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Evaluation of artificial intelligence technology success factors for an effective supply chain using interval-valued intuitionistic fuzzy AHP method

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Abstract

The increasing complexity of supply chains in today's globalizing world has increased the importance of effective supply chain management. Consequently, businesses increasingly rely on new technologies to maintain flexibility, efficiency, and competitiveness. In this context, artificial intelligence (AI) technologies have the potential to offer significant opportunities at many critical junctures in supply chain management. The valuable contributions AI algorithms make to effective supply chains in areas such as supplier relationships, logistics planning, inventory management, demand forecasting, and fast and accurate decision-making demonstrate the strategic importance of this technology. However, harnessing the potential of AI technology in supply chain management requires overcoming several challenges, including technical infrastructure, human resource adequacy, data integrity, and security. In this perspective, this study is motivated by the need to identify the critical factors that will enable businesses to overcome these challenges and maximize the effectiveness of AI technologies. Therefore, this study aims to identify, model, and systematically and strategically analyze the key factors affecting the success of integrating AI into the supply chain for an effective supply chain. To this end, a model consisting of four main dimensions and 16 criteria is proposed based on a literature review and expert opinions through the Delphi method. To test the applicability and validity of the proposed model, an application was conducted using a case study in Turkey. The Analytic Hierarchy Process (AHP), one of the multi-criteria decision-making (MCDM) techniques, was used in this application. To overcome the uncertainty, intuition, and hesitancy due to human perception inherent in real- life decision-making processes, the AHP method was extended to interval-valued intuitionistic fuzzy (IVIF) sets. The analysis conducted reveals that elements such as “Strategic Vision”, “Quality of Algorithms” and “Data Security and Compatibility” are of critical importance for effective supply chain management.

Keywords: Analytic hierarchy process, Artificial intelligence success factors, Delphi method, Effective supply chain, Interval-valued intuitionistic fuzzy sets

JEL Codes: C18, D81, O14, O33

Aralık değerli sezgisel bulanık AHS yöntemi kullanılarak etkin tedarik zinciri için yapay zekâ teknolojisi başarı faktörlerinin değerlendirilmesi

Öz

Günümüzde küreselleşen dünyada tedarik zincirlerinin giderek karmaşık hale gelmesi, etkin tedarik zinciri yönetiminin önemini artırmıştır. Bu sebeple, işletmeler esneklik, verimlilik ve rekabet güçlerini devam ettirebilmek için yeni teknolojilere daha fazla ihtiyaç duymaya başlamıştır. Bu bağlamda, yapay zekâ (YZ) teknolojileri, tedarik zinciri yönetiminde kritik birçok noktada önemli fırsatlar sunma potansiyeline sahiptir. YZ algoritmalarının etkin tedarik zinciri açısından; tedarikçi ilişkileri, lojistik planlama, envanter yönetimi, talep tahmini, hızlı ve doğru karar verme gibi alanlarda sağladığı değerli katkılar, bu teknolojinin stratejik önemini ortaya koymaktadır. Ancak, YZ teknolojisinin tedarik zinciri yönetimindeki potansiyelinden faydalanmak; teknik altyapı, insan kaynakları yeterliliği, veri bütünlüğü ve güvenliği gibi bazı zorlukların üstesinden gelmeyi gerektirmektedir. Bu bakış açısıyla, bu çalışmanın motivasyonu; işletmelerin pek çok zorluğun üstesinden gelebilmesi ve YZ teknolojilerinden en yüksek verimi elde edebilmesi için hangi faktörlerin kritik olduğunu belirleme ihtiyacıdır. Bu sebeple, bu çalışmada etkin tedarik zinciri için YZ’nin tedarik zincirine entegrasyonunda başarıyı etkileyen temel faktörlerin belirlenmesi, modellenmesi, sistematik ve stratejik olarak analiz edilmesi amaçlanmıştır. Bu amaç doğrultusunda, literatür taraması ve Delphi tekniğine dayalı uzman görüşlerine dayalı olarak 4 ana boyut ve 16 kriterden oluşan bir model önerilmiştir. Önerilen modelin uygulanabilirliğini ve geçerliliğini test etmek amacıyla, Türkiye’de örnek bir olay üzerinden bir uygulama gerçekleştirilmiştir. Bu uygulamada, yöntem olarak çok kriterli karar verme (ÇKKV) tekniklerinden biri olan Analitik Hiyerarşi Süreci (AHS) kullanılmıştır. Gerçek hayattaki karar verme süreçlerinin içerdiği insan algısından kaynaklanan belirsizlik, sezgisellik ve kararsızlığın önüne geçebilmek için AHS yöntemi, aralık değerli sezgisel bulanık kümelere genişletilmiştir. Yapılan analizler, “Stratejik Vizyon”, “Algoritmaların Kalitesi” ve “Veri Güvenliği ile Uyumluluk” gibi unsurların, etkin bir tedarik zinciri yönetimi açısından kritik öneme sahip olduğunu ortaya koymaktadır.

Anahtar Kelimeler: Analitik hiyerarşi sureci, Aralık değerli sezgisel bulanık kümeler, Delphi tekniği, Etkin tedarik zinciri, Yapay zekâ teknolojisi başarı faktörleri

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Introduction

Supply chains (SC) are essential to a company's success in today's competitive and global business environment. SCs facilitate the exchange of money, information, and goods among various stakeholders. They offer cost-effectiveness and are key factors in determining consumer satisfaction. Companies are placing significant importance on optimizing their SC operations to maintain competitiveness.

Although globalization accelerates the integration of SCs into international markets, enabling businesses to access diverse supplier networks, optimize costs, and increase efficiency, increasing global interdependence has made SCs more vulnerable to disruptions (Sudarshan, 2025). However, digitalization and the rapid shift in consumer expectations have made SCs more dynamic, uncertain, and complex. Furthermore, addressing global megatrends and the challenges they create becomes imperative as globalization increases business competition. These megatrends include increased demand volatility, sustainability awareness, new customer requirements, global SC disruptions, time to market, and shorter lifecycles. Maintaining competitive advantage requires businesses to have an agile, flexible, predictive, and effective SC structure in such an environment. This necessitates automation and a greater focus on data in decision-making processes. The role of technology in mitigating the challenges posed by globalization has been a significant focus of recent literature.

Emerging digital technologies such as artificial intelligence (AI) offer tremendous solutions to SC problems and revolutionize supply chain management (SCM) by enhancing real-time visibility, automation, and data-driven decision-making (Sudarshan, 2025). In this context, advanced computational techniques within theoretical approaches to AI provide a comprehensive framework for addressing the multifaceted and multidimensional challenges in SCM (Abaku et al., 2024). AI offers unique advantages, including processing complex processes, generating insights, predictive analytics, big data analysis, and advanced decision-making. These capabilities have transformed the way AI operates. Consequently, AI stands out from other digital technologies. This transformation has brought businesses greater efficiency, resilience, flexibility, and agility.

AI has become an innovative solution for businesses to address these challenges in SCM due to its potential benefits (Hoff et al., 2021). While all these benefits and capabilities demonstrate the potential of AI, they do not change the fact that implementing this technology in SCs and achieving success requires tremendous effort. The effectiveness of AI applications, influenced by multiple factors, requires identifying and prioritizing success factors. Therefore, the primary motivation for this study stems from the need to identify the factors that influence success in maximizing the opportunities presented by AI technologies in SCs. Based on this motivation, this study aims to identify, model, and systematically and strategically analyze the key factors that influence the success of integrating AI into SCs for an effective SC. In this context, the study proposes a model consisting of four dimensions and 16 factors, based on a literature review and the opinions of decision-makers, each an expert in the SC field. This model provides a holistic framework for the factors affecting the success of AI integration into the SC. The DMs' judgments used in developing and proposing the model were obtained using the Delphi technique.

An application was conducted using a case study in Turkey to test the applicability and validity of the proposed model. Since the proposed model includes multiple factors, the AHP (Saaty, 1987), a multi-criteria decision-making (MCDM) technique, was used in the application. To avoid the uncertainty, intuition, and hesitation arising from human perception in real-life decision-making processes, the AHP method has been extended to IVIF fuzzy sets (Atanassov, 1999).

In this context, this study aims to make four main contributions to the literature:

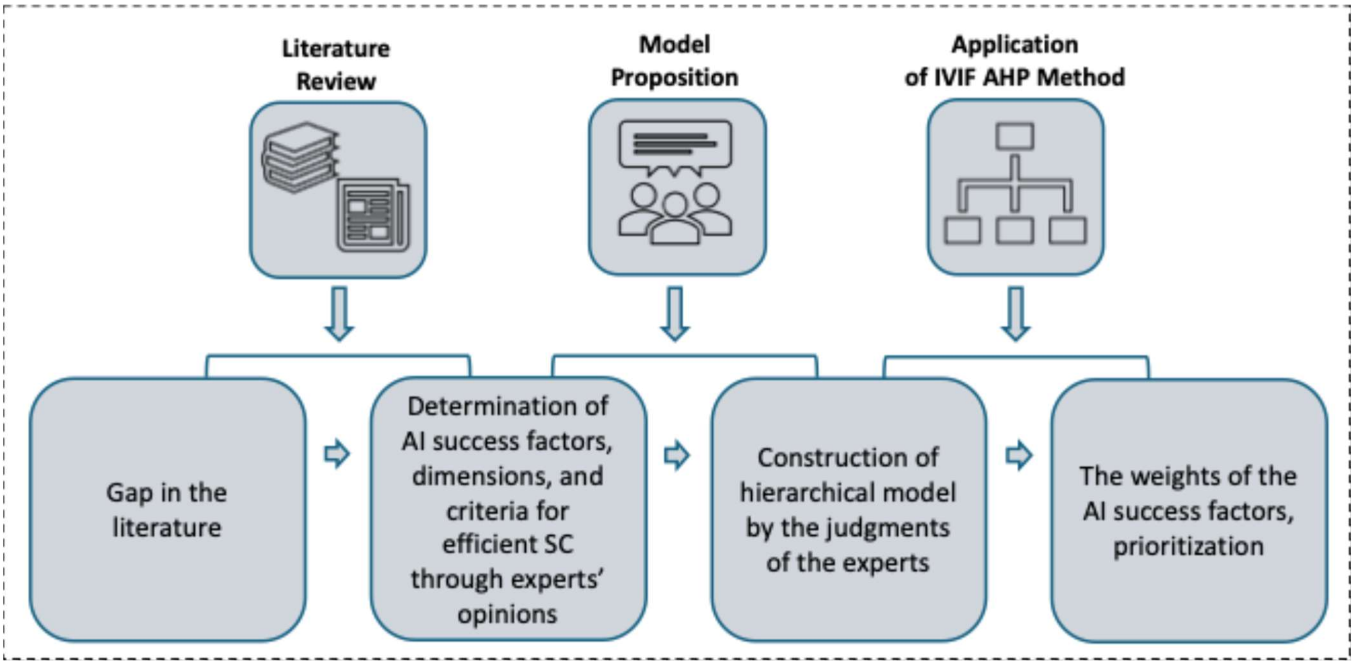
Delphi-based model proposition: AI success factors, which are discussed in scattered form in different sources in the literature, are systematically collected based on expert opinions obtained through the Delphi technique and combined in a holistic and structured framework through the proposed model.

Decision-making framework: The IVIF AHP method provides a strong methodological infrastructure while allowing the evaluation of both qualitative and quantitative data under uncertainty.

Case study: The practical validity of the model was tested with real data through the case study conducted within the scope of the study, and a contribution was made to the relatively limited number of applications in the scientific literature.

Methodology: This study proposes a methodology that is shown in Figure 1. The methodology consists of a literature review, model proposition, and application of the IVIF AHP method.

Figure 1. The steps of proposed methodology



Source: Authors

Based on the methodology shown in Figure 1, the study consists of the following sections. Section 1 gives details regarding the literature on AI and the impact of AI in SCs. Following that, Section 2 introduces the proposed model regarding the success factors of AI for efficient SC. The study presents the details of the methodology utilized in Section 3. After that, Section 4 explains the steps of the application in Turkey based on the computational steps of the method and discusses the results. Furthermore, this section provides valuable insights regarding the obtained results. Section 5 presents managerial implications including sensitivity analyses and details regarding this process. Finally, the study concludes in Section 6 through an overall reflection. Section 6 gives the future perspective of the study and the plans for future studies and offers insights regarding the parts of the study that need to be improved.

1. Literature Review

The world continues to move towards a digital future with the continuous technological developments and the spread of digital technologies. The most prominent of these technologies is AI technology. AI is the science and engineering of creating intelligent machines that turn data into information, then into knowledge and understanding, and then into competitive advantage (Hoff et al., 2021).

Today, the potential of AI has been investigated both for future goals and current needs due to the benefits and solutions it can provide for many challenges in many fields. AI has the potential to fundamentally change societies and economies in ways that include and benefit everyone. This change depends on AI technology's fair and responsible development and application. AI can help address key development challenges, facilitate innovative business models, and increase productivity (Couper et al., 2025). Since its inception, AI has seen both growth and decline for various reasons. However, in the last two decades, there has been a revival in the use of AI. Today, AI has a wide variety of applications in different areas. The complexity of evolving business scenarios and increased data flow have caused AI to gain interest in various sectors (Wu et al., 2024) such as transportation, healthcare, banking, agriculture technology, air transportation, automotive, e-commerce, water treatment (Ziegler et al., 2019) including logistics and SCM (Khadem et al., 2023; Cannas et al., 2024; Malhotra & Kharub, 2025; Weisz et al., 2025).

The emergence and use of AI technology in SCM represents a significant turning point in the evolution of global SCs (Eyo-Udo, 2024). AI technology's capabilities to speed up delivery, optimize routes, save costs, improve SC forecasting, reduce risk, and provide improved customer service have made this technology increasingly popular among the world's most successful businesses (Dagar, 2023).

Business owners can improve their data-driven and proactive decisions with analytics and AI-based SCs. This provides resilience, agility, cost savings, overall productivity improvements, configuration and reduced errors (Wu et al., 2024). Furthermore, providing an engaging customer experience is a way for organizations to ensure market leadership across industries and is now a must. However, customers may demand a range of features such as sustainability, personalization, increased transparency, last-mile tracking of shipments, and customization. These demands are significantly increasing competition in SCs. Global SCs also face challenges such as customer interactions, volatility, real-time insights, collaboration and transparency (Bosch, 2022). The use of AI in SCM plays a supporting role in critical issues such as meeting new requirements from customers and increasing efficiency by up to 20 percent. AI technology enables SC managers to see a clearer picture of the overall system, supporting more attentive customer service through the execution of intelligent decision-making processes (Hoff et al., 2021).Thanks to the advances in software development and AI technology in the last twenty years, organizations have begun to widely use AI tools in various SC operations in areas such as facilitating decision-making, risk management, inventory management, demand forecasting, and sustainability. Most businesses are improving their SC performance by using AI-powered SCM optimization software and platforms that provide analytical insights (Sharma et al., 2022).

AI has proven potential to improve decision-making processes within SCs. This demonstrates that AI technology can be used to enhance the competitive advantage and long-term performance of SCs (Akter et al., 2022). 90% of SC managers have a belief regarding that AI will be helpful in making better decisions. The benefits of AI applications in SCs can support the journey towards a more agile, more efficient, faster, and more resilient SCM. In recent years, developed AI tools which are ready-to-use to solve business problems, open-source frameworks, data availability, and fast and inexpensive hardware are supporting the adoption of AI. (Hoff et al., 2021). From this point of view the advantages of AI in SCs can be given as follows (Sharma et al., 2022; Eyo-Udo, 2024; Cannas et al., 2024; Shahzadi et al. 2024):

- AI allows to facilitate the practices of green SC.
- AI makes the SC systems more intelligent, responsive and agile.
- It provides end-to-end visibility and transparency, enabling fast and responsive decision-making.
- AI enablement in SCs helps to improve SC resilience, overall performance, knowledge management processes.
- It ensures inventory optimization and accurate planning based on supply-demand data. In this way, it supports the reduction of waste and costs.
- AI enables optimization, safe working conditions, improved quality, lower SC costs, and accurate forecasting in SCs.
- It reduces bullwhip effects with the ability to predict seasonal fluctuations based on real-time information.
- AI helps to transform the SCs and provides insights regarding consumer behavior, market trends, and potential disruptions.
- It improves operational efficiency, agility, customer service and customer satisfaction, effective communication sustainability, strategic decisions and planning by fostering greater collaboration.
- AI improves reliability and safety of processes by complementing, augmenting, replacing existing sharing systems.
- It plays a critical role in supplier selection, analyzing procurement data, and monitoring procurement and supplier performance.
- AI integrated SCM systems enables effective prediction of bottlenecks to facilitate areas such as production planning, smart production and scheduling, smart service operations, and smart maintenance.
- It provides unprecedented value and competitiveness to businesses by offering effective prediction and efficient risk management techniques.

The practical implications of AI technology in SCM research are immense. There are specific AI applications in operations and SCM in various industries such as energy, food, electronic, textile, manufacturing, technology, warehousing, logistics, and agriculture (Cannas et al., 2024). The academic literature on AI integration, adoption, and applications in SC and SCM can be summarized as follows: Daios et al. (2025) investigate the AI applications in SCM through a comprehensive survey. The study identifies the AI applications in SCM activities, future trends, challenges, and threats. Furthermore, this study highlights the critical role of AI in promoting sustainable, resilient, and flexible SCs, identifies barriers to AI adoption, and provides a roadmap for future applications and research. Malhotra & Kharub (2025) investigate the power of AI to elevate logistics performance in e-commerce to offer practical guidance for logistics firms. In this respect, the study constructs a model based on AI usage, SC consistency, logistics efficiency, last-mile logistics, coordination, and collaboration. The study employs a structural equational modeling approach to analyze the hypotheses based on the relations between the factors of the model. Samuels (2025) examines the integration of AI in SCM from Industry 4.0 to 6.0 perspective using a systematic literature review. The study reveals that AI integration improves SCM in terms of various aspects, operational efficiency, overall decision-making capabilities, sustainability, and resilience. Moreover, the study points out that the importance of AI has increased with the transition of supply networks from Industry 4.0

to Industry 6.0. Štreimikienė et al. (2025) proposes an MCDM based approach. To prioritize sustainability indicators in the context of digital transformation to enhance AI integrated sustainable global SC performance. Weisz et al. (2025) focus on AI capabilities and the proposition of related frameworks in developing SC collaborations. In this context, this study proposes a staged AI collaboration framework that considers the basic elements of trust and information sharing for SCs. In addition, the study investigates the interrelationships between AI technology, collaboration, information sharing, and trust.

Cannas et al. (2024) examine how AI applications can support operations and SCM based on multiple case studies and offer clear guidance for practitioners. The benefits and barriers regarding AI implementations in SC have been revealed in this study. The study emphasizes that AI increases competitiveness, service levels, safety, quality, sustainability, and reduces lead times and costs. Chukwu et al. (2024) focus on AI-enhanced SC security and efficiency integration for resilient chain and identifies various critical factors. Shahzadi et al. (2024) aims to develop a theoretical framework and research agenda for future studies by examining existing academic studies on the applications of AI technology in SCM. The study examines the drivers, barriers, and outcomes of AI integration in SCs, while highlighting the potential of this technology in areas such as sustainability, durability, process improvement, decision making, and efficiency. Vummadi & Hajarath (2024) discuss the AI and ML integration into strategic SC planning process to enhance decision-making and agility. Wang et al. (2024) proposes a decision support framework for humanitarian SCM using complex SF DEMATEL-MARCOS method to analyze the enablers of AI and humnan intelligence. Charles et al. (2023) analysis the integration of AI and blockchain for SC. The study performs a state-of-art review of both AI and blockchain in the field of SC and indicates that the concept is still in its early stages and the need for cross- and inter-disciplinary grounded research.

Khadem et al. (2023) discusses the AI applications for revolutionizing the efficiency and optimization in SCs. For this purpose, the study investigates most common AI applications in customer service, risk management, transportation management, demand forecasting, and warehouse management for SCM. Following that, the authors reveal the benefits and challenges of AI in SCs. The benefits have been determined as enhanced decision-making, reduced costs, improved efficiency, increased agility, and improved visibility. On the other hand, the study highlights challenges related to regulation, data availability, complexity, and data quality. Furthermore, the future trends regarding the growth of AI in SCM are emphasized in the study. Chaudhari (2022) focuses on AI in SCM and introduces it benefits as improved logistics capabilities, optimized procurement activities, increased end-to-end visibility, production planning, scheduling maintenance, and improved demand forecasting. Furthermore, the study gives applications of AI in SC. These applications are speech recognition, traffic prediction, self-language translation, problem detection, virtual personnel support, auto-driving cars, and image identification. Pournader et al. (2021) presents a systematic review regarding AI applications in SCM and highlight that the literature is still behind the industrial applications of AI to provide a roadmap for future studies. An examination of the academic literature reveals that successful applications focusing on the integration of AI technology into SCs are quite common. On the other hand, studies focusing on AI success factors for effective SCs are relatively limited.

However, scientific studies draw attention to the isolated use of AI methods in SCs. Moreover, these studies emphasize that understanding AI technology's ability to create SC-level capabilities is limited. Some studies state that the full potential of AI technology, which offers the promise of transforming business models, has not been fully realized in SCs and that organizations face many obstacles in benefiting from this potential (Pournader et al., 2021). Although AI technology brings many opportunities in operations and SCM, it also brings financial, organizational, strategic and technological barriers (Cannas et al., 2024). Furthermore, the research and expertise regarding the role of AI in SCM and operations management are limited (Helo & Hao, 2022). Those who understand the technological evolution of SC businesses are investing in transformation and AI-based optimization. A study revealed that 61% of managers in the sector stated that AI technology helps reduce the costs of managing their SCs. The successful implementation of AI technology reduces mishaps, errors, and costs, while improving productivity and increasing revenue. This makes AI technology an inevitable reality that makes it a must for all businesses managing complex SCs (McKinsey & Company, 2019). For this reason, determining the success factors of AI for an efficient SC is critical.

2.Proposed Model

For organizations, the promise of AI to increase the resilience, efficiency, and competitiveness of their SCs is critical (Chukwu et al., 2024). Effectively integrating and implementing AI technology into SC operations requires organizational alignment, meticulous planning, and strategic implementation (Brandon-Jones et al., 2014). A comprehensive understanding of SC constraints and identifying areas where AI can effectively solve problems and provide value are crucial for achieving company objectives (Chukwu et al., 2024). At this point, identifying, modeling, examining and analyzing critical AI success factors for efficient SCs play a critical role. In this context, this section aims to investigate the critical success factors and propose a model that includes these factors.

An examination of the academic literature reveals various studies examining critical success factors from an AI perspective. Chukwu et al. (2024) focus on AI-enhanced SC security and efficiency integration for resilient chain and identifies various critical factors and highlight the significance of 4 main concerns which are technical, organizational, ethical, and environmental in this manner. Culot et al. (2024) have clarified current technological approaches around four key categories and their contextual factors concerning AI in the field of SCM. The identified categories are provided as data and system requirements technology deployment processes, (inter)organizational integration, and performance implications. Al Hleewa & Al Mubarak (2023) focus on success factors of using AI and identify three dimensions as technology, organization, and environment. Kumar et al. (2023) focuses on identifying critical success factors for AI adoption in SC in the emerging economy context and they collect critical success factors under four major dimensions which are technological, organizational, institutional and human. Merhi (2023) reveals critical success factors impacting AI implementation under four categories which are organization, process, technology, environment and evaluates the factors using the AHP method. Wang et al. (2023) investigate the role of AI technologies in the construction industry using integrated fuzzy MCDM methodology. In this manner, the authors collected contributing criteria under three main categories. Dora et al. (2022) examine critical success factors influencing the adoption of AI in the food SC using a conceptual framework based on four dimensions which are technology, organization, environment, and human. While the aims, areas of application, and methods of these studies differ, they share a commonality. They group critical success factors or criteria under a few categories, themes, or dimensions.

Table 1. Some critical core issues highlighted by the studies in the academic literature

Source	**Some Critical Core Issues (Critical Success Factors)**
Chukwu et al. (2024)	"Data compatibility, system interoperability, and interaction, data quality, data protection, accessibility, and security, AI algorithm, effective change management strategies, ethical and legal AI adoption, transparency, scalability".
Culot et al. (2024)	"Data availability, quality, and volume, data security and confidentiality, (inter)organizational data-sharing, reduced data dependency, technological infrastructure, information system integration, compatibility, interoperability, scalability, AI strategy, strategic alignment, organizational culture and change management, reliability, transparency, workforce upskilling and retraining, process digitalization and standardization, (inter)organizational coordination mechanisms, flexibility, risk management, investments and resource allocation".
Havle & Büyüközkan (2024)	"AI strategy, AI trustworthiness, privacy, transparency, trust, high data quality, education and change management, interoperability, infrastructure and usability, security and robustness.
Nguyen et al. (2024)	"Organizational readiness, compatibility, competitive pressure, government involvement, managerial capability, technical capability, vendor partnership, market uncertainty".
Wang et al. (2023)	"Complexity, aesthetics, data and algorithm value, innovation advancements, government, sufficient budget, information exchange, interoperability, risk-taking ability, employee workforce, policy and laws, trust, copyright and ownership, regulatory measures, social impact".
Al Hleewa & Al Mubarak (2023)	"Compatibility, availability, data quality, security, reliability, scalability, technology management, governmental regulations, trust, customer and community support, technical competency, resources, organizational structure, organizational readiness, culture, organizational innovativeness, knowledge and information, interdisciplinary collaboration".
Merhi (2023)	"Top management support, strategic vision, organizational structure, organizational culture, technical expertise, ethics, responsibility and accountability, integration, data quality, IT infrastructure, security, confidentiality, data governance, system scalability, system flexibility, vendor selection, cost of AI".
Kumar et al. (2023)	"Technology sophistication, sustainable data quality and integrity, troubleshooting feasibility, interoperability, strategic alignment, organizational readiness, organization structure, organizational culture, financial resources, government support, policy framework, effective collaboration, user desirability, human resource team competency, training for AI integration".
Dora et al. (2022)	"Organizational culture, change management, resources and competencies, technological infrastructure, technology knowledge, regulatory environment, government support, ethics, privacy, employee competency and training".

Additionally, when the scientific studies have been examined, it is seen that these studies focus on some critical core issues as success factors in AI integration, AI adoption and AI efficiency. The critical success factors mentioned by some of these studies have been summarized in Table 1 to give a general perspective.

A review of the academic literature reveals that many critical success factors can be considered. In this case, the Delphi method was used to enable DMs to identify the most relevant factors and eliminate those that were not relevant to the study's objectives (Wang et al., 2023). The Delphi technique, first proposed by Dalkey and Helmer (1963), is a method used to identify solutions to real-world problems, meet future needs, or discover new concepts (Skulmoski et al., 2007). Today, this method is widely used and accepted by both management and researchers to reach a decision regarding a problem. This method relies on selecting a group of experts (DMs) and conducting face-to-face interviews, discussions, and brainstorming sessions. In this way, the experts' judgments and evaluations are collected (Joshi et al., 2011; Kumar et al., 2022). The Delphi method has been used in various fields as a structured approach to reach expert consensus on a specific topic. Furthermore, this method has proven effective in collecting and synthesizing expert opinions while preserving their anonymity. Furthermore, the Delphi method is valid and useful in determining criteria weights and preferences in the MCDM approach. (Wang et al., 2023).

Figure 2. The dimensions of the proposed model

Source. Authors

Based on the existing literature review, the Delphi technique was applied to identify the most critical elements serving the study's purpose, identify the factors contributing to these elements, and facilitate a more efficient process. This process involved face-to-face interviews, video conferences, discussions, and brainstorming sessions with DMs. The Delphi technique resulted in a model proposition based on the identification of four critical success dimensions and 16 contributing factors. As mentioned above, the number of success dimensions identified is consistent with those identified in previous studies on this topic. In this regard, the dimensions of the proposed model have been shown in Figure 2.

The proposed model consists of "*Data and Governance Maturity*", "*Human Resources and Organizational Readiness*", "*Strategic Alignment*", and "*Technology Competency*". These dimensions and their contributing factors determined by the Delphi technique have been supported by scientific literature. The AI success dimensions are explained as follows (Howells, 2020; Kumar et al., 2023; Culot et al., 2024; Schrage et al., 2024; Expert Opinions):

Data and Governance Maturity (DGM) refer to the ability to clearly define those responsible for the information used to achieve business objectives, the actions that can be taken, and how this information is used, and to ensure the quality and security of data with policies, roles, standards, and measurements based on continuous improvement in this context.

Human Resources and Organizational Readiness (HOR) represent the willingness, readiness, and ability to adapt to change in people and organizational structures by adopting AI technology.

Strategic Alignment (SA) refers to the use of intelligent key performance indicators aligned with technology, processes and people that have their own strategies in the networked organization to align strategic expectations with strategic performance.

Technology Competency (TC) is being able to be competent by having the basic technological infrastructure and capabilities required to develop and implement AI applications using large, complex and unstructured data sources.

Table 2 shows the scientific sources of the factors contributing to these dimensions explained above. In this context, definitions of the success factors contributing to the dimensions are presented below.

The explanations of the factors contributing to the "Data and Governance Maturity (DGM)" dimension determined based on the results of the literature survey and expert opinions obtained through the Delphi technique are as follows (Felzmann et al., 2020; Pal, 2023; Ayinla et al., 2024; Chukwu, 2024; Gaikwad, 2024; Folorunso et al., 2024; Sustainability Directory, 2025):

Data Security and Compatibility (DGM_1) refers to the ability to adapt to the design and implementation of regulations and standards that can protect sensitive data and information systems with a proactive strategy that can ensure the prediction and prevention of possible security risks and breaches to increase the security of the SC and protect SC data, and a balanced approach that enables the minimization of security vulnerabilities without compromising these standards.

Data Transparency (DGM_2) means that the AI models and algorithms are capable of being visible, open, explainable, accessible, reliable, and trustable in terms of the data they are based, the possible biases they contain, their decision-making styles, the training data they use, their effects on environmental and social outcomes to support sustainability of SCs.

Ethical AI Practices (DGM_3) refers to the ability to provide social benefit and eliminate harm through the development and use of AI algorithms in a transparent, fair, accountable, responsible, compatible with ethical behavior principles, and impartial manner in harmony with human values, social norms and ethical standards, in response to ethical issues that may arise in decision-making processes in SCM.

Risk Management (DGM_4) means having AI-based multi-layered security and defense mechanisms seamlessly integrated into the SC and a strong, durable, accountable and reliable AI governance to ensure a strong performance of the SC, which is open to various risks, including uncertainties, disruptions and market fluctuations.

Table 2. Contributing success factors of the proposed model

Dimensions	Criteria	Sources
Data and Governance Maturity (DGM)	Data Security and Compatibility (DGM_1)	(Al Hleewa & Al Mubarak; 2023; Chukwu, 2024; Culot et al., 2024; Folorunso et al., 2024; Gaikwad, 2024; Goswami et al., 2025)
	Data Transparency (DGM_2)	(Felzmann et al., 2020; Havle & Büyüközkan 2024; Sustainability Directory, 2025)
	Ethical AI Practices (DGM_3)	(Dora et al., 2022; Merhi, 2023; Muthukalyani, 2023; Pal, 2023; Yerra, 2023; Ayinla et al., 2024; Chukwu, 2024; Havle & Büyüközkan, 2024; Goswami et al., 2025)
	Risk Management (DGM_4)	(Wang et al., 2023; Culot et al., 2024; Gaikwad, 2024; Shahzadi et al., 2024; Goswami et al., 2025)
Human Resources and Organizational Readiness (HOR)	Change Management Competencies (HOR_1)	(Muthukalyani, 2023; Chukwu, 2024; Culot et al., 2024; Havle & Büyüközkan, 2024; Shahzadi et al., 2024)
	Cross-Functional Collaboration (HOR_2)	(Norris-Green & Maxwell, 2022; Al Hleewa & Al Mubarak, 2023; Kumar et al., 2023)
	Technology Leadership (HOR_3)	(Odilov, 2024; Shahzadi et al., 2024)
	Training and Development (HOR_4)	(Dora et al., 2022; Kumar et al., 2023; Culot et al., 2024; Muehlemann, 2024)
Strategic Alignment (SA)	Flexibility and Adaptability (SA_1)	(Lagunas & Riedl, 2022; Merhi, 2023; Muthukalyani, 2023; Culot et al., 2024)
	Resource Allocation (SA_2)	(Dora et al., 2022; Al Hleewa & Al Mubarak, 2023; Kumar et al., 2023; Culot et al., 2024)
	Strategic Vision (SA_3)	(Merhi, 2023; Culot et al., 2024; Havle & Büyüközkan, 2024; Shahzadi et al., 2024)
	Vendor and Partner Collaboration (SA_4)	(Al Hleewa & Al Mubarak, 2023; Kumar et al., 2023; Muthukalyani, 2023; Goswami et al., 2025)
Technology Competency (TC)	Data Integration and Cleansing (TC_1)	(Muthukalyani, 2023; Yerra, 2023)
	Quality of Algorithm (TC_2)	(Wang et al., 2023; Chukwu et al., 2024; Shahzadi et al., 2024)
	Real-Time Analytics Capability (TC_3)	(Demigha, 2020; Yerra, 2023; Goswami et al., 2025)
	System Scalability (TC_4)	(Al Hleewa & Al Mubarak, 2023; Merhi, 2023; Yerra, 2023; Culot et al., 2024; Chukwu et al., 2024; Wang et al., 2024)

The explanations of the factors contributing to the "Human Resources and Organizational Readiness (HOR)" dimension determined based on the results of the literature survey and expert opinions obtained through the Delphi technique are as follows (Lemos et al., 2022; Norris-Green & Maxwell, 2022; Culot et al., 2024; Leuba & Piricz, 2024; Muehlemann, 2024; Odilov, 2024; Shahzadi et al., 2024; Cooper, 2025; Mary, 2025):

Change Management Competencies (HOR_1) refers to the competencies and willingness of SCs and organizations to change and transform their directions, goals, structures, infrastructures, organizational policies and management, capabilities, flexibility, adaptability, leadership and human resources in the transition to AI and the application of AI to improve their ability to meet the needs and expectations of stakeholders and customers in an environment of uncertainty and to increase the efficiency of their activities.

Cross-Functional Collaboration (HOR_2) represents the development of collaboration across the SC to successfully integrate AI into SC processes and achieve a comprehensive understanding of all business aspects of SC decisions. This means providing an environment of coordination, strategic interaction and collaboration between departments, SC professionals, functions, components and institutions by strategically promoting a data-driven culture based on effective communication, transparency and openness.

Technology Leadership (HOR_3) refers to personalized and effective leadership that empowers teams to focus on strategic planning and human relations by leveraging AI technology and innovation in their work. Technology leadership refers to the ability of business leaders to leverage their prior knowledge, combine traditional methods with AI-based approaches, implement decisions, and possess the ability to prevent change and new challenges, and seize opportunities arising from technological advancements by driving transformation. Technological advancements and the adoption of AI technology in SCs have shifted skill requirements and the need for in-house expertise.

Training and Development (HOR_4) are key to adapting to this change, facilitating AI integration, and meeting these needs through structured training and initiatives that address critical issues such as initial training, ongoing training, systematic skill development, and fostering data-driven environments, all with initiatives that foster workforce development, well-being, and competence.

The explanations of the factors contributing to the "Strategic Alignment (SA)" dimension determined based on the results of the literature survey and expert opinions obtained through the Delphi technique are as follows (Raweewan &Ferrell, 2018; Enrique et al., 2022; Lagunas & Riedl, 2022; Al-Bayed et al., 2024; Culot, 2024; Shahzadi et al., 2024; Beta et al., 2025; Jubair, 2025; Weisz et al., 2025):

Flexibility and Adaptability (SA_1) refer to companies' ability to adapt quickly and with minimal resource consumption to changing environments, supply and demand shifts, and uncertainties by leveraging the predictive capabilities of AI technology. It also refers to the ability to rapidly align necessary processes with all internal and external SC activities, operations, and processes, enabling SCM to evolve and navigate uncertainties.

Resource Allocation (SA_2) refers to more adequate and efficient allocation and use of human, technological and financial resources in SCM with sufficient information infrastructure, compatible with the insights and resource organization and knowledge-based views provided by AI technology.

Strategic Vision (SA_3) is the ability to align AI strategies with business objectives, integrate these strategies with corporate goals considering external challenges such as regulatory requirements and market conditions, create a well-defined roadmap at the board level, select AI tools aligned with the organization's goals and effectively integrate them into existing processes, and proactively address ethical concerns through governance frameworks that uphold transparency and fairness.

Vendor and Partner Collaboration (SA_4) refer to the effective collaboration of partners and vendors in the context of AI technology, where the benefits of this collaboration greatly outweigh the associated risks, and where collaboration across the SC is determined by the level of information sharing and trust between SC partners.

The explanations of the factors contributing to the "Technology Competency (TC)" dimension determined based on the results of the literature survey and expert opinions obtained through the Delphi technique are as follows (Demigha, 2020; Yerra, 2023; Saini, 2024; Wang et al., 2024):

Data Integration and Cleansing (TC_1) is critical for effective SCM and involves combining data from multiple sources into a single holistic view to provide a consistent, stable, and accessible information structure; reducing manual intervention by automatically detecting and correcting inconsistencies with AI-supported data cleansing processes, increasing operational efficiency, and strengthening the predictive accuracy of AI models by eliminating errors in master data.

Quality of Algorithm (TC_2) is the ability to have robustness, safety, reliability, interpretability, accuracy and scalability of AI models and techniques in solving challenges regarding SC.

Real-Time Analytics Capability (TC_3) refers to the ability to capture flow data, analyze quickly and efficiently, and obtain meaningful and valuable information from it through data analytics, as well as to support efficient and effective decision-making processes to transform them into actionable services.

System Scalability (TC$_4$) refers to the ability of the system to maintain or improve its performance depending on the increase in the amount of data it processes and the workload as the requirements of the SC evolve.

3.Utilized Method

This section gives details regarding the utilized method in the study. In this regard, first, the use of MCDM approach by studies with AI perspective in the academic literature is shown. Second, the advantages of the AHP method are presented. Third, the use of IVIF sets in the academic literature has been shown before the preliminaries of the IVIF sets are given. Finally, the computational steps of the IVIF AHP method are provided.

3.1. MCDM In Studies with AI Perspective

Today's world is rapidly changing and becoming more complex. Increasing complexity and change lead to problems that require DMs to use complex tools to compare different criteria, goals, and stakeholder views. Real-life issues are complex due to their characteristics, such as competing goals, various levels of consensus, and doubt. At this point, multi-criteria MCDM techniques supporting decision-making processes in many areas have become essential in coping with these problems (Kumar, 2025). In this respect, this study adopts the MCDM approach to analyze and prioritize AI success factors for efficient SC. When the scientific literature is examined, it is seen that there are different studies from the AI perspective with successful applications of MCDM. Bozkurt et al. (2025) assess the risks of AI support in military command and control cycle using Best-Worst decision-making method expanded to spherical fuzzy z numbers to support more informed decision-making and risk mitigation strategies. Havle & Büyüközkan (2024) have evaluated requirements of AI using fuzzy cognitive map method in a case study focusing on the aviation industry. Nguyen et al. (2024) have proposed a new hybrid MCDM methodology integrating AHP and CoCoSo methods for adoption of AI technologies Pythagorean fuzzy environment in a case study conducted in a telecom corporation. The study utilizes the AHP method to calculate the weights of the critical elements whereas CoCoSo method helps to rank the benefit expectations of AI adoption. Arora et al. (2023) use the Fuzzy-AHP method to identify the primary factors and sub-factors influencing customers' experiences with AI-enabled finance services in the FinTech industry. Wang et al. (2023) have used an integrated fuzzy MCDM methodology relying on Delphi, ANP and TOPSIS methods to investigate the role of AI technologies in the construction industry.

Sharma et al. (2022) revealed that there are various SCM studies with AI perspective in the academic literature. These studies can be categorized as SC network design, supplier selection, green SCM, inventory management, demand planning, healthcare SCM. The authors discovered that MCDM machine learning is utilized in supplier selection, green SCM, demand planning, healthcare SCM. Within the scope of MCDM machine learning, fuzzy sets, TOPSIS, AHP and ANP have been utilized. On the other hand, yearly trends of AI-SCM articles and their methodology show that use of genetic algorithm is extremely popular. Sharma et al. (2022) highlight that the number of MCDM studies in SCM with AI perspective is limited in around 2020. Moreover, the use of AI and MCDM in studies focusing on SC is quite different from the use in this study. Sharma et. (2022) states that AI in academic literature studies is AI used to support MCDM techniques. Therefore, academic literature is relatively restricted in terms of scientific articles with the perspective of this study. This study analyzes the AI success factor for efficient SC with MCDM approach.

3.2. The Use and Advantages of AHP Method

Determining priorities correctly in decision-making processes is an extremely critical issue and the AHP has popularity in this area (Shiraishi & Obata, 2025). The AHP has been applied to a numerous area due to its simple architecture, ease of use, user-friendly interface, and applicability to real problems (Sato & Tan, 2023). The AHP is information communication and making sense of language or semiotics, allowing the production of relative ratio measurement scales. In the AHP method, a hierarchical model of the problem is constructed that does not have to be complete. The hierarchical structure of AHP starts from a general goal and descends to criteria, sub-criteria, and alternatives at successive levels. This hierarchical structure is different from traditional decision trees. Different levels can represent a different cut depending on the problem. More importantly, a decision-maker who takes part in determining priorities can add or remove elements and levels as necessary in situations requiring clarification of the decision-making process (Saaty, 1990). The AHP method employs pairwise comparisons for decision-making. Although making decisions through pairwise comparisons may seem easy, it becomes difficult when complexity increases (Brunelli, 2014; Shiraishi & Obata, 2025). This part is the point where the most powerful feature of the AHP method comes to the fore. The AHP method uses consistency ratio $(C.R)$ based on consistency index $(C.I.)$ for measuring inconsistency of the judgments among pairwise comparisons (Sato & Tan, 2023). The Saaty's consistency criterion (Saaty, 1990) is a powerful tool and a significant advantage of the AHP method (Shiraishi & Obata, 2025). The wide range of uses of the AHP method, strengths, and advantages are the main reasons for its preference in this study. However, decision-making by the DMs to model and solve the real-life problems contains uncertainty. Fuzzy set theory was introduced by Zadeh (1965) to dispose of the uncertainty in decision-making. However, subjective human thinking is involved in decision-making, and the ordinary fuzzy sets may not be sufficient to represent human perception which contains hesitancy, and intuition.

To overcome these challenges fuzzy extensions have been proposed in the academic literature. Furthermore, the AHP has been integrated these fuzzy extensions. Moreover, successful examples of the integration of the AHP method with these fuzzy extensions are available in the scientific literature. For this reason, some examples of studies using fuzzy extensions by integrating them with AHP in the academic literature for the 5-year period covering the years 2021 and 2025 are given. Havle & İlhan (2025) utilize spherical fuzzy AHP to analyze the requirements for transitioning sustainable aviation fuels. Büyüközkan et al. (2025) use intuitionistic fuzzy AHP to strategically analyze digital service quality in digital healthcare. Nguyen et al. (2024) integrate the pythagorean fuzzy AHP with another MCDM method for AI technology adoption. Yildirim et al. (2024) employ interval-valued fermatean fuzzy AHP to assess seismic vulnerability for the urban roadway. Özkan et al. (2023) assess soil quality using the neutrosophic fuzzy AHP method. Buran & Erçek (2022) evaluate public transportation business model using both spherical fuzzy AHP and intuitionistic fuzzy AHP methods. Ayyildiz et al. (2021) utilize the pythagorean fuzzy AHP to assess risks for hazardous material transportation. Gündoğdu et al. (2021) use picture fuzzy AHP to evaluate public transport service quality. These studies prove the success of integrating AHP with fuzzy extensions and the usability, suitability and success of AHP integrated with fuzzy extensions in solving different decision-making problems in different industrial application areas. Therefore, this study expands the classical AHP into interval-valued intuitionistic fuzzy (IVIF) environment to eliminate uncertainty, hesitancy and intuition. In this respect, this section of the study provides information regarding IVIF sets and gives details related to the computational steps of the IVIF AHP methodology.

3.3. Overview of the IVIF Sets

Atanassov (1999) introduced IVIF sets as an extended version of IF sets to overcome ambiguity, intuition, hesitancy, and complexity originating from human perception in decision-making. Since IVIF sets enable evaluation of linguistic expressions as realistic as possible, researchers are extending traditional MCDM methods to the IVIF environment (Kokoç & Ersöz, 2021). IVIF sets allow to represent the belonging of an element to a set by a membership degree, a non-membership degree, and a hesitancy degree in intervals rather than fixed or ordinary (crisp) values (Kokoç & Ersöz, 2021). In the academic literature there are various studies using different MCDM methods such as AHP, ANP, ARAS, CODAS, COPRAS, DEMATEL, EDAS, ELECTRE, MABAC, MOORA, PROMETHEE, TODIM, TOPSIS, VIKOR, AND WASPAS integrated with IVIF sets in different MCDM problems (Kokoç & Ersöz, 2021). The existence of these scientific studies in the academic literature has proven that the extension of MCDM methods to IVIF sets is a practical and realistic approach to managing decision-making problems (Kokoç & Ersöz, 2021). Since the AHP alone cannot provide effective solutions to eliminate uncertainties in the subjective judgments of experts, the AHP method, extended to IVIF sets, was used to determine the final weight values of the criteria to avoid the disadvantages that may arise from the use of fuzzy set theory (Aka, 2025). Assume that $\tilde{A}$ is an IVIF set that is represented as in Equation 1.

$$\tilde{A} = \{\langle x, \tilde{\mu}_{\tilde{A}}(x), \tilde{v}_{\tilde{A}}(x) \rangle | x \in E\} \quad (1)$$

The IVIF set $\tilde{A}$ in Equation 1 is defined based on E, $\tilde{\mu}_{\tilde{A}}(x)$, and $\tilde{v}_{\tilde{A}}(x)$ where E represents a fixed set, and $\tilde{\mu}_{\tilde{A}}(x)$ and $\tilde{v}_{\tilde{A}}(x)$ show membership and non-membership functions at intervals. Furthermore, $\tilde{\mu}_{\tilde{A}}(x) = [\mu_{\tilde{A}}^L, \mu_{\tilde{A}}^U] \subset [0,1]$ and $\tilde{v}_{\tilde{A}}(x) = [v_{\tilde{A}}^L, v_{\tilde{A}}^U] \subset [0,1]$, $\forall\, x \in E$ conditions characterizes the IVIF set. The conditions regarding the $\tilde{\mu}_{\tilde{A}}(x)$ and $\tilde{v}_{\tilde{A}}(x)$ intervals are $\mu_{\tilde{A}}^L = \inf(\tilde{\mu}_{\tilde{A}}(x))$, $\mu_{\tilde{A}}^U = sup(\tilde{\mu}_{\tilde{A}}(x))$, $v_{\tilde{A}}^L = inf(\tilde{v}_{\tilde{A}}(x))$, $v_{\tilde{A}}^U = sup(\tilde{v}_{\tilde{A}}(x))$ and $0 \le sup(\tilde{\mu}_{\tilde{A}}(x)) + sup(\tilde{v}_{\tilde{A}}(x)) \le 1$. Additionally, $\tilde{\pi}_{\tilde{A}}(x) = [\pi_{\tilde{A}}^L, \pi_{\tilde{A}}^U], x \in E$ where $\pi_{\tilde{A}}$ denotes the uncertainty degree. The lower and upper points of $\pi_{\tilde{A}}$ is computed using Equation 2 and Equation 3.

$$\pi_{\tilde{A}}^L = 1 - \mu_{\tilde{A}}^U - v_{\tilde{A}}^U \quad (2)$$

$$\pi_{\tilde{A}}^U = 1 - \mu_{\tilde{A}}^L - v_{\tilde{A}}^L \quad (3)$$

Let $\tilde{A}$ and $\tilde{B}$ be two IVIF sets based on lower and upper end points. $\tilde{A}$ and $\tilde{B}$ can be shown as follows:

$$\tilde{A} = \langle [\mu_{\tilde{A}}^L, \mu_{\tilde{A}}^U], [v_{\tilde{A}}^L, v_{\tilde{A}}^U], [\pi_{\tilde{A}}^L, \pi_{\tilde{A}}^U] \rangle \text{ and } \tilde{B} = \langle [\mu_{\tilde{B}}^L, \mu_{\tilde{B}}^U], [v_{\tilde{B}}^L, v_{\tilde{B}}^U], [\pi_{\tilde{B}}^L, \pi_{\tilde{B}}^U] \rangle.$$

Arithmetic operations using these two IVIF sets can be expressed as follows:

$$\tilde{A} \le \tilde{B} \leftrightarrow \mu_{\tilde{A}}^L \le \mu_{\tilde{B}}^L, \mu_{\tilde{A}}^U \le \mu_{\tilde{B}}^U, v_{\tilde{B}}^L \le v_{\tilde{A}}^L, v_{\tilde{B}}^U \le v_{\tilde{A}}^U \quad (4)$$

$$\tilde{A} \oplus \tilde{B} = \left(\begin{bmatrix} \mu_{\tilde{A}}^L + \mu_{\tilde{B}}^L - \mu_{\tilde{A}}^L \mu_{\tilde{B}}^L, \\ \mu_{\tilde{A}}^U + \mu_{\tilde{B}}^U - \mu_{\tilde{A}}^U \mu_{\tilde{B}}^U \end{bmatrix}, \begin{bmatrix} v_{\tilde{A}}^L v_{\tilde{B}}^L, \\ v_{\tilde{A}}^U v_{\tilde{B}}^U \end{bmatrix} \right) \quad (5)$$

$$\tilde{A} \ominus \tilde{B} = \left(\left[\frac{\mu_{\tilde{A}}^L - \mu_{\tilde{B}}^L}{1 - \mu_{\tilde{B}}^L}, \frac{\mu_{\tilde{A}}^U - \mu_{\tilde{B}}^U}{1 - \mu_{\tilde{B}}^U} \right], \left[\frac{v_{\tilde{A}}^L}{v_{\tilde{B}}^L}, \frac{v_{\tilde{A}}^U}{v_{\tilde{B}}^U} \right] \right) \quad (6)$$

$$\tilde{A} \otimes \tilde{B} = \left(\begin{bmatrix} \mu_{\tilde{A}}^L \mu_{\tilde{B}}^L, \\ \mu_{\tilde{A}}^U \mu_{\tilde{B}}^U \end{bmatrix}, \begin{bmatrix} v_{\tilde{A}}^L + v_{\tilde{B}}^L - v_{\tilde{A}}^L v_{\tilde{B}}^L, \\ v_{\tilde{A}}^U + v_{\tilde{B}}^U - v_{\tilde{A}}^U v_{\tilde{B}}^U \end{bmatrix} \right) \quad (7)$$

$$\tilde{A} \oslash \tilde{B} = \left(\left[\frac{\mu_{\tilde{A}}^L}{\mu_{\tilde{B}}^L}, \frac{\mu_{\tilde{A}}^U}{\mu_{\tilde{B}}^U} \right], \left[\frac{v_{\tilde{A}}^L - v_{\tilde{B}}^L}{1 - v_{\tilde{B}}^L}, \frac{v_{\tilde{A}}^U - v_{\tilde{B}}^U}{1 - v_{\tilde{B}}^U} \right] \right) \quad (8)$$

$$\lambda\tilde{A} = \left(\left[1-\left(1-\mu_{\tilde{A}}^{L}\right)^{\lambda}, 1-\left(1-\mu_{\tilde{A}}^{U}\right)^{\lambda}\right], \left[\left(\nu_{\tilde{A}}^{L}\right)^{\lambda}, \left(\nu_{\tilde{A}}^{U}\right)^{\lambda}\right]\right) \tag{9}$$

$$\tilde{A}^{\lambda} = \left(\left[\left(\mu_{\tilde{A}}^{L}\right)^{\lambda}, \left(\mu_{\tilde{A}}^{U}\right)^{\lambda}\right], \left[1-\left(1-\nu_{\tilde{A}}^{L}\right)^{\lambda}, 1-\left(1-\nu_{\tilde{A}}^{U}\right)^{\lambda}\right]\right) \tag{10}$$

3.4. COMPUTATIONAL STEPS OF THE IVIF AHP METHOD

This section explains the computational steps of the IVIF AHP method that is shown in Figure 3. The computational steps that are adapted from Büyüközkan et al. (2018) are explained below.

Step 1. *Selection of the DMs, determine the evaluation scales:* In this step, the DMs have been selected based on their knowledge levels, experiences, willingness to be involved into the decision-making process, and academic backgrounds. Additionally, linguistic scales have been selected for criteria evaluation and calculating the DMs weights. Details regarding the determined scales are given in the relevant step.

Step 2. *Identification of the evaluation criteria:* This step helps to identify the main dimensions and criteria regarding the decision-making problem and its goal based on the opinions of the DMs and results of the literature survey.

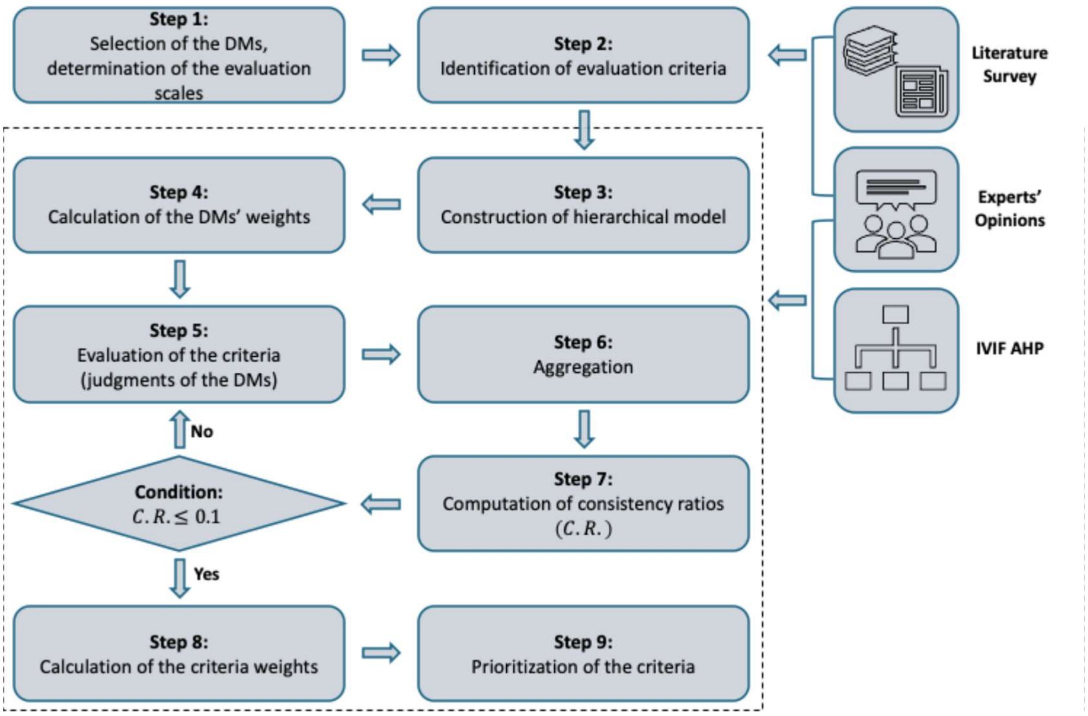
Step 3. *Construction of hierarchical model:* This step constructs a hierarchical model based on the identified dimensions and criteria concerning the goal. The basis of constructing the hierarchical model is the opinions of the DMs.

Step 4. *Calculation of the DMs' weights:* In this step, the linguistic scale presented in Table 3 is used to calculate the weights of the DMs and determine their importance degrees. For this purpose, Equation 11 is employed.

$$\lambda^{(k)} = \frac{\sqrt{\frac{1}{2}\left[\left(1-\pi_{\tilde{A}}^{L}{}^{(k)}\right)^{2}+\left(1-\pi_{\tilde{A}}^{U}{}^{(k)}\right)^{2}\right]}}{\sum_{k=1}^{K}\sqrt{\frac{1}{2}\left[\left(1-\pi_{\tilde{A}}^{L}{}^{(k)}\right)^{2}+\left(1-\pi_{\tilde{A}}^{U}{}^{(k)}\right)^{2}\right]}} \tag{11}$$

Let $\lambda^{(k)}$ be the weight of the k^{th} DM. Here, $\lambda^{(k)} = \left\{\lambda^{(1)}, \lambda^{(2)}, \dots, \lambda^{(K)}\right\}$ indicates the sets of the weights of the K number of DMs where $\sum_{k=1}^{k}\lambda^{(k)} = 1$.

Figure 3. The steps of the IVIF AHP method 110



Source. Authors

Table 3. Linguistic scale to calculate the weights of the DMs

Linguistic Terms	IVIF Values	
	$[\mu_{\tilde{A}}^{L}, \mu_{\tilde{A}}^{U}]$	$[\nu_{\tilde{A}}^{L}, \nu_{\tilde{A}}^{U}]$
Extremely qualified (EQ)	[0.95, 1.00]	[0.00, 0.00]
Very qualified (VQ)	[0.80, 0.85]	[0.05, 0.10]
Qualified (Q)	[0.60, 0.65]	[0.10, 0.15]
Less qualified (LQ)	[0.30, 0.35]	[0.25, 0.30]
Very less qualified (VLQ)	[0.20, 0.25]	[0.30, 0.35]
Extremely less qualified (ELQ)	[0.00, 0.05]	[0.45, 0.50]

Source. Büyüközkan et al. (2018)

Step 5. *Evaluation of the criteria:* The judgments of the DMs through pairwise comparisons are obtained. To evaluate the criteria, the DMs use the linguistic scale given in Table 4.

Table 4. Linguistic scale for pairwise comparisons

Linguistic Terms	IVIF values		Reciprocals	
	$[\mu_{\tilde{A}}^{L}, \mu_{\tilde{A}}^{U}]$	$[\nu_{\tilde{A}}^{L}, \nu_{\tilde{A}}^{U}]$	$[\mu_{\tilde{A}}^{L}, \mu_{\tilde{A}}^{U}]$	$[\nu_{\tilde{A}}^{L}, \nu_{\tilde{A}}^{U}]$
Equally Important (EI)	[0.38, 0.42]	[0.22, 0.58]	[0.22, 0.58]	[0.38, 0.42]
Intermediate Value (IV)	[0.29, 0.41]	[0.12, 0.58]	[0.12, 0.58]	[0.29, 0.41]
Moderately More Important (MMI)	[0.10, 0.43]	[0.03, 0.57]	[0.03, 0.57]	[0.10, 0.43]
Intermediate Value 2 (IV2)	[0.03, 0.47]	[0.03, 0.53]	[0.03, 0.53]	[0.03, 0.47]
Strongly More Important (SMI)	[0.13, 0.53]	[0.07, 0.47]	[0.07, 0.47]	[0.13, 0.53]
Intermediate Value 3 (IV3)	[0.32, 0.62]	[0.08, 0.38]	[0.08, 0.38]	[0.32, 0.62]
Very Strongly More Important (VSMI)	[0.52, 0.72]	[0.08, 0.28]	[0.08, 0.28]	[0.52, 0.72]
Intermediate Value 4 (IV4)	[0.75, 0.85]	[0.05, 0.15]	[0.05, 0.15]	[0.75, 0.85]
Extremely More Important (EMI)	[1.00, 1.00]	[0.00, 0.00]	[0.00, 0.00]	[1.00, 1.00]

Source. Abdullah & Najib (2016)

Step 6. *Aggregation:* This step uses the IVIFWA operator (Yue, 2011) in Equation 12 to aggregate the individual evaluations of the DMs.

$$IVIFWA_{\lambda} = \left(\begin{bmatrix} 1-\prod_{k=1}^{K}\left(1-\mu_{\tilde{A}}^{L}\right)^{\lambda^{(k)}}, \\ 1-\prod_{k=1}^{K}\left(1-\mu_{\tilde{A}}^{U}\right)^{\lambda^{(k)}} \end{bmatrix}, \begin{bmatrix} \prod_{k=1}^{K}\left(\nu_{\tilde{A}}^{L}\right)^{\lambda^{(k)}}, \\ \prod_{k=1}^{K}\left(\nu_{\tilde{A}}^{U}\right)^{\lambda^{(k)}} \end{bmatrix}\right) \tag{12}$$

where $\sum_{k=1}^{K}\lambda^{(k)} = 1$.

Step 7. *Computation of the consistency ratios:* In this step, the consistency ratio $(C.R.)$ is computed using Equation 13 (Abdullah & Najib, 2016) to check the consistency of the DMs' evaluations.

$$C.R. = \frac{RI\frac{\sum \pi_{ij}^{U}(x)}{z}}{z-1} \tag{13}$$

If the consistency condition $(C.R. \leq 0.1)$ is satisfied (Saaty, 1990), then revising the evaluation is unnecessary. Otherwise, inconsistent evaluation process requires revision of the evaluation process with the help of the DMs. In Equation 13, z is used to show the number of the criteria and RI shows the randomness indices given in Table 5. Additionally, $\pi_{ij}^{U}(x)$ expresses the degree of hesitation (Abdullah & Najib, 2016).

Table 5. Randomness indices

z	1-2	3	4	5	6	7	8	9
RI	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45

Source. Saaty (1977)

Step 8. *Calculation of the criteria weights:* In this step, the weights of the criteria are computed using Equation 14. Here, let $w = \{w_1, w_2, \ldots w_n\}$ be set of the criteria weights where $w_j \geq 0, j = 1,2, \ldots, n$ and $\sum_{j=1}^{n} w_j = 1$.

$$w_j = \frac{1-\tilde{w}_j}{n-\sum_{j=1}^{n}\tilde{w}_j}, \tilde{w}_j = 1 - \frac{\sum_{k=1}^{K}\frac{\lambda^{(k)}\left(\mu_{\tilde{A}_j}^{L}+\mu_{\tilde{A}_j}^{U}\right)}{2}}{\sqrt{\sum_{k=1}^{K}\frac{\lambda^{(k)}\left({\mu_{\tilde{A}_j}^{L}}^{2}+{\mu_{\tilde{A}_j}^{U}}^{2}+{\nu_{\tilde{A}_j}^{L}}^{2}+{\nu_{\tilde{A}_j}^{U}}^{2}\right)}{2}}} \tag{14}$$

Step 9. *Prioritization of the criteria:* The priorities of the main dimensions are identified using their weights while the priorities of the criteria are determined through the local weights.

4.Application of Proposed Methodology

SCs, which are at the center of businesses' operations, provide a competitive advantage by accelerating production and other operational processes, reducing costs, and increasing customer satisfaction. SCs play a critical role in the stability and sustainability of economic growth, as well as the smooth functioning of global trade. For this reason, businesses need to be successful and manage SCs effectively.

The success of SCs in this regard is directly related to AI, one of today's most popular digital technologies. From this perspective, examining the AI success factors that increase the efficiency of SCs will provide meaningful and valuable insights. Therefore, this study employs the proposed methodology given in Figure 1 for an application in Turkey. This section provides the details of the application of the proposed methodology to analyze AI success factors for an efficient SC by following the steps of the IVIF AHP method explained in the previous section. The steps are explained as follows:

Step 1. *Selection the DMs, determine the evaluation scales:* In the decision-making processes of the case study, three highly competent DMs who are experienced experts in the SC field and with a high level of knowledge have been determined as decision makers (DMs). The details regarding the DMs who support the formation of the decision-making group are provided in Step 4. Additionally, the evaluation scales in Table 3 and Table 4 are determined based on the sources in the academic literature. The sources and details of these scales have been provided in the relevant steps (Step 4 and Step 5).

Step 2. *Identification of the evaluation criteria:* The evaluation criteria in this section are directly those of the model proposed in Section 2. The dimensions and their criteria have been identified based on DMs' opinions and the results of a detailed literature survey.

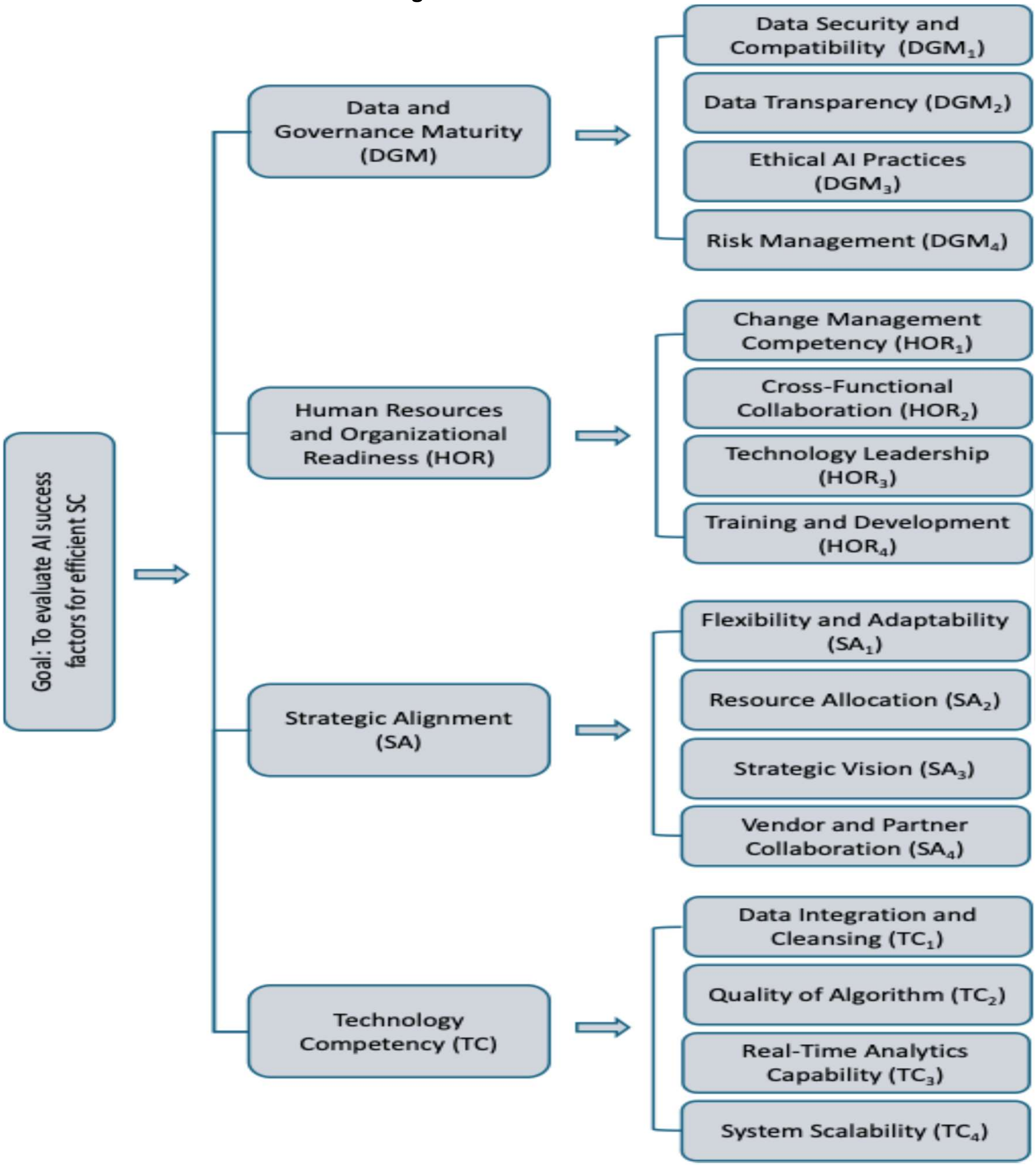
Step 3. *Construction of hierarchical model:* In this step, a hierarchical model has been constructed based on the main dimensions and their criteria concerning the goal as in Figure 4. The construction process of the model was supported by the opinions of the DMs.

Step 4. *Calculation of the DMs' weights:* In this step, the weights of the DMs are computed. For this purpose, three highly skilled DMs who have valuable reputation and high level of knowledge are selected based on their features provided below. For reasons of confidentiality and privacy, no further information can be provided beyond the characteristics of the selected DMs presented below.

- DM_1 is a university professor with 25 years of technology and SC experience and a strong knowledge of both the sector and the scientific literature. Furthermore, DM_1 is experienced in conducting many sectoral case studies regarding SCs.
- DM_2 is an extremely knowledgeable digital technologies director who has been working on SCs and technology integration for many years. DM_2 has extensive knowledge of evaluation processes as the director has previously been involved in such scientific studies as a DM.
- DM_3 is a SC consultant who has implemented hundreds of projects with many companies in 8 years. The DM_3 is highly knowledgeable about the SC transformation processes of companies and is incredibly well-versed in the popular technologies of recent times.

Based on the provided information regarding the DMs, the importance degree of each DM has been assigned as in Table 6 using the linguistic terms provided in Table 3. Following this, the weights of the DMs have been computed using Equation 11. Table 6 shows the details concerning the weights of the DMs.

Figure 4. The hierarchical model



Source. Authors

Table 6. Importance degree and weight of the DMs

DMs	Importance Degree	IVIF Values			λ
		$[\mu_{\tilde{A}}^{L}, \mu_{\tilde{A}}^{U}]$	$[\nu_{\tilde{A}}^{L}, \nu_{\tilde{A}}^{U}]$	$[\pi_{\tilde{A}}^{L}, \pi_{\tilde{A}}^{U}]$	
DM_1	VQ	[0.800, 0.850]	[0.050, 0.100]	[0.050, 0.150]	0.316
DM_2	EQ	[0.950, 1.000]	[0.000, 0.000]	[0.000, 0.050]	0.342
DM_3	EQ	[0.950, 1.000]	[0.000, 0.000]	[0.000, 0.050]	0.342

Source. Authors

Step 5. *Evaluation of the criteria:* In this step face-to-face interviews have been conducted to obtain the judgments of the DMs. DMs used the linguistic terms in Table 4 to identify the priorities of the criteria.

Table 7. Evaluation of the main dimensions (pairwise comparisons)

DM_1					**DM_2**					**DM_3**				
Goal	DGM	HOR	SA	TC	Goal	DGM	HOR	SA	TC	Goal	DGM	HOR	SA	TC
DGM	EI				DGM	EI	IV		EI	DGM	EI			
HOR	EI	EI			HOR		EI			HOR	MMI	EI		
SA	MMI	IV2	EI	MMI	SA	SMI	SMI	EI	SMI	SA	IV3	IV3	EI	IV3
TC	MMI	MMI		EI	TC				EI	TC	IV3	SMI		EI

Source. Authors

Table 7 has been provided to explain the evaluation process of the main dimensions. The same evaluation process has been applied to the criteria of the dimensions, but the evaluations of the criteria are not provided due to page limitations.

Step 6. *Aggregation:* In this step, the linguistic terms regarding the evaluations are converted into IVIF values through Table 4. This step utilizes the IVIFWA operator in Equation 12 to aggregate the IVIF values to obtain group decision values. For this purpose, the first aggregation is employed to integrate IVIF values regarding linguistic terms. Additionally, the second aggregation (main) is utilized to incorporate the individual evaluation of the DMs into group decision matrices. To explain the aggregation process concerning the main dimensions, Tables 8 and 9 are given.

Table 8. Aggregation of IVIF values of the main dimensions

	Pairwise Comparisons by DM_1				IVIF Values (Aggregated)					
Goal	**DGM**	**HOR**	**SA**	**TC**	$\mu_{\tilde{A}}^L$	$\mu_{\tilde{A}}^U$	$\nu_{\tilde{A}}^L$	$\nu_{\tilde{A}}^U$	$\pi_{\tilde{A}}^L$	$\pi_{\tilde{A}}^U$
DGM	EI				0.220	0.625	0.106	0.375	0.000	0.673
HOR	EI	EI			0.275	0.572	0.061	0.428	0.000	0.664
SA	MMI	IV2	EI	MMI	0.203	0.517	0.022	0.483	0.000	0.774
TC	MMI	MMI		EI	0.203	0.548	0.033	0.452	0.000	0.764
	Pairwise Comparisons by DM_2				**IVIF Values (Aggregated)**					
Goal	**DGM**	**HOR**	**SA**	**TC**	$\mu_{\tilde{A}}^L$	$\mu_{\tilde{A}}^U$	$\nu_{\tilde{A}}^L$	$\nu_{\tilde{A}}^U$	$\pi_{\tilde{A}}^L$	$\pi_{\tilde{A}}^U$
DGM	EI	IV		EI	0.374	0.537	0.086	0.460	0.003	0.540
HOR		EI			0.229	0.578	0.132	0.418	0.003	0.639
SA	SMI	SMI	EI	SMI	0.264	0.617	0.039	0.383	0.000	0.697
TC				EI	0.333	0.643	0.090	0.357	0.000	0.577
	Pairwise Comparisons by DM_3				**IVIF Values (Aggregated)**					
Goal	**DGM**	**HOR**	**SA**	**TC**	$\mu_{\tilde{A}}^L$	$\mu_{\tilde{A}}^U$	$\nu_{\tilde{A}}^L$	$\nu_{\tilde{A}}^U$	$\pi_{\tilde{A}}^L$	$\pi_{\tilde{A}}^U$
DGM	EI				0.206	0.552	0.124	0.448	0.000	0.669
HOR	MMI	EI			0.223	0.532	0.061	0.468	0.000	0.716
SA	IV3	IV3	EI	IV3	0.428	0.692	0.045	0.308	0.000	0.527
TC	IV3	SMI		EI	0.310	0.609	0.069	0.391	0.000	0.621

Source. Authors

Step 7. *Computation of the consistency ratios:* The $(C.R.)$ values are computed using Equation 13 to check the consistency of the DMs' evaluations in each evaluation matrix. All the computed $(C.R.)$ values are less than 0.1, there for the condition has been satisfied, and there is no need to revise the evaluations. The computed $(C.R.)$ values are given in Tables 9 and 10.

Table 9. Main aggregated IVIF values and weights of the main dimensions

Main Dimensions	IVIF Values (Main Aggregated)						w_j
	$\mu_{\tilde{A}}^L$	$\mu_{\tilde{A}}^U$	$\nu_{\tilde{A}}^L$	$\nu_{\tilde{A}}^U$	$\pi_{\tilde{A}}^L$	$\pi_{\tilde{A}}^U$	
DGM	0.272	0.571	0.104	0.428	0.001	0.623	0.2448
HOR	0.242	0.561	0.079	0.438	0.001	0.679	0.2377
SA	0.308	0.618	0.034	0.382	0.000	0.658	0.2621
TC	0.286	0.603	0.059	0.397	0.000	0.654	0.2554
(C.R.= 0.082)							

Source. Authors

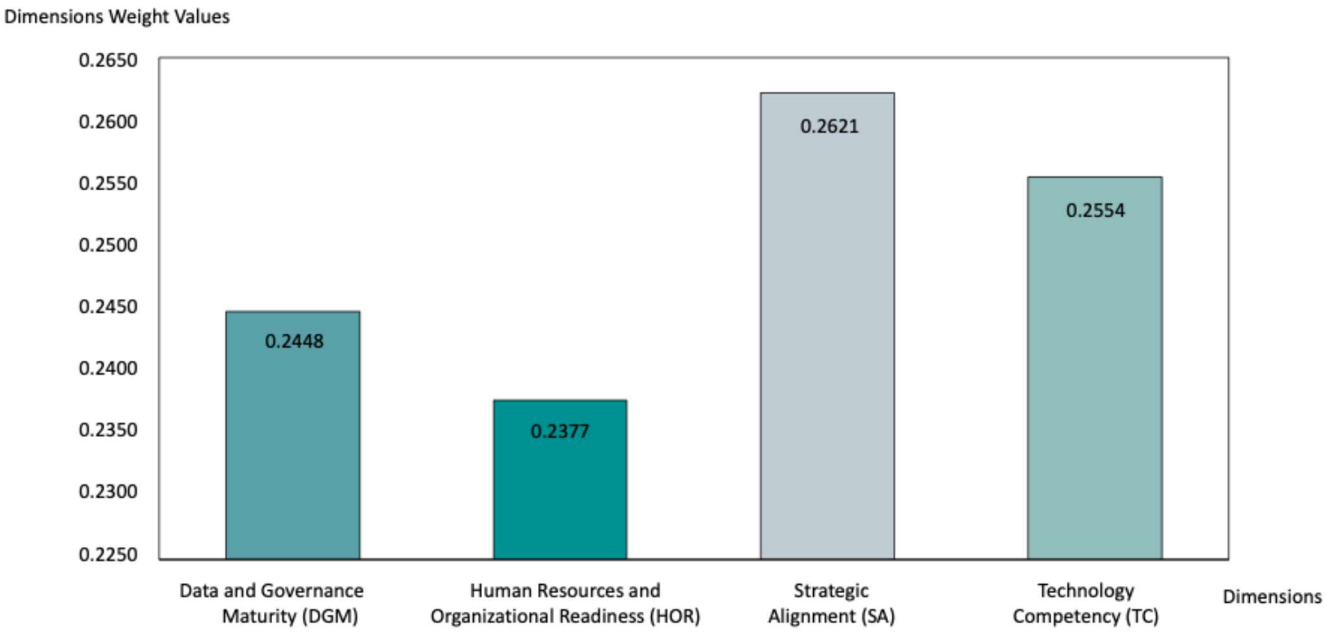
Step 8. *Calculation of the criteria weights:* In this step, the weights (w_j) of the criteria are computed using Equation 14. The computed weights are presented in Tables 9 and 10, respectively. Furthermore, the distribution of the weights of the dimensions are presented in Figure 5.

Table 10. Aggregated IVIF values and entropy weights (criteria)

Criteria	IVIF Values (Main Aggregated)						
DG	$\mu_{\tilde{A}}^{L}$	$\mu_{\tilde{A}}^{U}$	$\nu_{\tilde{A}}^{L}$	$\nu_{\tilde{A}}^{U}$	$\pi_{\tilde{A}}^{L}$	$\pi_{\tilde{A}}^{U}$	w_j
DGM_1	0.363	0.604	0.036	0.395	0.001	0.601	0.269
DGM_2	0.304	0.639	0.047	0.361	0.001	0.649	0.267
DGM_3	0.196	0.535	0.082	0.465	0.000	0.722	0.223
DGM_4	0.217	0.587	0.040	0.413	0.000	0.743	0.241
(C.R. = 0.074)							
HR	$\mu_{\tilde{A}}^{L}$	$\mu_{\tilde{A}}^{U}$	$\nu_{\tilde{A}}^{L}$	$\nu_{\tilde{A}}^{U}$	$\pi_{\tilde{A}}^{L}$	$\pi_{\tilde{A}}^{U}$	w_j
HOR_1	0.267	0.560	0.101	0.440	0.000	0.633	0.238
HOR_2	0.378	0.653	0.044	0.347	0.000	0.578	0.274
HOR_3	0.278	0.570	0.086	0.430	0.000	0.635	0.243
HOR_4	0.271	0.581	0.060	0.419	0.000	0.669	0.245
(C.R. = 0.090)							
SA	$\mu_{\tilde{A}}^{L}$	$\mu_{\tilde{A}}^{U}$	$\nu_{\tilde{A}}^{L}$	$\nu_{\tilde{A}}^{U}$	$\pi_{\tilde{A}}^{L}$	$\pi_{\tilde{A}}^{U}$	w_j
SA_1	0.249	0.503	0.132	0.497	0.000	0.620	0.220
SA_2	0.243	0.602	0.030	0.398	0.000	0.727	0.247
SA_3	0.514	0.726	0.034	0.274	0.000	0.452	0.297
SA_4	0.243	0.557	0.078	0.443	0.000	0.680	0.236
(C.R. = 0.093)							
TE	$\mu_{\tilde{A}}^{L}$	$\mu_{\tilde{A}}^{U}$	$\nu_{\tilde{A}}^{L}$	$\nu_{\tilde{A}}^{U}$	$\pi_{\tilde{A}}^{L}$	$\pi_{\tilde{A}}^{U}$	w_j
TC_1	0.242	0.583	0.052	0.417	0.000	0.706	0.245
TC_2	0.316	0.627	0.039	0.373	0.000	0.646	0.267
TC_3	0.280	0.607	0.058	0.393	0.000	0.662	0.257
TC_4	0.214	0.549	0.076	0.451	0.000	0.709	0.231
(C.R. = 0.073)							

Source. Authors

Figure 5. The distribution of the weights of the main dimensions



Source. Authors

Step 9. *Prioritization of the criteria:* The priorities of the dimensions are revealed using their entropy weights while the priorities of the criteria are determined through the local weights. The priorities of the main dimensions and criteria are shown in Table 11.

Table 11. Priorities of dimensions and contributing factors

Dimensions	Weights	Priority	Criteria	Local Weights	Global Weights	Priority
Data and Governance Maturity (DGM)	0.2448	3	**Data Security and Compatibility (DGM_1)**	**0.269**	**0.0659**	**3**
			Data Transparency (DGM_2)	0.267	0.0654	5
			Ethical AI Practices (DGM_3)	0.223	0.0545	16
			Risk Management (DGM_4)	0.241	0.0590	10
Human Resources and Organizational Readiness (HOR)	0.2377	4	Change Management Competency (HOR_1)	0.238	0.0566	15
			Cross Functional Collaboration (HOR_2)	0.274	0.0651	6
			Technology Leadership (HOR_3)	0.243	0.0578	13
			Training and Development (HOR_4)	0.245	0.0582	12
Strategic Alignment (SA)	**0.2621**	**1**	Flexibility and Adaptability (SA_1)	0.220	0.0577	14
			Resource Allocation (SA_2)	0.247	0.0648	7
			Strategic Vision (SA_3)	**0.297**	**0.0778**	**1**
			Vendor and Partner Collaboration (SA_4)	0.236	0.0618	9
Technology Competency (TC)	0.2554	2	Data Integration and Cleansing (TC_1)	0.245	0.0626	8
			Quality of Algorithm (TC_2)	**0.267**	**0.0682**	**2**
			Real-Time Analytics Capability (TC_3)	0.257	0.0657	4
			System Scalability (TC_4)	0.231	0.0589	11

Source. Authors

Table 11 shows the results obtained regarding the success factors for an efficient SC. These factors are already crucial for an efficient SC. The main issue here is how these factors should be prioritized. When the results have been examined, it is evident that the strategic alignment dimension stands out more than the others. The technology dimension follows it. For an efficient SC, it is not enough to consider AI in terms of technology. A correct roadmap as a priority strategy is essential for success. It does not mean that the other main dimensions are not necessary. The priorities for the main dimensions and the contributing success factors can be given as follows:

- **Priorities of the dimensions:** Strategic alignment ≻ Technology ≻ Data and governance ≻ Human resources and organizational readiness.
- **Priorities of the factors (Top 3):** Strategic vision ≻ Quality of algorithm ≻ Data security and compatibility.
- **Priorities of the factors (Last 3):** Flexibility and adaptability ≻ Change management competency ≻ Ethical AI practices.

Further explanations and insights regarding the obtained results have been provided in the following section.

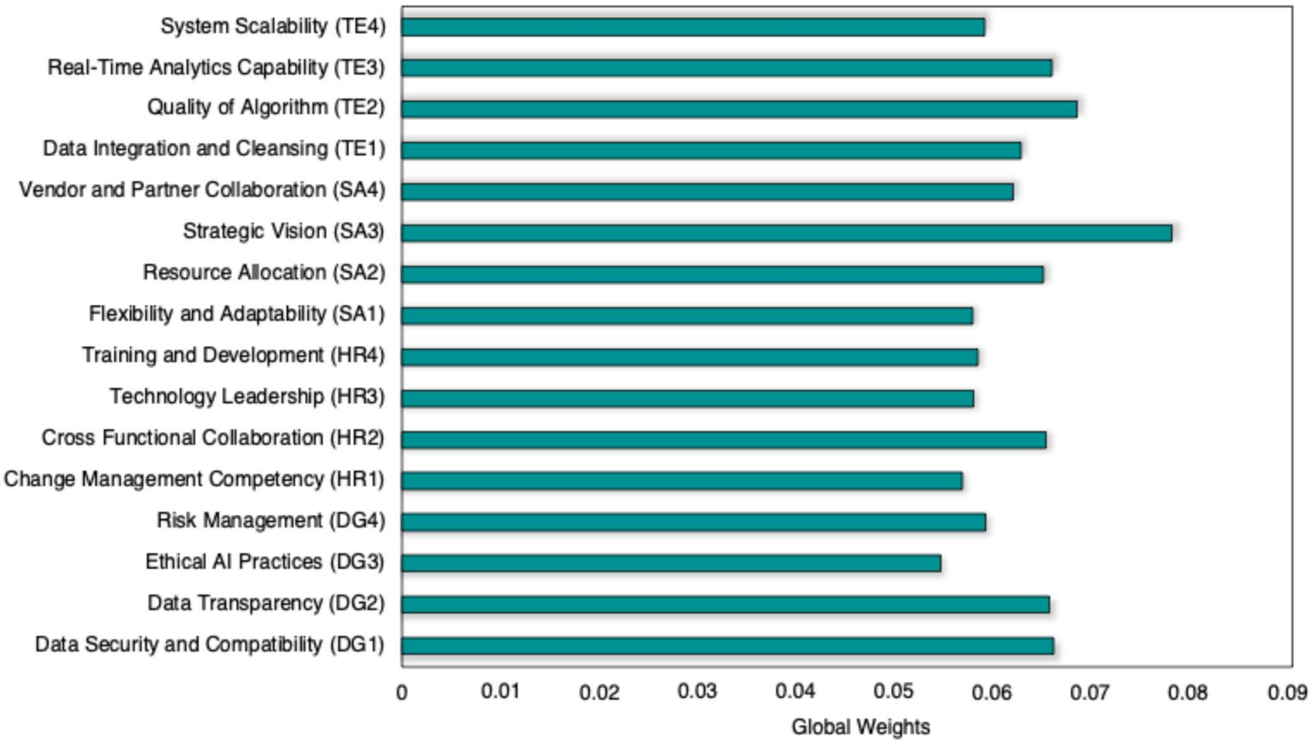
5. Managerial Implications

This section of the study provides comprehensive insights into practical applications and sensitivity analyses. The first section discusses the practical strategic implications of the study's results, while the second section presents the results of sensitivity analyses conducted under different scenarios and their interpretations.

5.1. Practical Implications

The results reveal that Strategic Alignment (SA) dimension has the highest priority among the dimensions. This result demonstrates that AI technology integrated into SC processes is more than just a tool; it must be fully aligned with companies' strategic objectives as a strategic lever that will create long-term competitive advantage. AI integrations that are not aligned with strategic goals cannot create strategic transformation since they only provide operational benefits. However, strategic alignment accelerates return on investment by increasing internal ownership. Integrating AI technologies into SC processes requires managing the transformation at the corporate level, rather than simply being a technology project that enables digitalization. Therefore, AI should be placed at the core of corporate strategy to serve multiple objectives, such as flexibility, customer experience, and sustainability.

Figure 6. The weights of the success factors



Source. Authors

When the weights and priorities of the success factors that are shown in Figure 6 are examined, it is observed that some factors come to the fore while others are relatively less important. Strategic Vision (SA_3) has the highest priority among all contributing factors. This is followed by Quality of Algorithm (TC_2) and Data Security and Compatibility (DGM_1), respectively. The priority of the strategic vision factor highlights the need for AI technology to shape both the current and future state of SC companies, highlighting its role throughout the organization. AI use should be linked to the future business model, and this should be supported by senior management. Having a developed vision in such critical areas provides a competitive advantage. Furthermore, the quality of AI technology algorithms underpins the accuracy and reliability of SC decisions. Algorithm quality contributes to the efficient operation of the system by preventing chaotic processes. Subsequently, the fact that Data Security and Compatibility is among the top three priorities demonstrates the critical importance of security vulnerabilities in terms of both data loss and SC integrity. The integration of AI technologies with the existing infrastructure of system security and SC processes helps prevent business disruptions. This allows for faster implementation of compatible systems and less resistance.

On the other hand, it is critical to examine factors that appear to be less important than other success factors. In this context, the three factors listed last in terms of priority can be considered. These factors are Flexibility and Adaptability (SA_1), Change Management Competency (HOR_1), and Ethical AI Practices (DGM_3), respectively. The findings indicate that flexibility and adaptability are not considered innovations but a standard expectation and a fundamental requirement for AI applications integrated into SC activities. If businesses are not flexible and lack adaptability, it is not easy to achieve a competitive advantage, regardless of the AI strategy for effective SC. Indeed, AI solutions are now flexible and modular in terms of architecture. Therefore, the low priority of this factor may indicate that the strategic outcomes of flexibility and adaptability are more important than the ability of the AI system to adapt to its own needs. Furthermore, while flexibility and adaptability appear to be critical factors, their contributions to risk management, cost advantage, and decision-making speed should also be considered. Integrating AI technologies into SC activities, processes, and operations is a transformation. While transforming and changing mindsets and cultures is more challenging than transforming technology, the impacts of this transformation are more long-term and indirect, particularly from the human factor. Furthermore, organizations still prioritize technological infrastructure and data-driven success. This may have contributed to this factor's low ranking. AI success is not just about accuracy; it is also about reliability. While AI systems must be designed in compliance with regulations and be accountable, ethical, and transparent, organizations' primary expectations from AI technology are increased performance and efficiency. Considering the ethical aspects of AI technologies integrated into SC activities is secondary to this expectation. Furthermore, the low ranking of this factor may be due to the challenges associated with measuring it in the short term.

The study's results also provide a different insight. The calculated weights are numerically very close to each other. Even the criterion with the lowest importance has a value very close to the most important one. Therefore, it can be said that all the identified criteria have a certain level of importance.

5.2. Sensitivity Analysis

The findings obtained using the IVIF AHP method demonstrate that the applied analytical technique provides meaningful and consistent outputs in line with specific factors. However, the model's sensitivity to different scenarios is also significant. Therefore, sensitivity analyses have been conducted in this section to assess the robustness of the results and the model's response to parameter changes to increase the confidence in the presented outputs. In this regard, the influence of the weights of the dimensions in ranking the success factors has been investigated.

Different weights given in Table 12 concerning the dimensions of AI success factors for efficient SC in 10 different cases have been applied. Based on the changes in dimensions, different weights of the AI success factors have been computed as in Table 13. Increasing the weights of certain dimensions caused a significant shift in the priorities of some factors. For this purpose, it is necessary to examine the changes that caused this situation.

The results of the sensitivity analyses conducted indicate that the importance of AI success factors for effective SC is dynamic. The weights of the main dimensions of the proposed model are the primary drivers of the success factors contributing to these dimensions. A change in the weight of a dimension directly and significantly affects the success factors included within that dimension. Therefore, a change in an SC company's strategic priorities alters the weights of the dimensions, which can have a direct and measurable critical impact on the success factors. Sensitivity analysis conducted based on various scenarios reveals several different strategic approaches for an SC company, each with its own priorities and implications. In this regard, to provide meaningful insights in this regard, some scenarios in the sensitivity analysis are detailed as follows:

- **Case 9. Focusing on Strategic Alignment and Technology Competency:** In this case, the initial weights of Strategic Alignment (SA) and Technology Competency (TC) have been increased to 0.350, while the initial weights for Data and Governance Maturity (DGM) and Human Resources and Organizational Readiness (HOR) have been reduced to 0.150. In this scenario, an aggressive and high-growth oriented strategy is assumed. Here, it is seen that initial weights of Strategic Vision (SA_3) and Quality of Algorithm (TC_2) have increased from 0.0778 and 0.0682 to 0.1039 and 0.0934, respectively. This scenario may be suitable for companies where being the first mover and quickly establishing a competitive advantage are prioritized over a perfect foundation.

- **Case 3. Focusing on Data and Governance Maturity and Human Resources and Organizational Readiness:** In this case, the highest weights have been assigned to Data and Governance Maturity (DGM) and Human Resources and Organizational Readiness (HOR) dimensions as 0.300. On the other hand, this scenario presents the opposite strategy where lower weights (0.200) are assigned to SA and TC. When this change has been introduced, it is seen that initial weights of Ethical AI Practices (DGM_3) and Training and Development (HOR_4) have increased significantly from 0.0545 and 0.0582 to 0.0668 and 0.0735, respectively. This approach may be ideal for SCs in highly regulated industries, where a management team focuses on risk mitigation and internal preparedness, where data compliance and ethical use are highly valued.

- **Case 1. Focusing on Balance:** This case represents the strategy where the weights of the four dimensions are assigned as 0.250 in a balanced, equal and unbiased manner. Here, even when the dimensions' weights are equal, the individual weights of the AI success factors for effective SC have changed significantly. For example, the weight of Cross-Functional Collaboration (HOR_2) increased from 0.0651 to 0.0684. Such changes indicate that some factors have intrinsic importance and require a perspective beyond a strategic focus. Therefore, a balanced approach in this case is valuable for identifying globally critical factors.

Sensitivity analyses demonstrate that there is no single "correct" AI success factor for a company in an efficient SC manner, and that each company has its own unique strategic objectives. Therefore, an SC company must define its core strategic objectives before investing in AI technology. Companies' desire to operate as a highly adaptable and low-risk enterprise, or their aim to achieve market dominance by leveraging the latest technology, translates into a complete shift in the weighting of the dimensions. This, in turn, significantly impacts the weighting of the success factors and, consequently, their prioritization. At this point, the following general conclusions can be highlighted:

- The weights of the dimensions and the contributing success factors can provide a clear roadmap for accurate, effective, and efficient resource allocation. Weights aligned with strategic objectives reveal the areas in which investments should be made and enable budget planning to be tailored to these investments.
- Furthermore, since changes in the weights of dimensions create noticeable differences in the weights of factors, combining these factors can be crucial for SC companies. Ignoring any one of these dimensions can lead to failure.
- Another critical conclusion revealed by the various cases in sensitivity analyses is that a company's priorities can change

over time. These priorities can vary depending on the SC company's stage of development. For example, a company's priorities will differ initially and during its maturity. In this case, it is crucial for a company to be aware of its changing priorities and to reassess its success factors accordingly.

Table 12. Different weights of the dimensions in different cases

AI Success Dimensions	Base	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8	Case 9	Case 10
DGM	0.2448	0.250	0.200	0.300	0.300	0.200	0.400	0.400	0.350	0.150	0.350
HOR	0.2377	0.250	0.200	0.300	0.200	0.300	0.400	0.100	0.350	0.150	0.150
SA	0.2621	0.250	0.300	0.200	0.300	0.200	0.100	0.400	0.150	0.350	0.350
TC	0.2554	0.250	0.300	0.200	0.200	0.300	0.100	0.100	0.150	0.350	0.150

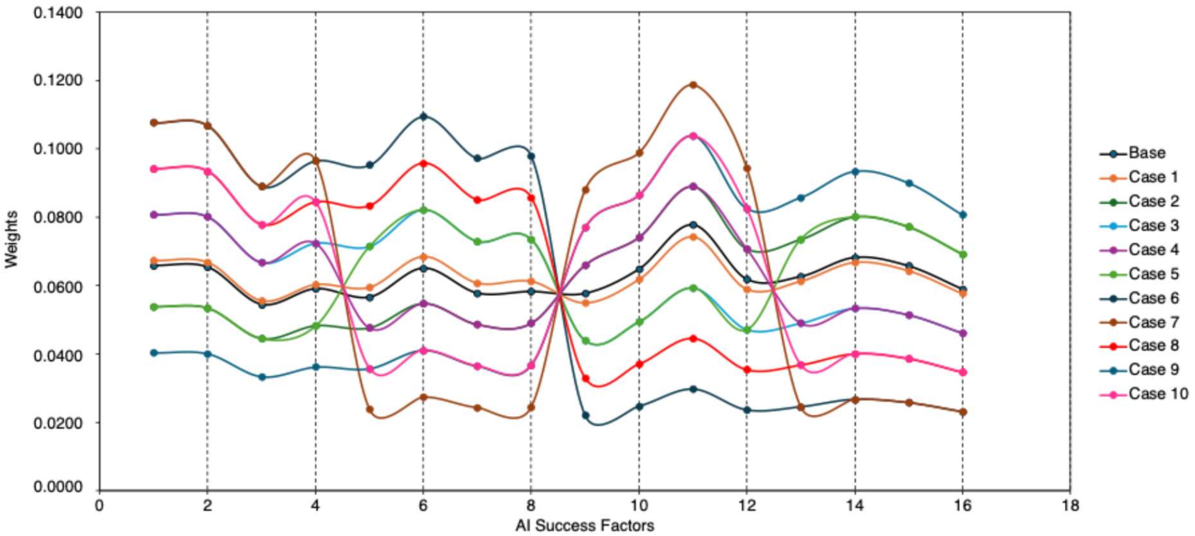
Source. Authors

Table 13. Different weights of AI success factors in different cases

Contributing Factors	Base	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8	Case 9	Case 10
DGM_1	0.0659	0.0673	0.0538	0.0808	0.0808	0.0538	0.1077	0.1077	0.0942	0.0404	0.0942
DGM_2	0.0654	0.0668	0.0534	0.0801	0.0801	0.0534	0.1068	0.1068	0.0935	0.0401	0.0935
DGM_3	0.0545	0.0556	0.0445	0.0668	0.0668	0.0445	0.0890	0.0890	0.0779	0.0334	0.0779
DGM_4	0.0590	0.0603	0.0482	0.0724	0.0724	0.0482	0.0965	0.0965	0.0844	0.0362	0.0844
HOR_1	0.0566	0.0595	0.0476	0.0714	0.0476	0.0714	0.0953	0.0238	0.0833	0.0357	0.0357
HOR_2	0.0651	0.0684	0.0548	0.0821	0.0548	0.0821	0.1095	0.0274	0.0958	0.0411	0.0411
HOR_3	0.0578	0.0608	0.0486	0.0729	0.0486	0.0729	0.0972	0.0243	0.0851	0.0365	0.0365
HOR_4	0.0582	0.0612	0.0490	0.0735	0.0490	0.0735	0.0980	0.0245	0.0857	0.0367	0.0367
SA_1	0.0577	0.0550	0.0660	0.0440	0.0660	0.0440	0.0220	0.0880	0.0330	0.0770	0.0770
SA_2	0.0648	0.0618	0.0742	0.0494	0.0742	0.0494	0.0247	0.0989	0.0371	0.0865	0.0865
SA_3	0.0778	0.0742	0.0891	0.0594	0.0891	0.0594	0.0297	0.1187	0.0445	0.1039	0.1039
SA_4	0.0618	0.0590	0.0708	0.0472	0.0708	0.0472	0.0236	0.0944	0.0354	0.0826	0.0826
TC_1	0.0626	0.0613	0.0735	0.0490	0.0490	0.0735	0.0245	0.0245	0.0368	0.0858	0.0368
TC_2	0.0682	0.0667	0.0801	0.0534	0.0534	0.0801	0.0267	0.0267	0.0400	0.0934	0.0400
TC_3	0.0657	0.0643	0.0772	0.0515	0.0515	0.0772	0.0257	0.0257	0.0386	0.0900	0.0386
TC_4	0.0589	0.0577	0.0692	0.0461	0.0461	0.0692	0.0231	0.0231	0.0346	0.0807	0.0346

Source. Authors

Figure 7. The results of sensitivity analysis



Source. Authors

From this point of view, organizations should consider the AI success factors with a hierarchical approach for their SC efficiency. Using the right technology in the right place with a correctly positioned strategic vision is critical. Aligning the AI technology with key performance indicators, goals and strategies ensures correct construction, positioning and operation of data and governance structure that feeds the AI. At this point the readiness of the organization and its assets such as human resources play a crucial role in supporting this structure. This is where the combination of harmony, alignment and collaboration of these essential elements comes in. In this way, the efficiency of SCs is increased. On the other hand, the priorities of the criteria show that strategic vision is essential for efficient SCs. The following criteria that are quality of algorithm, data security and compatibility, real-time analytics capability, and data transparency supports the technology dimension. Hence, the organizations and business world should consider the adoption of AI technology as a transformation rather than an information technology project. The AI technology encourages a holistic change of organizations and triggers end-to-end transformation forcing them to make long-term plans. The obtained support this idea. Furthermore, the results that show that technology and data are a following topic highlight that data and technology act as facilitating elements, while the readiness of human resources and the organization for transformation stands out as an element that guarantees the sustainability of the transformation journey regarding the increase in the efficiency of SCs.

Conclusion and Perspectives

In recent years, the acceleration of technological developments has paved the way for the widespread use of digital technologies. Digital technologies serving different purposes have begun to change daily life and the business world fundamentally. In an increasingly competitive environment, companies must integrate digital technologies into their business processes to increase efficiency, ensure profitability, grow, and meet the expectations of their customers. Undoubtedly, AI is the most talked-about technology of our day. The benefits offered by AI technology dragged the companies towards a holistic transformation. AI, a technology that the world has turned its eyes to due to its potential and advantages, has begun to take its place in almost all sectors. One of the areas affected by this technology is SCs, which are significant for the world economy, people, businesses, and employment. As the importance of SC increases in today's globalizing world, companies have realized that adopting technology is the way to improve their SCs' efficiency.

The integration of AI increases efficiency and productivity of SCs by enabling more accurate decisions based on high level data analyses. The automation systems offered by the AI technologies allow to accelerate processing while they are reducing the labor costs. The AI technology offers abilities in terms of decision support systems and real-time monitoring that enable to detect and correct SC disruptions quickly. AI technologies help to identify the most reliable and efficient options in a decision-making process related to selection of logistics and suppliers. Additionally, the contribution of AI to risk management helps to increase flexibility and resilience by offering effective and fast solutions to possible disruptions. Furthermore, efficiency of AI integrated SCs increases that improving customer satisfaction, which brings competitive advantages to companies. Moreover, the AI contributes to the SCs' long-term success through cost-effective, dynamic and quick operations. For this reason, the contributions of AI to the efficiency of SCs have become a topic of focus for many companies, managers, academics, and practitioners. It has become essential to investigate the elements to consider increasing the efficiency of SCs using AI technology and provide a roadmap to SC companies.

Therefore, this study aims to investigate, analyze and prioritize AI success factors for an efficient SC. For this purpose, the study firstly proposes a model consisting of 4 dimensions and their criteria which are relying on DMs' opinions and literature survey. The study conducts a case study in Turkey for the verification of the validity, applicability, and usability of the proposed model. In this respect, the study adopts the MCDM approach and employs the AHP method based on the structure of the decision-making problem in the conducted case study. However, since the complexity of the problem and the perceptual differences of the DMs supporting the execution of the decision-making processes bring about issues such as uncertainty, hesitation, and intuition, the classical AHP method has been extended to the IVIF environment. The study utilizes the IVIF AHP method to calculate criteria weights through pairwise comparisons and prioritize them. The study contributes to both academic and industrial literature due to its content and features. In this context, the originality of the study stems from the features mentioned below.

- It contributes to academia and industry by investigating, identifying, and prioritizing AI success factors for an efficient SC.
- It provides valuable insights to organizations looking to integrate AI into their SC operations.
- The study proposes a strategic roadmap based on a decision-making framework in this area.
- The application in Turkey proves the functionality, usability, and applicability of (i) the proposed model, (ii) the analytical technique used, and (iii) the decision-making approach.
- When the academic literature has been examined, it is possible to reach successful examples of fuzzy MCDM applications in various studies focusing on AI from the SC perspective. In fact, some of these studies have been included in the above sections. However, this study is the first to propose a model based on AI success factors and applying it for efficient SC in a real case using the IVIF AHP to the extent of our knowledge based on available evidence.

The model and approach proposed in the study provide valuable insights. On the other hand, for future studies, the proposed model can be further developed and expanded. The proposed model is a generic model, and it can be applied to different areas. As another application, other fuzzy extensions such as spherical fuzzy sets, Pythagorean fuzzy sets, and Fermatean fuzzy sets can be integrated with different MCDM methods to capture the uncertainty of the subjective judgments of experts. Additionally, the results of these can be compared since each uses different aggregation operators and defines the membership and non-membership functions in different ways. Furthermore, the number of the DMs can be increased. Different analyses such as scenario and sensitivity can be employed.

Author Contributions

The author contributions have been declared as follows: Gülçin Büyüközkan: %50, Celal Alpay Havle: %50

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The author(s) did not report ethical committee approval as the research content does not require.

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