^2 + (\vartheta_\alpha)^2 \quad S(\alpha) \in [-1,1], K(\alpha) \in [0,1], \quad (4)$$

In parallel, the accuracy function gauges the credibility of each evaluation by measuring its overall level of certainty. These functions are normalized, as shown in Eq. 5 [46], to ensure uniform scaling and enhance interpretive clarity. The normalized score is adjusted to fall within $[0,1]$, and the normalized accuracy reflects the residual uncertainty.

$$S^*(\alpha) = \frac{1}{4}(2 * (\mu_\alpha)^2 + (1 - (\vartheta_\alpha)^2) + ((\vartheta_\alpha)^2)^2), K^*(\alpha) = 1 - K(\alpha) \quad (5)$$

$$S(\alpha), K(\alpha) \in [0,1],$$

In the evaluation framework, input is collected from n decision-makers, whose individual weights are calculated through the method outlined in Eq. 6 [46]. This weighting process integrates their membership, non-membership, and hesitation degrees, thereby representing the overall reliability and consistency of their inputs.

$$w_m = \frac{\left(\mu_m^2 + \pi_m^2 * \frac{(\mu_m^2)}{(\mu_m^2 + \vartheta_m^2)} \right)}{\sum_{m=1}^n \left(\mu_m^2 + \pi_m^2 * \frac{(\mu_m^2)}{(\mu_m^2 + \vartheta_m^2)} \right)} \quad (6)$$

Table 2 [48] details the linguistic scale employed for assessing expert reliability.

Table 2. Linguistic explanations for experts.

Linguistic Terms	Brief	Pythagorean Fuzzy Numbers	
Thrillingly Significant	THS	0.9	0.1
Typically Significant	TS	0.8	0.2
Noteworthy	N	0.6	0.4
Reasonable	R	0.5	0.5
Inconsequential	IC	0.45	0.55
Trivial	TR	0.3	0.75
Pitty	P	0.1	0.9

Table 3 [48] presents the linguistic framework used to evaluate the relative importance of criteria.

Table 3. Linguistic explanations for criteria.

Linguistic Terms	Brief	Pythagorean Fuzzy Numbers	
Extremely Small	ES	0	1
Very Small	VS	0.1	0.9
Small	S	0.2	0.8
Slightly Small	SS	0.3	0.7
Below Intermediate	BI	0.4	0.6
Intermediate	I	0.5	0.5
Above Intermediate	AI	0.6	0.4
Slightly Big	SB	0.7	0.3
Big	B	0.8	0.2
Very Big	VB	0.9	0.1
Extremely Big	EB	1	0

The aggregation of expert opinions is conducted using the Pythagorean Fuzzy Weighted Average (PFWA) and Pythagorean Fuzzy Weighted Geometric (PFWG) operators, formalized in Eqs. 7 and 8 [46], respectively. These operators consolidate multiple expert inputs into a single representative value, proportionally weighted according to individual credibility.

$$PFWA(P_1, P_2, \dots, P_n) = (\sqrt{(1 - \prod_{i=1}^n (1 - (\mu_i)^2)^{w_i}}, \prod_{i=1}^n (\vartheta_i)^{w_i}) \quad (7)$$

$$PFWG(P_1, P_2, \dots, P_n) = (\prod_{i=1}^n (\vartheta_i)^{w_i}, \sqrt{(1 - \prod_{i=1}^n (1 - (\mu_i)^2)^{w_i})}) \quad (8)$$

The process of applying the PIPRECIA method to compute the weight of evaluation criteria is outlined as follows [49]:

Step 1. Identify the pertinent evaluation criteria and optionally arrange them in a descending hierarchy according to their anticipated importance. It is worth noting that the prioritization of criteria is not obligatory and may be excluded depending on the context.

Step 2. Beginning with the second criterion in the sequence, assign a relative importance coefficient, denoted s_j as to reflect its perceived comparative weight.

$$s_j = \begin{cases} > 1 & \text{if } c_j > c_{j-1} \\ 1 & \text{if } c_j = c_{j-1} \\ < 1 & \text{if } c_j < c_{j-1} \end{cases} \quad (9)$$

where c_j represents the weight attributed to the j -th criterion, and c_{j-1} refers to the weight assigned to the criterion immediately preceding it in the sequence.

The comparative coefficient (k_j) is derived through Eq. 10, serving to capture the variation in importance across the set of criteria.

$$k_j = \begin{cases} 1, & \text{if } j = 1 \\ (2 - s_j), & \text{if } j > 1 \end{cases} \quad (10)$$

Subsequently, the preliminary weight (q_j) of each criterion is computed using Eq.11, facilitating a structured prioritization grounded in expert judgments.

$$q_j = \begin{cases} 1, & \text{if } j = 1 \\ \frac{q_{(j-1)}}{k_j}, & \text{if } j > 1 \end{cases} \quad (11)$$

The final significant weight (w_j) is determined by Eq. 12. Normalization is also utilized to compute the final significance weights of the criteria.

$$w_j = \frac{q_j}{\sum_{i=1}^m q_i} \quad (12)$$

The linguistic terms and their corresponding scales used in the evaluation of the experts are presented in Table 2. The linguistic terms and scales used for evaluating the criteria are given in Table 3.

4. Determination of Barriers within the SSCM 4.0 Framework

The analysis began with the careful identification of domain experts who possess extensive theoretical and practical knowledge of SSCM 4.0. Particular emphasis was placed on selecting professionals with demonstrated competence and hands-on experience in the field. A summary of the experts' qualifications and professional profiles is outlined in Table 4.

Following the expert selection process, a comprehensive review of the literature was performed and supplemented by preliminary feedback from the expert panel. This integrated approach enabled the systematic identification and refinement of key obstacles relevant to the SSCM 4.0 paradigm.

A two-stage approach was adopted to identify the barriers used in this study. In the first stage, a comprehensive review of the recent literature on data-driven and SSCM was conducted. Frequently discussed concepts and themes identified in empirical and conceptual studies were extracted from the literature. In the second stage, expert opinions were obtained from selected professionals in the industry to evaluate and refine the identified barriers. By integrating theoretical insights with practical expertise, the consolidation of main and sub-criteria was achieved, ensuring a coherent linkage between theory and practice. For the study, four experts with substantial knowledge in both supply chain management and digitalization were selected from the firm. Two of these experts hold managerial positions, while the other two possess strong expertise in operational processes. The selection of domain experts was intentionally emphasized to ensure informed and reliable evaluations. Expert opinions were collected through face-to-face meetings, during which a high level of agreement among the participants was observed. Since the data were gathered in the same meeting session, the evaluations demonstrated a high degree of internal consistency and close alignment in the results.

In the literature, studies focusing on the weighting of SSCM 4.0 barriers remain limited. A review of the research reveals that various analytical methods have been employed to evaluate SSCM-related barriers. Specifically, Grey and DEMATEL [30] methods have been applied to SSCM barriers; Rough DEMATEL [23] has been used for SSCM 4.0 barriers; fuzzy DEMATEL [26], fuzzy DELPHI and fuzzy DEMATEL [28], and Pythagorean AHP and DEMATEL [27] have also been implemented in related contexts. Moreover, Pythagorean AHP has been utilized in blockchain-based SSCM studies [29]. However, to date, no researchers have applied the Pythagorean fuzzy PIPRECIA method to evaluate SSCM 4.0 barriers. The number of researchers employing the Single-Valued Pythagorean fuzzy PIPRECIA (SVPFP) method in the literature is extremely limited. The method has been applied to solve a sustainable circular supplier selection problem [49] and to technology assessment and digital transformation contexts [48]. The Single-Valued Pythagorean Fuzzy PIPRECIA (SVPFP) method was applied in this study to effectively interpret the high level of uncertainty involved in evaluating barriers to data-driven supply chain sustainability. The Pythagorean fuzzy structure enables membership and non-membership degrees to be assessed within a broader decision space, thereby providing a more flexible and realistic representation of expert judgments compared to classical and intuitionistic fuzzy

approaches. In this context, SVPFP is capable of producing more robust and reliable results. Moreover, due to the inherent structure of the PIPRECIA method, its pairwise comparative evaluation process facilitates decision-making for experts by reducing cognitive complexity. The method enables efficient and rapid management of interrelationships among a large number of criteria while minimizing inconsistency risks arising from multi-criteria evaluations. For these reasons, the SVPFP method was considered an appropriate and effective approach for the proposed analysis. The choice was motivated by its capability to handle a large number of criteria, its criterion-weighting-based structure, and its calculation mechanism that relies on the initial reference value, ensuring more consistent and reliable assessments.

In the subsequent phase, the SVPFP technique was utilized, as it effectively accounts for the independent expression of affirmation, rejection, and hesitation within expert appraisals. Prior to the assessment, the linguistic scales for evaluation were defined.

Using the established linguistic framework, the decision-makers (DMs) assessed the significance and potential impact of each barrier based on their subject-matter expertise and professional insight. This structured linguistic evaluation framework ensured a consistent interpretation of inherently subjective judgments.

The individual expert inputs were then synthesized into a collective evaluation, incorporating each expert's weight. The aggregated data were normalized to yield standardized scores for each barrier. A visual representation of the methodological workflow is presented in Figure 1.

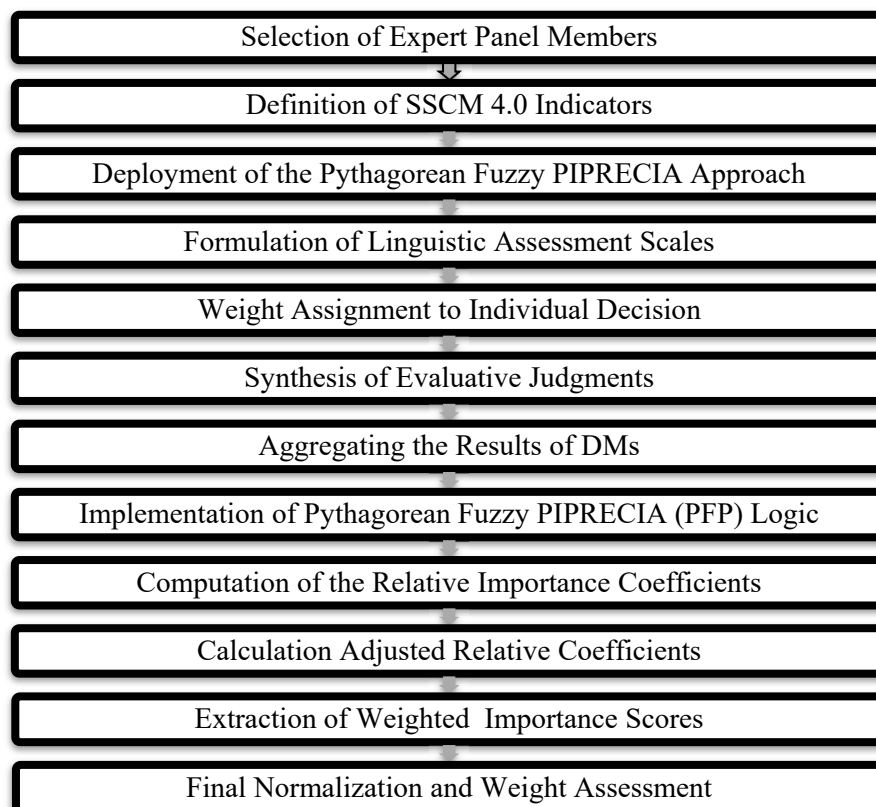


Figure 1. Overall Procedural Framework of the Research.

In the final stage, the fuzzy linguistic evaluations were transformed into crisp numerical values through the application of a scoring function followed by normalization. The relative importance of each criterion was determined by computing the incremental differences between adjacent normalized scores. These differences were adjusted by adding one, yielding relative coefficients. Based on these values, initial and final significance weights of the criteria were systematically calculated.

Figure 1 presents the comprehensive methodological framework implemented throughout the study.

In this research, we aimed to illuminate the underlying barriers to SSCM 4.0 by systematically identifying pertinent evaluation criteria and assessing their relative significance. By elucidating these core determinants, we intended to contribute to the development of more targeted and effective strategies for managing the complexities inherent in sustainable supply chain practices within Industry 4.0 frameworks. The assessment procedure was conducted by a panel of decision-makers (DMs), whose selection is summarized in Table 2. Considerable effort was invested in identifying and recruiting suitably qualified experts, as well as in ensuring the completeness and reliability of their individual evaluations. Furthermore, integrating these expert judgments into the broader analytical model demanded additional methodological rigor. To enhance the robustness and credibility of the outcomes, the fuzzy methodology was applied with input from four domain specialists, whose professional profiles are presented in Table 4.

Table 4. Professional Backgrounds of the Decision-Makers.

DMs	Academic Qualification	Highest Degree Attained	Professional Experience (Years)	Area of Specialization
DM1	Ind. Eng.	Bachelor Science	18	OPEX Manager
DM2	Mec. Eng.	Master Science	21	SCM Manager
DM3	Mec. Eng.	Bachelor Science	9	SCM Chief
DM4	Ind. Eng.	Bachelor Science	8	OPEX Chief

Both the OPEX Manager and OPEX Chief have backgrounds in industrial engineering, and due to their extensive experience with continuous improvement methodologies such as Lean and Six Sigma, they possess strong proficiency in data-driven decision-making. Moreover, OPEX models inherently encompass sustainability and supply chain management perspectives, aligning closely with the principles of industrial engineering. Similarly, the SCM Manager and SCM Chief demonstrate expertise in supply chain management, sustainability, and the real-time management of logistics networks through data-driven technologies. Their professional experience enables a comprehensive understanding of how digitalization supports efficient, resilient, and sustainable supply chain operations. Therefore, all four experts have a deep understanding of technological capabilities, OPEX, and sustainability, ensuring a well-rounded and multidisciplinary evaluation of the barriers to data-driven supply chain sustainability.

Our principal aim of this research was to systematically evaluate and rank the critical factors influencing SSCM 4.0. The empirical investigation was conducted in Gebze, which is one of Turkey's most industrially dynamic regions recognized for its strategic importance as a key organized industrial zone.

Gebze is strategically located at the very heart of Turkey's industrial landscape. To its north lies Istanbul, the country's most populous city and a major industrial hub, while to its south is Kocaeli, one of Turkey's leading centers of manufacturing and heavy industry. Positioned between these two key regions, Gebze serves as a critical industrial district, approximately 40 kilometers from Istanbul.

Moreover, Gebze is the closest point to Bursa, another prominent industrial city in Turkey. The district is also in close proximity to other significant industrial regions such as Sakarya and Tekirdağ. Owing to its central position within this industrial and logistical corridor, Gebze holds exceptional importance in terms of supply chain and transportation networks. Consequently, many major logistics companies have established their headquarters or operational centers in Gebze, reinforcing its role as a strategic hub for industrial and logistical activities in Turkey. Therefore, Gebze was selected as the study area since it provides a comprehensive representation of the industrial structure of Turkey as a whole. Moreover, the inclusion of four decision-makers was deemed sufficient for the effective implementation of the applied method.

The selection of decision-makers (DMs) was facilitated by prior professional engagements involving consultancy and training, which enabled a precise understanding of their domain-specific expertise. To ensure methodological robustness and contextual relevance, input was obtained from four DMs who are actively employed within the logistics sector in Gebze. These participants were deliberately chosen based on their dual experience in continuous improvement strategies and technological adaptation within supply chain operations.

Data collection was undertaken through in-person interviews, wherein the DMs conducted pairwise comparisons employing a structured set of predefined linguistic variables. To ensure consistency and mitigate interpretive ambiguity, the methodology was introduced through illustrative examples, and the evaluation framework, including the criteria and scales, was meticulously explained.

After data collection from DMs, the method was implemented. Our core methodological approach involved the application of the Single-Valued Pythagorean Fuzzy PIPRECIA (PFP) technique, which is a recent advancement in multi-criteria decision-making methods. This technique is particularly distinguished by its ability to capture and differentiate the dimensions of affirmation, negation, and uncertainty in expert judgment. Although this method has garnered increasing attention in the literature, it has not been applied in the context of SSCM 4.0 barrier analysis. Its adoption was justified by its analytical rigor and enhanced capability to yield nuanced, reliable results. The linguistic evaluations of the DMs is presented in Table 5.

Table 5. The linguistic assessment for DMs.

DMs	Linguistic Assessments
DM1	TS
DM2	THS
DM3	TS
DM4	N

The verbal evaluation set employed during the evaluation phase is detailed in Table 6.

The outcomes of the weight determination process for the criteria, conducted in accordance with Eqs. 3 through 12, are detailed in Table 7. The analysis up to Eq. 9 was conducted using the Single-Valued Pythagorean Fuzzy approach. Subsequently, based on the defuzzified results, the PIPRECIA method was applied through Eqs. 9 to 12 to determine the final criterion weights.

Based on the linguistic assessments presented in Table 6, the PFWA (Pythagorean Fuzzy Weighted Aggregation) values were computed in accordance with Eq. 7. Subsequently, the score function (s_j) was derived through Eq. 9. The corresponding relative importance coefficient (k_j) was

then calculated via Eq. 10, followed by the determination of the significance degree (q_j) using Eq. 11. Finally, the overall weight (w_j) was obtained through the application of Eq. 12.

Table 6. Verbal Evaluation Scheme for Criteria Weighting.

Criteria	DM1	DM2	DM3	DM4
TB1	EB	VB	EB	EB
TB2	VB	VB	SB	VB
TB3	SB	I	SB	BI
TB4	VB	SB	VB	SB
TB5	AI	I	BI	AI
OB1	AI	AI	SB	AI
OB2	I	I	AI	AI
OB3	AI	AI	AI	SB
OB4	SS	BI	I	I
OB5	SS	SS	BI	SS
OB6	BI	SS	I	BI
OB7	I	BI	BI	I
EB1	SB	AI	SB	AI
EB2	SS	SS	I	I
EB3	SS	I	SS	I
EB4	SS	BI	BI	BI
IEB1	VS	VS	ES	ES
IEB2	VS	ES	VS	ES
IEB3	ES	VS	VS	VS
IEB4	ES	ES	ES	VS
IEB5	ES	ES	VS	ES
IEB6	ES	VS	ES	ES
IEB7	ES	ES	VS	ES
IEB8	ES	ES	ES	ES

Table 7. Outcomes of PFP -Based Prioritization of SSCM 4.0 Barriers.

Sub-Criteria	$S^*(\alpha)$	s_j	k_j	q_j	w_j
TB1	1	0	1	1	0.063734
TB2	0.864229	0.864229	1.135771	0.880459	0.056115
TB3	0.531447	0.667218	1.332782	0.660617	0.042104
TB4	0.820617	1.28917	0.71083	0.929361	0.059232
TB5	0.4397	0.619083	1.380917	0.673003	0.042893
OB1	0.554022	1.114322	0.885678	0.759873	0.04843
OB2	0.461503	0.90748	1.09252	0.695524	0.044329
OB3	0.54481	1.083307	0.916693	0.758731	0.048357
OB4	0.338241	0.793432	1.206568	0.628834	0.040078
OB5	0.248711	0.91047	1.08953	0.577161	0.036785

Continued on next page

Sub-Criteria	$S^*(\alpha)$	s_j	k_j	q_j	w_j
OB6	0.317096	1.068385	0.931615	0.619527	0.039485
OB7	0.357789	1.040693	0.959307	0.645806	0.04116
EB1	0.587321	1.229533	0.770467	0.838201	0.053422
EB2	0.316802	0.729481	1.270519	0.659731	0.042047
EB3	0.31922	1.002418	0.997582	0.66133	0.042149
EB4	0.289573	0.970353	1.029647	0.642288	0.040936
IEB1	0.040869	0.751297	1.248703	0.514364	0.032783
IEB2	0.03995	0.99908	1.00092	0.513891	0.032752
IEB3	0.054153	1.014204	0.985796	0.521296	0.033224
IEB4	0.015356	0.961203	1.038797	0.501826	0.031984
IEB5	0.020683	1.005327	0.994673	0.504514	0.032155
IEB6	0.02167	1.000987	0.999013	0.505012	0.032187
IEB7	0.020683	0.999013	1.000987	0.504514	0.032155
IEB8	0	0.979317	1.020683	0.494291	0.031503

Table 8. Allocation of Weights Across SSC 4.0 Main Barriers and Sub-Criteria.

Main Barriers	Abbreviation	Main Barriers Weights	Sub-Criteria	Sub-Criteria Weights
Technological Barriers	TB	0.264079	TB1	0.063734
			TB2	0.056115
			TB3	0.042104
			TB4	0.059232
			TB5	0.042893
Organizational Barriers	OB	0.298624	OB1	0.04843
			OB2	0.044329
			OB3	0.048357
			OB4	0.040078
			OB5	0.036785
			OB6	0.039485
			OB7	0.04116
Economical Barriers	EB	0.178555	EB1	0.053422
			EB2	0.042047
			EB3	0.042149
			EB4	0.040936
Internal and External Environmental Barriers	IEB	0.258742	IEB1	0.032783
			IEB2	0.032752
			IEB3	0.033224
			IEB4	0.031984
			IEB5	0.032155
			IEB6	0.032187
			IEB7	0.032155
			IEB8	0.031503

The resulting weight allocations for the major dimensions (perspectives) and their associated sub-dimensions (criteria) within the barriers hindering the implementation of data-driven sustainable supply chain framework are summarized in Table 8.

Upon examining the barriers resulting from the application of the method according to the methodology, the analysis revealed that among the barriers evaluated within the scope of SSCM 4.0, organizational barriers hold the highest level of importance, accounting for 29.86%. This finding indicates that companies face various internal structural and managerial challenges in achieving digital transformation and sustainability objectives. Factors such as leadership deficiencies, employee resistance, cultural barriers to change, and a lack of organizational agility are among the major obstacles directly affecting the implementation of digital sustainability strategies. These results suggest that mere access to technology is insufficient, and organizational infrastructure alongside human factors play a critical role in successful transformation. Furthermore, technical barriers, representing 26.41%, rank second and reflect difficulties related to the integration of digital technologies. Challenges such as data security, system interoperability, infrastructure inadequacies, and technological complexity diminish the effectiveness of digital SSCM implementations. Internal and external environmental barriers, at 25.87%, are also of comparable significance, emphasizing the influence of external factors like regulations, supplier compliance, and market pressures on the transformation process. Conversely, economic barriers, with a weight of 17.86%, possess the least significance, indicating that although firms continue their transformation efforts despite investment costs, financial constraints may delay certain initiatives. Collectively, these findings highlight that SSCM 4.0 encounters multifaceted obstacles that require systematic attention not only from technical but also organizational and environmental perspectives.

These weightings indicate that internal organizational factors are the most critical determinants of sustainability performance. At this stage, decision-making capacity and human capital emerge as the dominant elements shaping firms' ability to achieve sustainable outcomes. Interpreting what this model reveals about companies in the examined region, the findings likely reflect organizations that either possess advanced technological infrastructure or recognize its importance but lack the institutional readiness to effectively implement and integrate these technologies into their operations. Similar to other research, the significance of technological barriers remains evident; however, organizational approaches and managerial practices underlying these technological challenges may explain the observed differences in emphasis.

Upon reviewing the sub-criteria, challenges in data quality and accessibility (TB1) emerge as the most critical factor. Cybersecurity threats (TB4) are identified as the second most important concern, followed by difficulties encountered in integrating new systems (TB2) in third place. In contrast, the sub-criterion considered least significant is the long, complicated bureaucracy and documentation process (IEB8). When examining the sub-criteria, challenges related to data quality and accessibility (TB1) emerge as the most critical issue. This highlights the fundamental role of ensuring data security and accuracy, as these aspects form the foundation for digitalization and data-driven decision-making processes within SSCM, thereby constituting a prerequisite for success.

Ranked second are cybersecurity threats (TB4), which reflect significant risks encountered by firms due to increased data flow and system integration during the digitalization process. These threats pose potential operational disruptions and information loss, thus necessitating urgent and prioritized attention.

The third most important sub-criterion is the difficulties in integrating new systems (TB2), which underline the complexities involved in harmonizing new technologies with infrastructures and processes, as well as the consequent impact on organizational efficiency.

Conversely, the sub-criterion of prolonged and complex bureaucracy and documentation processes (IEB8) is considered the least significant. This suggests that, compared to technical and security-related barriers, firms perceive operational and technical obstacles as more immediate and critical in their digital transformation efforts. Although the criterion “long, complicated bureaucracy and documentation process (IEB8)” received the lowest weight, the difference compared with other sub-criteria is minimal. This suggests that long bureaucratic procedures are not viewed as major constraints but rather as routine processes within operational systems. In practice, firms may perceive bureaucratic requirements as part of standard administrative procedures rather than obstacles that impede technological or organizational transformation. Consequently, when process simplifications or digital documentation systems are introduced, bureaucratic barriers may naturally recede in importance relative to technological and organizational ones. Overall, these findings are context-specific, reflecting the structural and managerial characteristics of firms operating in the studied region.

In summary, these findings emphasize that technical issues such as data management and cybersecurity should be addressed as priority areas within the context of digitalization and SSCM.

A sensitivity analysis was conducted to test the reliability of the results. The results presented in Table 8 correspond to Case 1. The sensitivity of the results was further examined across four additional cases. These case scenarios were developed based on the varying weights assigned by the decision-makers and are presented in Table 9.

Table 9. Cases for DMs.

Cases	DMS	Linguistic Terms
Case 1	DM1	TS
	DM2	THS
	DM3	TS
	DM4	N
Case 2	DM1	THS
	DM2	THS
	DM3	THS
	DM4	THS
Case 3	DM1	THS
	DM2	THS
	DM3	TS
	DM4	TS
Case 4	DM1	THS
	DM2	TS
	DM3	N
	DM4	N
Case 5	DM1	TS
	DM2	THS
	DM3	N
	DM4	N

For each case, the corresponding criterion weights are provided in Table 10. The analysis revealed that there were no significant differences in the importance weights.

Table 10. Sub-Criteria Weights for Cases.

Criteria	Case 1	Case 2	Case 3	Case 4	Case 5
TB1	0.06373	0.06827	0.0683	0.06842	0.06846
TB2	0.05612	0.05538	0.05547	0.05591	0.05594
TB3	0.0421	0.04123	0.04126	0.04147	0.0414
TB4	0.05923	0.05738	0.0574	0.05755	0.05738
TB5	0.04289	0.04264	0.04266	0.04281	0.04277
OB1	0.04843	0.04699	0.04695	0.04675	0.04677
OB2	0.04433	0.04371	0.04366	0.04337	0.04339
OB3	0.04836	0.04725	0.04722	0.04703	0.04705
OB4	0.04008	0.04008	0.04003	0.03972	0.03976
OB5	0.03678	0.03712	0.03711	0.03703	0.03704
OB6	0.03949	0.03942	0.03938	0.0392	0.03917
OB7	0.04116	0.04093	0.04094	0.04098	0.04095
EB1	0.05342	0.05063	0.05064	0.0507	0.05063
EB2	0.04205	0.04139	0.04133	0.04099	0.04099
EB3	0.04215	0.04139	0.04141	0.04148	0.04156
EB4	0.04094	0.04028	0.04028	0.04027	0.04031
IEB1	0.03278	0.03351	0.03354	0.03372	0.03373
IEB2	0.03275	0.03351	0.03352	0.03359	0.03357
IEB3	0.03322	0.03395	0.03395	0.03393	0.03396
IEB4	0.03198	0.03308	0.03308	0.03307	0.03307
IEB5	0.03215	0.03308	0.03308	0.03307	0.03307
IEB6	0.03219	0.03308	0.0331	0.03321	0.03324
IEB7	0.03215	0.03308	0.03308	0.03307	0.03308
IEB8	0.0315	0.03262	0.03263	0.03268	0.03269

Based on the weight values in Table 10, Pearson correlation analysis was conducted, and the results are compared in Figure 2. It was observed that there were no substantial differences among the weights.

Furthermore, the ranking values derived from each set of weights in Table 11 were compared using Spearman correlation analysis, as shown in Figure 3.

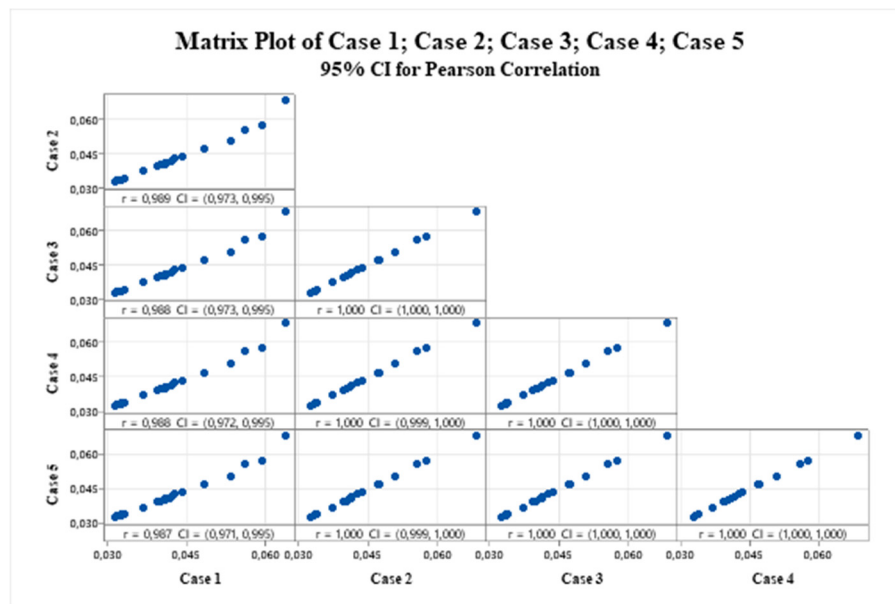


Figure 2. Pearson Correlation for Cases.

Table 11. The Ranking of the Criteria for Spearman Correlation.

Criteria	Case 1	Case 2	Case 3	Case 4	Case 5
TB1	1	1	1	1	1
TB2	3	3	3	3	3
TB3	10	11	11	10	10
TB4	2	2	2	2	2
TB5	8	8	8	8	8
OB1	5	6	6	6	6
OB2	7	7	7	7	7
OB3	6	5	5	5	5
OB4	14	14	14	14	14
OB5	16	16	16	16	16
OB6	15	15	15	15	15
OB7	12	12	12	12	12
EB1	4	4	4	4	4
EB2	11	9	10	11	11
EB3	9	9	9	9	9
EB4	13	13	13	13	13
IEB1	18	18	18	18	18
IEB2	19	19	19	19	19
IEB3	17	17	17	17	17
IEB4	23	20	21	22	21
IEB5	21	20	21	22	21
IEB6	20	20	20	20	20
IEB7	21	20	21	21	21
IEB8	24	24	24	24	24

In Figure 3, the findings indicated that there were no significant differences in the ranking result.

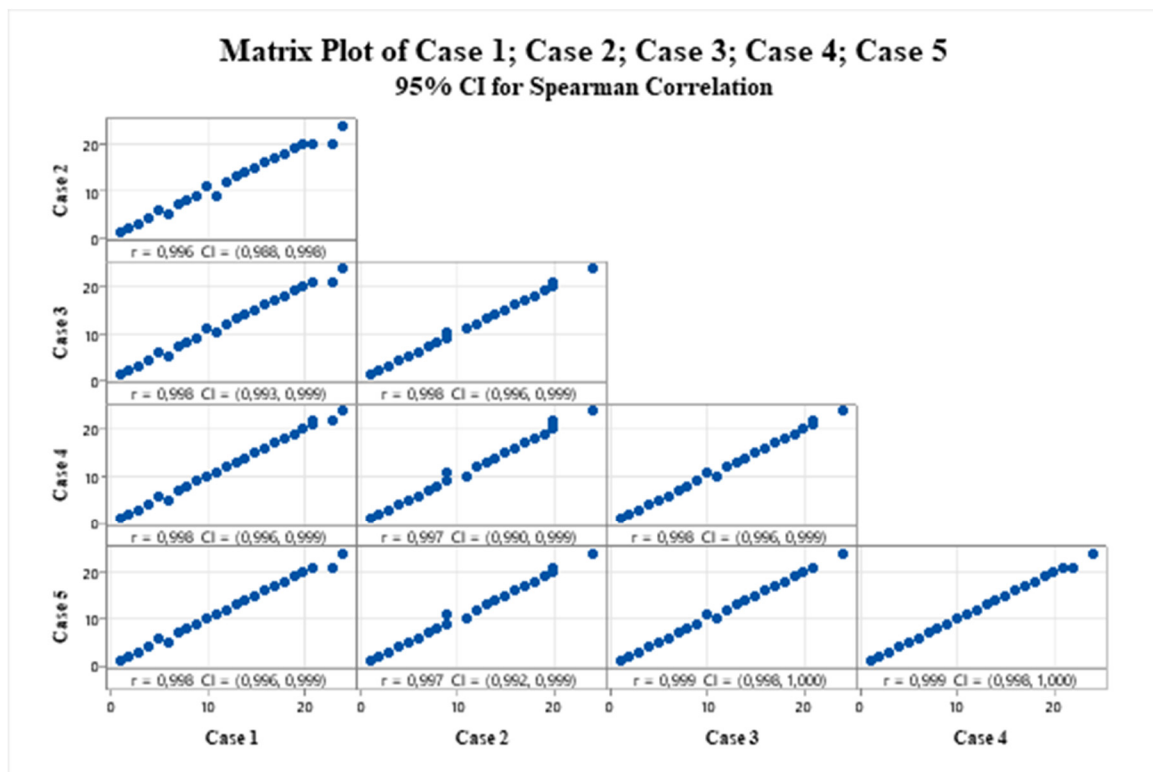


Figure 3. Spearman Correlation for Cases.

5. Conclusions

SSCM 4.0 has become an extremely important topic for companies in terms of competitiveness and environmental sustainability. The integration with Industry 4.0 has facilitated real-time monitoring, increased flexibility, and management based on predictive analytics in SSCM. This integration enables companies to utilize resources efficiently while operating in an environmentally responsible manner. Through data-driven management and monitoring, a more resilient supply network is established. Addressing potential challenges in implementing SSCM 4.0 in advance helps prevent operational issues in practice. Accordingly, we examine the barriers to SSCM 4.0 implementation, analyzing their major and sub-categories. By identifying the priority of these barriers, we aim to assist firms in effectively managing and overcoming challenges in sustainable supply chain adoption. To ensure the robustness of the results, a sensitivity analysis is conducted, and it is observed that the outcomes remain almost unchanged.

To effectively address the organizational barriers, firms should prioritize the development of transformational leadership capabilities and foster a culture that embraces change through continuous communication and employee engagement programs. Enhancing organizational agility by implementing flexible structures and encouraging cross-functional collaboration can mitigate resistance and promote adaptability. Capacity-building initiatives, such as targeted training and change management frameworks, are essential to equip personnel with the skills required for digital sustainability adoption. The organizational barriers, which hold the highest level of importance,

indicate the need of strengthening change management and leadership capabilities to address leadership deficiencies, employee resistance, and the need for enhanced organizational flexibility.

Regarding technical barriers, investments in robust IT infrastructure and cybersecurity measures are critical to ensure secure and seamless technology integration. Establishing standardized protocols for system interoperability and encouraging collaboration between technology providers and supply chain partners can alleviate compatibility issues. Furthermore, adopting scalable and modular technology solutions can reduce complexity and support incremental implementation. The prominence of technical barriers highlights the requirement for restructuring data management practices, digitalization strategies, and cybersecurity architectures.

To overcome environmental barriers, organizations must actively engage with regulatory bodies to stay abreast of compliance requirements and foster stronger supplier relationships through collaborative sustainability programs. Proactive monitoring of market trends and competitor strategies can enable firms to better anticipate external pressures and adjust their supply chain strategies accordingly. Environmental barriers demonstrate that, in addition to internal solutions, the effective management of external stakeholders is essential for successful transformation.

Finally, economic challenges can be mitigated by adopting strategic investment planning and leveraging financial incentives, such as government grants or green financing options, to support sustainability initiatives. Implementing comprehensive cost-benefit analyzes can assist decision-makers in prioritizing investments that yield long-term value. Overall, a holistic and integrated approach that simultaneously addresses organizational, technical, environmental, and economic dimensions is essential to successfully navigate the multifaceted barriers inherent in SSCM 4.0 implementation. Although economic barriers appear relatively less significant compared to others, their management requires investments to be guided by a data-driven, sustainability-oriented, and value-based approach.

When examining the sub-criteria, the most significant factor identified is challenges in data quality and accessibility (TB1). This is followed by cybersecurity threats (TB4) as the second most critical issue. Ranked third is difficulties encountered in integrating new systems (TB2). Conversely, the sub-criterion with the least importance is the long, complicated bureaucracy and documentation process (IEB8). Among the sub-criteria, issues pertaining to data quality and accessibility (TB1) are identified as the most pressing concern. This underscores the crucial importance of maintaining data integrity and security, which serve as the foundational elements for successful digital transformation and data-driven decision-making in SSCM. The identification of data quality and accessibility issues as the most critical sub-barrier emphasizes the need for transitioning toward systematic, traceable, and sustainable data architectures.

Following closely are cybersecurity threats (TB4), which represent considerable risks faced by organizations due to the heightened flow of information and increased system integrations inherent in digitalization efforts. These vulnerabilities can lead to significant operational interruptions and data breaches, thereby requiring immediate and focused mitigation strategies. The ranking of cybersecurity threats as the second most important sub-barrier reflects the increased risks associated with data growth and data sharing, thereby necessitating blockchain-based security measures and real-time monitoring mechanisms.

The third-ranking sub-criterion involves the challenges associated with integrating new systems (TB2), highlighting the difficulties of aligning emerging technologies with organizational infrastructures and workflows, and the resultant effects on overall efficiency. The high ranking of

challenges related to new system integration suggests that firms must proactively address digitally driven operational disruptions to ensure continuity and efficiency.

In contrast, the issue of extensive and cumbersome bureaucracy and documentation procedures (IEB8) is deemed the least critical. This indicates that organizations view technical and security challenges as more urgent barriers compared to administrative and procedural complexities in their digital transformation journeys. Finally, the low importance assigned to long and complex bureaucratic and documentation processes indicates that firms should prioritize operational and technical transformation efforts over administrative streamlining initiatives.

Overall, these results indicate that addressing technical concerns, particularly in data management and cybersecurity, should be prioritized to facilitate effective digitalization within SSCM frameworks.

Organizational barriers primarily arise from a lack of leadership, employee resistance, and insufficient internal communication. Inadequate support from top management and limited investment further exacerbate these challenges, hindering organizational adaptability and innovation. Technological barriers stem from insufficient and poor-quality data, weak system integration, and inadequate technical infrastructure. The lack of advanced hardware and software also contributes to these issues, while cybersecurity threats further complicate the adoption of digital and data-driven systems. Internal and external environmental barriers are mainly caused by deficiencies in regulatory frameworks, lengthy bureaucratic procedures, negative perceptions, social pressure, limited international operational capacity, and the complex structure of supply chain management. Economic barriers, on the other hand, result from insufficient capital, high operational costs, and difficulties in accessing financial resources, all of which limit firms' ability to invest in sustainable and data-driven transformation initiatives.

To prevent organizational barriers, it is essential to ensure strong top management support, establish a participatory structure that reduces employee resistance, promote investments in R&D and innovation, and implement an effective internal communication system. In addressing technological barriers, organizations should enhance data quality, ensure seamless integration among systems, and monitor critical supply networks through blockchain-based cybersecurity systems.

For internal and external environmental barriers, it is necessary to monitor and manage the maturity levels of suppliers, prepare legal frameworks related to sustainable data management, and establish infrastructure that facilitates the management of international data. Regarding economic barriers, public sustainability incentives should be increased, digitalization practices that enhance energy efficiency should be implemented, and access to financial resources, especially for small and medium-sized enterprises (SMEs), should be improved.

Our study's findings may have limited generalizability to wider target populations, different countries, and a range of industrial sectors. To overcome this limitation, in future research, researchers could focus on identifying sector-specific barriers within diverse industries. Additionally, alternative fuzzy set theories could be explored to approach the problem from different perspectives, and the results might be assessed using a variety of weighting techniques; either within the same fuzzy framework or across different ones. Researchers may also consider applying other fuzzy-based methodologies.

Use of Generative-AI tools declaration

The authors declare that they did not utilize any artificial intelligence (AI) tools in the creation of this article.

Author Contributions

Conceptualization, H.T. and E.Ç.B.; methodology, H.T. and E.Ç.B.; formal analysis, H.T. and E.Ç.B.; data curation, H.T.; writing—original draft preparation, H.T. and E.Ç.B.; writing—review and editing, H.T.; visualization, H.T. and E.Ç.B. All authors have read and agreed to the published version of the manuscript.

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