AN IT INVESTMENTS ASSESSMENT FRAMEWORK IN TEXTILE PRODUCTION FROM A DIGITAL SUSTAINABILITY PERSPECTIVE

(DİJİTAL SÜRDÜRÜLEBİLİRLİK PERSPEKTİFİNDEN TEKSTİL ÜRETİMİNDE BİR BT YATIRIM DEĞERLENDİRME ÇERÇEVESİ)

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Elif Can Edge KURTUL, B.S.

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LIST OF SYMBOLS

AI	: Artificial Intelligence
AHP	: Analytic Hierarchy Process
AR/VR	: Augmented Reality / Virtual Reality
BWM	: Best-Worst Method
CBA	: Cost-Benefit Analysis
CDO	: Chief Digital Officer
COO	: Chief Operations Officer
DM	: Decision-Maker
DPP	: Digital Product Passport
EMS	: Energy Management System
ERP	: Enterprise Resource Planning
ESG	: Environmental Social Governmental
EU	: European Union
IoT	: Internet of Things
IT	: Information Technology
LCA	: Life-Cycle Assessment
MES	: Manufacturing Execution System
MCDM	: Multi-Criteria Decision-Making
SC	: Social Compliance
SDG	: Sustainable Development Goals
SF-AHP	: Spherical Fuzzy Analytic Hierarchy Process
SF-TOPSIS	: Spherical Fuzzy Technique for Order Preference by Similarity to Ideal Solution
SF-PIS	: Spherical Fuzzy Positive Ideal Solution
SF-NIS	: Spherical Fuzzy Negative Ideal Solution
SF	: Spherical Fuzzy
SFS	: Spherical Fuzzy Sets
SI	: Scale Indicator (in SF scoring)
SIRI	: Smart Industry Readiness Index
SME	: Small and Medium-Sized Enterprise
SWAM	: Spherical Weighted Arithmetic Mean

SWGM : Spherical Weighted Geometric Mean
TOPSIS : Technique for Order Preference by Similarity to Ideal Solution

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ABSTRACT

The textile industry, one of Türkiye's and the world's leading and most significant industries, is undergoing an intensive digitalization process driven by the need to enhance competitiveness through operational efficiency, social compliance, and sustainability requirements. In this context, companies are increasingly required to make complex IT investment decisions that align not only with economic performance, but also with environmental and social sustainability goals. However, the lack of a structured, transparent, and sector-specific decision-making methodology poses a critical challenge—especially for small and medium-sized enterprises (SMEs).

This study proposes a comprehensive multi-criteria decision-making (MCDM) framework designed to evaluate and prioritize IT investment alternatives in textile production from a digital sustainability perspective. The framework structured around eight key criteria: technological infrastructure, cost, data security, strategic fit, organizational culture, management support, environmental impact, incentives and policies. Each main criterion is further broken down into sub-criteria to facilitate a systematic and detailed analysis.

The evaluation applied on nine IT investment alternatives: Internet of Things (IoT), Digital Twin (DT), Enterprise Resource Planning (ERP) Systems, Image Processing (IP), Energy Management Systems (EMS), Manufacturing Execution Systems (MES), Smart Logistics and Inventory Management (SL/IM), Block-chain (BC), and Augmented Reality and Virtual Reality Applications (AR/VR).

To manage the uncertainty and vagueness inherent in expert judgments, the framework employs Spherical Fuzzy Logic, integrated with Analytic Hierarchy Process (AHP) for criteria weighting and Technique for Order Preference by Similarity to Ideal Solution

(TOPSIS) for ranking alternatives. This hybrid methodology enables the incorporation of subjective expert input, while maintaining mathematical rigor and decision stability. The use of Spherical Fuzzy Sets—as opposed to classical or intuitionistic fuzzy approaches—provides enhanced flexibility in capturing degrees of membership, non-membership, and hesitation simultaneously.

The model was validated through expert input from three senior professionals within the textile industry, representing distinct decision-making roles. A series of sensitivity analyses was also conducted to test the robustness of the results, including variations in key criteria, decision-maker influence, and closeness ratio proximity. Findings show that IoT and ERP-based solutions are prioritized due to their strategic relevance, operational efficiency, and sustainability alignment. The proposed framework not only aids decision-makers in identifying the most appropriate IT solutions for digital transformation, but also strengthens sustainable value creation by integrating economic, environmental, and social dimensions into the investment decision process.

Although the empirical scope of the study is focused on Türkiye's textile sector, the modular and adaptable design of the framework allows for its application in other industrial contexts with suitable customization. The paper concludes with a discussion on the framework’s potential enhancements and outlines avenues for future empirical application, aiming to contribute to the broader discourse on sustainable digital transformation in manufacturing.

ÖZET

Türkiye'nin ve dünyanın önde gelen ve en önemli sektörlerinden biri olan tekstil sektörü, operasyonel verimlilik, sosyal uyumluluk ve sürdürülebilirlik gereklilikleri odağında rekabet gücünü artırma ihtiyacının etkisiyle yoğun bir dijitalleşme sürecinden geçmektedir. Bu bağlamda, şirketlerin yalnızca ekonomik performansla değil, aynı zamanda çevresel ve sosyal sürdürülebilirlik hedefleriyle de uyumlu, karmaşık BT yatırım kararları almaları giderek daha fazla gerekmektedir. Ancak, yapılandırılmış, şeffaf ve sektöre özgü bir karar alma metodolojisinin eksikliği, özellikle küçük ve orta ölçekli işletmeler (KOBİ'ler) için kritik bir zorluk oluşturmaktadır.

Bu çalışma, tekstil üretiminde BT yatırım alternatiflerini dijital sürdürülebilirlik perspektifinden değerlendirmek ve önceliklendirmek üzere tasarlanmış kapsamlı bir Çok Kriterli Karar Alma (ÇKKV) çerçevesi önermektedir. Çerçeve, sekiz temel kriter etrafında yapılandırılmıştır: teknolojik altyapı, maliyet, veri güvenliği, stratejik uygunluk, kurum kültürü, yönetim desteği, çevresel etki, teşvikler ve politikalar. Her ana kriter, sistematik ve ayrıntılı bir analizi kolaylaştırmak için alt kriterlere ayrılmıştır.

Değerlendirme, dokuz BT yatırım alternatifine uygulanmıştır. Bunlar: Nesnelerin İnterneti (IoT), Dijital İkiz (DT), Kurumsal Kaynak Planlama (ERP), Görüntü İşleme (IP), Enerji Yönetim Sistemleri (EMS), Üretim Yürütme Sistemleri (MES), Akıllı Lojistik ve Envanter Yönetimi (SL/IM), Blok Zinciri (BC) ve Artırılmış Gerçeklik ve Sanal Gerçeklik Uygulamaları (AR/VR).

Uzman kararlarındaki belirsizlik ve muğlaklığı yönetmek için çerçeve, kriter ağırlıklandırması için Analitik Hiyerarşi Süreci (AHP) ve alternatifleri sıralamak için İdeal Çözüme Benzerliğe Göre Sıralama Tercihi Tekniği TOPSIS ile entegre Küresel Bulanık Mantık kullanır. Bu hibrit metodoloji, matematiksel kesinlik ve karar istikrarını korurken öznel uzman girdilerinin dahil edilmesini sağlar. Klasik veya sezgisel bulanık

yaklaşımların aksine Küresel Bulanık Kümelerin kullanımı, üyelik, üyelik dışılık ve tereddüt derecelerini aynı anda yakalamada gelişmiş esneklik sağlar.

Model, tekstil sektöründe farklı karar alma rollerini temsil eden üç kıdemli profesyonelin uzman girdileriyle doğrulanmıştır. Sonuçların sağlamlığını test etmek için, temel kriterlerdeki farklılıklar, karar verici etkisi ve yakınlık oranı da dahil olmak üzere bir dizi duyarlılık analiz yürütülmüştür. Bulgular, IoT ve ERP tabanlı çözümlerin stratejik önemleri, operasyonel verimlilikleri ve sürdürülebilirlik uyumları nedeniyle önceliklendirildiğini göstermektedir. Önerilen çerçeve, karar vericilerin dijital dönüşüm için en uygun BT çözümlerini belirlemelerine yardımcı olmakla kalmayıp, aynı zamanda ekonomik, çevresel ve sosyal boyutları yatırım karar sürecine entegre ederek sürdürülebilir değer yaratımını da güçlendirmektedir.

Çalışmanın ampirik kapsamı Türkiye'nin tekstil sektörüne odaklanmış olsa da, çerçevenin modüler ve uyarlanabilir tasarımı, uygun özelleştirmelerle diğer endüstriyel bağlamlarda da uygulanmasına olanak sağlamaktadır. Makale, çerçevenin potansiyel iyileştirmeleri üzerine bir tartışmayla sona ermekte ve gelecekteki ampirik uygulama yollarını özetleyerek, üretimde sürdürülebilir dijital dönüşüm konusundaki daha geniş tartışmaya katkıda bulunmayı amaçlamaktadır.

1 INTRODUCTION

Türkiye plays a crucial role in the European Union (EU) textile market, positioning itself as a key supplier (IHKIB, 2024). The Turkish textile sector has demonstrated remarkable resilience, recovering swiftly from supply chain disruptions caused by the COVID-19 pandemic. The preference for geographically closer suppliers has further strengthened Türkiye's market position. However, the industry has also faced significant challenges, particularly due to the earthquakes in the Southern and Eastern Anatolia Regions, which severely impacted cotton production, workforce availability, and overall manufacturing capacity (Digilina & Gasimova, 2024).

Despite these adversities, Türkiye's textile exports have shown significant growth. As of 2024, Türkiye's share in EU textile imports has increased by 16.4% compared to the previous year, whereas China, the leading supplier, has experienced a decline (Digilina & Gasimova, 2024). This trend highlights Türkiye's growing importance in the global textile market (Dinçer et al., 2023). Additionally, risk assessments and contingency planning by large-scale textile firms have demonstrated that digital transformation enhances operational resilience. However, the slow adoption of digital technologies by small and medium-sized enterprises (SMEs) has hindered their recovery, underlining the necessity for increased awareness and infrastructure development. (Dinçer et al., 2023). This digital divide exacerbates systemic fragilities and undermines sector-wide progress toward Industry 4.0 and sustainability targets.

From a sustainability perspective, digital technologies such as IoT, digital twins, ERP systems, and AI-powered quality control tools offer significant opportunities. These innovations not only enhance productivity and reduce operational costs but also support circular economy practices and carbon footprint reduction (Kohler et al., 2021). Yet, integrating such technologies requires careful evaluation, especially for SMEs with constrained resources. Strategic IT investment planning—aligned with economic, environmental, and social goals—is therefore essential.

To address this need, the present study proposes a comprehensive IT investment evaluation framework specifically tailored for textile production. The framework leverages two robust multi-criteria decision-making (MCDM) methods—Spherical Fuzzy Analytic Hierarchy Process (SF-AHP) for deriving the weights of sustainability criteria, and Spherical Fuzzy TOPSIS (SF-TOPSIS) for ranking alternative IT solutions. These methods are selected due to their superior ability to handle uncertainty, hesitation, and vagueness in expert judgments—common characteristics in sustainability assessments. By integrating spherical fuzzy logic, the framework ensures that subjective expert opinions are captured with greater realism and mathematical rigor.

SMEs, which often struggle with resource limitations, are at a disadvantage when attempting to implement digital transformation initiatives. Their reliance on external support and the uncertainties surrounding digital investments make strategic decision-making crucial (Jia et al., 2024). Addressing this challenge requires a structured approach to guide SMEs in prioritizing investments that provide the most sustainable benefits.

This study proposes a comprehensive framework to evaluate IT investments in textile production from a digital sustainability perspective. By selecting key technologies as investment alternatives and applying This study develops a comprehensive IT investment assessment framework using SF-AHP for criteria weighting and SF-TOPSIS for alternative ranking, this framework aims to help firms allocate their limited resources effectively. The proposed approach will support companies in optimizing their digital transformation strategies, ensuring both economic efficiency, social adaptivity and long-term sustainability.

2 LITERATURE REVIEW

This literature review is structured into three main sections to comprehensively examine the current knowledge on the selection of IT investments in the textile sector. The first section, 'Digital Transformation and Sustainability in Textile Production', examines the perspective of the global textile sector on digital transformation, the obstacles it has encountered in the transformation and the studies carried out, and addresses the importance of sustainability for the sector. The second section, 'Türkiye's Textile Industry and Industry 4.0 Adoption', examines the efforts of the Turkish textile sector to adopt Industry 4.0, the difficulties encountered and the studies carried out in the sector on the subject. This review aims to provide a holistic understanding of current practices and emerging trends in IT project evaluation and selection by detailing both the importance and methodologies. The third section, "IT Investment Decision-Making Methodologies", examines the decision-making processes, methodologies and the criteria of these methodologies in IT investments.

The aim of this literature review is to comprehensively analyze the current knowledge on the evaluation and selection of information technology (IT) investments in the Turkish textile sector and to reveal the relationship between digital transformation, sustainability and decision-making methodologies. In this context, the study aims to understand the effects of digital transformation processes on the sector both globally and in Türkiye, to emphasize the importance of technology investments from a sustainability perspective and to define appropriate methods that can be strong guide decision makers. Thus, it is aimed to contribute to the planning of future IT investments in a more strategic, sustainable and effective manner.

A search was conducted with the keywords "digital transformation" AND "textile industry" AND sustainability, "IT investment" AND decision-making AND methodology OR "fuzzy AHP", "Industry 4.0" AND "Turkey" AND "textile sector", "ERP systems" OR "IoT" OR "MES" OR "Digital Twins" OR "Machine vision" OR "AR&VR" OR "EMS" OR "Blockchain" AND evaluation AND manufacturing as the title. Then, the abstract or keyword sections were examined in EBSCO and Google Scholar databases. The articles that were out of scope were eliminated and a comprehensive analysis was conducted on the remaining articles.

2.1 Digital Transformation and Sustainability in Textile Production

The textile industry, one of the oldest and most significant manufacturing sectors, has undergone substantial digital transformation. Emerging digital technologies such as the Internet of Things (IoT), artificial intelligence (AI), big data analytics, and cloud computing are reshaping traditional production processes by enhancing automation, efficiency, and adaptability (Tao & Liu, 2019). Industry 4.0 technologies play a crucial role in optimizing production, reducing waste, and improving product quality (Kohler et al., 2021). Despite these advancements, sustainability remains a critical challenge in the textile sector due to its significant environmental and social impacts. Issues such as excessive water consumption, high energy usage, and carbon emissions have been widely highlighted in the literature. Research emphasize sustainable manufacturing practices, including cleaner production technologies, circular economy principles, and energy-efficient solutions (Shen, 2014) (Muthu, 2018).

In their study, Tian et al. (2025) examined the impact of environmental, social and governance (ESG) performance on corporate value, the relationship between innovation competence and the role of digital transformation in these interactions between 2013 and 2023 in the textile and apparel sector with a sample of 408 firms in China. According to the findings: The level of digital transformation strengthens the impact of ESG on firm value. ESG practices provide sustainable competitive advantage by balancing the expectations of different stakeholders and convey companies' sustainability commitments as a trust signal to external stakeholders. For textile companies, the necessity of creating competitive advantage by integrating ESG with innovation and the necessity of optimizing resource use with digital tools (big data, blockchain, IoT) are among the conclusions of the article.

The systematic literature review published by Tomaschko & Krommes (2024) covers the years 2016-2023 and examines how digitalization technologies are evaluated in terms of economic and environmental sustainability in production systems. While technologies such as digital twins (DT), cyber-physical systems (CPS) and IoT are accepted as providing efficiency and resource savings, the need for life cycle-based evaluation of these technologies is emphasized, considering energy consumption, raw material use and investment costs. According to the article, for holistic sustainability assessment, the need for new models that cover the entire life cycle, combine economic + environmental dimensions, and provide direct support to the decision-making process is emphasized (Tomaschko & Krommes, 2024).

Le et al. (2024) examines the impact of digitalization on corporate sustainable performance, how it is realized through green innovation and green supply chain management. The study was conducted on SMEs in Vietnam (especially in the food and beverage sector) and analyzed with the PLS-SEM method. The article emphasized the necessity of companies to comply with social expectations with environmental practices in the context of legitimacy theory. It was suggested that digital infrastructure and green strategies be implemented together for sustainability. The conclusions of the study include the necessity of integrating digitalization investments not only with operational efficiency but also with environmental sustainability goals. At the same time, the study emphasized the need for increased customer satisfaction, recycling, energy saving and environmental awareness development, increased market share and competitive advantage, and the need to spread the culture of digitalization within the organization.

IT investments have emerged as a key enabler of sustainable textile production (Sharma & Singhal, 2020). Case studies in the textile industry suggest that digital twins enable data-driven decision-making, assisting companies in transitioning to more sustainable and resilient production systems (Tao et al., 2019).

In their study, Orisidare et al. (2024) introduce a new hybrid decision-making framework developed by utilizing Industry 4.0 (I4.0) technologies to measure circular economy (CE) performance in the textile sector. The main goal is to systematically and measurably evaluate the applications at the intersection of digitalization and sustainability. In the study, I4.0 technologies (IoT, artificial intelligence, cyber-physical systems, big data, blockchain, etc.) are integrated with circular economy strategies. The developed framework provides an evaluation system that takes into account both environmental and economic impacts. The study aims to provide solutions to gaps in areas such as standardization of sustainability metrics, data security, investment costs, and institutional transformation challenges. The article presents an integrated framework that addresses the lack of decision support structures required for sustainable digital transformation and develops guiding recommendations for both academic research and industry practices (Orisidare et al., 2024).

However, a significant research gap remains in linking digital transformation to long-term sustainable outcomes in the textile industry, making the development of integrated assessment frameworks increasingly important.

2.2 Türkiye's Textile Industry and Industry 4.0 Adoption

The Turkish textile and apparel industry has long been a pillar of the economy and a major exporter, and it has proactively invested in technology upgrades to maintain a competitive edge (IHKIB, 2021). However, the adoption of IT solutions in textile production is not without challenges. Financial, technical, and organizational barriers—such as high initial investment costs, lack of skilled labor, and resistance to change—pose significant obstacles to widespread implementation (Raj & Seetharaman, 2021).

In their published study, Divrik and Baykal investigate the role of organizational learning in the digitalization processes of SMEs in the Turkish textile and apparel sector and its impact on internationalization. This research, which was conducted using mixed methods (quantitative + qualitative), reveals that managers' knowledge and perceptions are particularly decisive in digital transformation. The sample includes 347 managers from textile and apparel SMEs in Istanbul. Their conclusions emphasize the necessity of creating an organizational learning culture for digitalization investments to be effective, that trainings should be designed not only for orientation but also for strategic development, and that government supports (e.g. digitalization incentives) are an important tool to accelerate this process (Divrik & Baykal, 2024).

In their study, Yilmaz et al. (2025), analyzed sustainable production practices using deep learning-based prediction models (LSTM and ANN) in order to reduce the environmental impacts of textile dyeing processes and increase energy efficiency. The research focuses on a textile company's dyehouse facility in Adana and presents concrete gains regarding process improvement and carbon footprint reduction through real production data. Among the conclusions, it is emphasized that conducting prediction studies with deep learning in energy-intensive textile processes is critical for planning, budgeting and achieving sustainability goals. In addition, concrete outputs were obtained on the fact that solar power plant investments provide high returns in terms of carbon footprint and cost reduction and that layout and process revisions increase both employee productivity and production capacity

Gök et al. (2024), propose a method based on materiality analysis to develop industry-wide sustainability strategies for textile SMEs in Turkey. The study was conducted in textile SMEs in 4 different cities (Ankara, Gaziantep, Kahramanmaraş) and was conducted with the participation of internal and external stakeholders based on GRI 2021 standards. The achievements of the study include; SMEs becoming aware of sustainability, obtaining information on SDGs and the EU Green Deal, starting preparations for corporate sustainability reporting and determining a sectoral roadmap. The recommendations were; the need to continue active stakeholder participation, the need for SMART targets, the need to act on common sector priorities, and the need to establish measurement and evaluation systems (Gök et al. 2024).

Özbek et al. (2024) developed a comprehensive model with the fuzzy DEMATEL method to analyze the obstacles encountered in the digitalization process in the ready-made clothing sector. The aim of this study, in which they analyzed the barriers to digitalization in the sector, was to determine the cause-effect relationships between the obstacles and to guide digital transformation strategies. The study, which was conducted with the participation of 16 academics, lists the four most critical obstacles as follows: Lack of Expertise, Lack of Management Support, Insufficient Financial Resources, Lack of IT Systems. When the results and recommendations of the study are examined; It is seen that SMEs must first develop expertise and provide managerial support in order to see the benefits of digitalization, and that policymakers must produce sector-specific digitalization policies and incentives. The study is one of the rare sector-specific analyses conducted with MCDM and fuzzy logic, and fills an important gap in the literature. It offers a workable roadmap for companies with SMART targets and impact-importance matrices.

Duman Altan et al. (2024) investigate the impact of digital technology adoption on sustainability performance through supply chain traceability, supply chain resilience and circular economy practices in their study. The survey results conducted with 235 production managers in Türkiye show that digital transformation alone is not sufficient to achieve sustainability goals, but is effective when integrated with supply chain traceability and supply chain resilience. The recommendations made to production managers as a result of the study are as follows; When investing in digital technologies, they need to integrate them with traceability and resilience systems. Circular economy practices (e.g. recycling, reuse) support sustainability, but are not sufficient on their own. In order to achieve sustainability performance goals, DT investments need to be integrated with strategic alignment and operational structures.

2.3 IT Investment Decision-Making Methodologies

Given the complexities associated with sustainable IT investments in textile manufacturing, robust decision-making methodologies have become indispensable. This chapter provides an overview of current and important MCDM techniques used in the evaluation of such investments.

To address these challenges above, various frameworks and methodologies have been proposed for evaluating IT investments and their impact on sustainability. Multi-Criteria Decision-Making (MCDM), Life-Cycle Assessment (LCA), and Cost-Benefit Analysis (CBA) are commonly applied approaches. Among these, fuzzy Best-Worst Method (BWM) and TOPSIS have been widely used to assess sustainable systems, providing a foundation for similar evaluation models in textile production (Zhao et al., 2022).

Hamzeh and Xu's review (2019) found that AHP, fuzzy logic, Data Envelopment Analysis, and hybrid techniques are among the most frequently used approaches for technology selection. Pour et al. (2023) performed a manufacturing system and firm selection framework by using Fuzzy AHP and Fuzzy TOPSIS methods (Pour et al., 2023). Mondragon et al. used AHP and Fuzzy AHP approachs for selection of a manufacturing method for textile industry (Mondragon et al., 2019) Spherical Fuzzy Sets (SFS) was developed by Kutlu and Kahraman. Gündoğdu and Kahraman also used SF-AHP for industrial robot selection, and renewable energy application (Kutlu Gündoğdu, F., & Kahraman, C., 2020). Kahraman et al. used SF-TOPSIS for hospital location selection (Kahraman, et al., 2019). Kocakaya et al. used that methodology in their research article in 2021 for plane type selection (Kocakaya et al., 2021).

In their study, Görçün et al. (2024) aim to develop a decision support system based on the multi-criteria decision making approach to evaluate digital transformation enablers in the manufacturing sector. SF-AHP and SF-TOPSIS used in their study. It has been shown that with the proposed method, companies can make digital transformation decisions more sustainably, systematically and strategically (Görçün et al.,2024).

In their study, Lamrani Alaoui et al. develop a hybrid multi-criteria decision-making (MCDM) framework that combines three different fuzzy logic approaches (interval-valued, intuitionistic, hesitant) to overcome the uncertainty and decision-making difficulties experienced in the selection of digital technologies in the context of Industry 4.0. They used the entropy-weighted VIKOR method implemented with three separate fuzzy logic extensions. These are; Interval-valued fuzzy VIKOR, Intuitionistic fuzzy VIKOR, Hesitant fuzzy VIKOR. As a final stage, hybrid ranking was performed with principal component analysis (PCA) to combine the ranking differences between the different approaches (Lamrani et al., 2024).

Despite the advancements, gaps remain in understanding the long-term usability and impact of industry 4.0 solution IT investments on environmental, economic, and social sustainability in Türkiye’s textile industry. There is lack of empirical research exploring how IT investments contribute to sustainability outcomes over extended periods and maintain itself in a successful way for Textile and Apparel Industry.

3 IT INVESTMENTS AND KEY SUSTAINABILITY CRITERIA ON TEXTILE INDUSTRY

The textile industry, which is of critical importance both globally and especially for Turkey, is undergoing a significant transformation by adopting advanced IT systems and technologies. These innovations aim to significantly increase operational efficiency, optimize resource management and promote sustainability practices (Altepost et al., 2024). Digitalization initiatives, which include technologies such as IoT, artificial intelligence, digital twins, ERP and blockchain, are the main tools that enable textile manufacturers to achieve greater productivity, reduce environmental impacts and maintain their competitiveness in increasingly challenging markets. However, this transformation poses certain challenges, especially for SMEs, due to resource constraints, financial barriers and technological integration complexities. Therefore, a structured, sustainable investment strategy is essential to effectively overcome these challenges and achieve long-term success.

In the next section, there are chosen IT investment alternatives driving change in textile production.

3.1 IT Investments on Textile Industry

In this section, various IT investment alternatives that a textile factory can incorporate are examined and their contributions to sustainability are taken into account. Within this context, decision makers have evaluated the contribution of investments to sustainability by considering economic, environmental, social and cultural aspects for each investment.

Chosen IT alternatives are schematized in Figure 3.1 below.

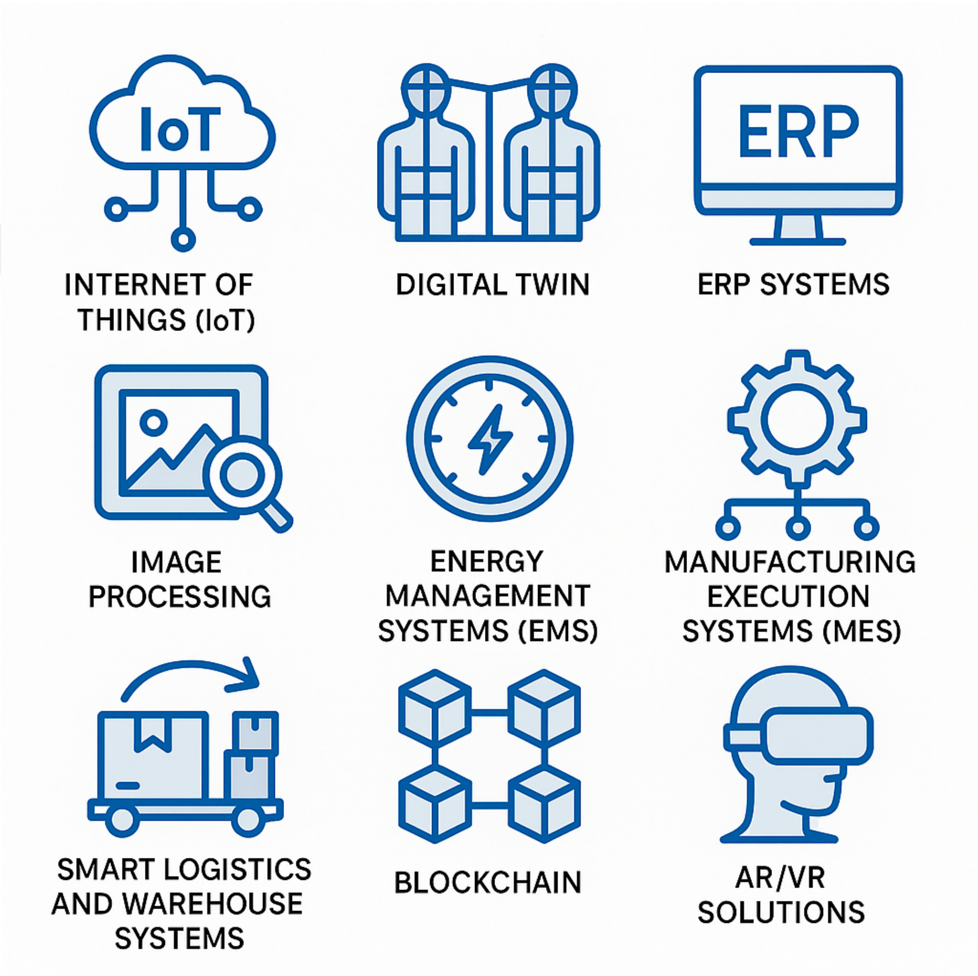

Figure 3.1: Evaluated IT alternatives

Those nine IT-investment options were chosen because:

1. They cover value chain end to end; data capture → simulation → execution → quality → energy → logistics → traceability → customer/worker interaction.

2. Each of the alternatives directly contributes to at least one pillar—cost reduction, resource efficiency, social inclusivity or cultural engagement—in the SF-AHP hierarchy.
3. All alternatives are well-documented in the textile and manufacturing literature as high-impact, high-priority investments under Industry 4.0 and digital sustainability frameworks.
4. Consolidated sector reports investigated and consolidated Smart Industry Readiness Index (SIRI) reports are investigated
5. Discussions made with sector representatives.

3.1.1 Internet of Things (IoT)(A_1)

IoT optimizes production processes by connecting physical devices over the internet and sharing data. It is integrated with various sensors used in textile production (temperature, humidity, pressure, RPM, water level, light, GPS, PIR motion detectors, etc.) to increase the efficiency of machines, reduce energy and resource consumption, and ensure safety. Data from these sensors can be monitored in real time in a central graphical user interface (GUI), thus speeding up decision-making processes and making them more effective (Petrillo et al., 2024).

IIoT (Industrial Internet of Things) is the use of connected smart devices, sensors, and data analytics in industrial environments. It is a key component of Industry 4.0.

The adoption of IoT technologies in the textile industry has revolutionized processes by enhancing operational efficiency, reducing waste, supporting sustainability initiatives, improving energy management, predictive maintenance, and resource optimization by real-time monitoring, automating quality control and data collection (Das et al., 2025) (Ahmad et al., 2020). It plays a pivotal role in sustainable digital transformation, addressing industry-specific challenges such as natural resource consumption and production inefficiencies (Dantas, 2024). As part of the broader Industry 4.0 framework, IoT fosters smart manufacturing through interconnected systems, which facilitate circular economy practices, ensuring greater transparency and precision in production (Dal Forno et al., 2023) (Wiegand & Wynn, 2024).

3.1.2 Digital Twin (A_2)

Digital Twin is the creation of a virtual copy of a physical system. This copy enables monitoring, simulation, prediction and optimization processes by feeding with real-time data. It aims to improve the performance of physical systems with "real-virtual-real" data flow.

It is designed as a structure that provides modeling with systems such as CAD; data collection with systems such as IoT, electronic communication; data analysis with systems such as AI, ML; data processing with systems such as cloud, edge computing; and interaction with VR&AR systems. It can be applied in processes such as process monitoring, predictive maintenance, decision support, product development, and operator training in production.

DT technology is one of the cornerstones of Industry 4.0. It will be indispensable in smart production systems of the future with real-time monitoring, cost reduction, resource optimization and decision support systems (Pires et al., 2019) (Parrot & Warshaw, 2017).

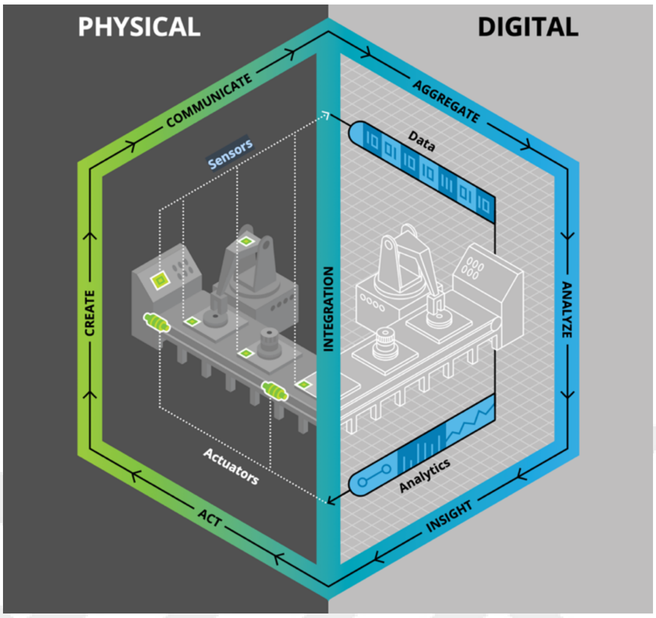

Figure 3.2: Manufacturing process digital twin model. Source: Deloitte University Press.

Through digital twins, textile manufacturers can predict equipment failures, reduce downtime, and improve operational efficiency by analyzing real-world data in a virtual environment (Ahmad et al. 2020). This technology supports sustainable practices by enhancing resource management and minimizing waste, aligning with circular economy principles (Wiegand & Wynn, 2024). Moreover, digital twins are instrumental in reshaping work processes and fostering sustainable innovation in the textile industry by reshaping physical operations with digital workflows (Altepost et al., 2024). The broader digitalization trends, including green strategies, further emphasize the role of digital twins in improving energy efficiency and reducing environmental impacts across textile and apparel sectors (Orisadare et al., 2024).

Digital twin technology stands out as an innovative tool that increases sustainability in textile processes. In systems where this technology is integrated, for example, in a study conducted, a virtual copy of the dyeing machine was created and process parameters (temperature, pH, energy and water consumption, etc.) were monitored and optimized in real time. Working together with the analysis module, the digital twin automatically determined alkaline addition and washing points, shortened the dyeing time by 17.5%, and provided a reduction of approximately 12% in electricity and steam consumption. Thanks to this optimization, greenhouse gas emissions also decreased by 12.1%, and these were ensured without compromising production quality. This system, which can be easily integrated into existing dyeing machines thanks to its modular structure, offers an accessible sustainability solution especially for small and medium-sized enterprises. In this respect, digital twin technology plays a critical role in the textile sector's transition to low-carbon production (Kim et al., 2024).

In Figure 3.2, a textile industry application of digital twins. A service-oriented digital twin architecture developed for weaving workshops is seen. It aims to increase real-time monitoring, forecasting and production optimization capabilities.

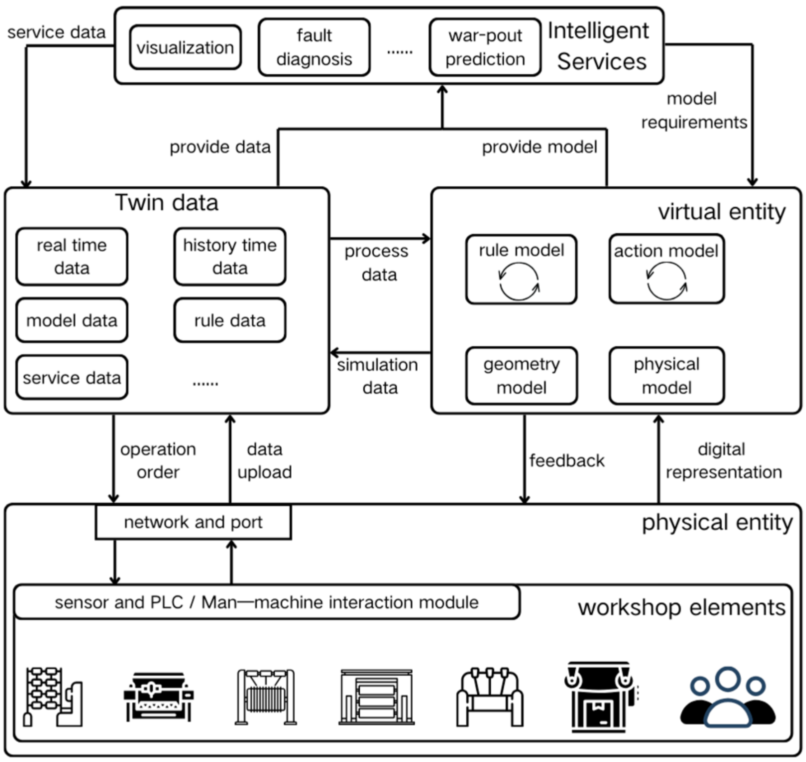

Figure 3.3: Digital Twin Architecture in weaving workshop (Yu et al., 2024)

3.1.3 ERP (Enterprise Resource Planning) Systems (A_3)

ERP is a software system that integrates all basic business functions from production to human resources. It facilitates the flow of information between all departments by collecting data in a single center.

ERP increases operational efficiency and saves time and labor. The process that started with inventory control systems in the 1960s continued with MRP (1970s) and MRP II (1980s). ERP became widespread in the 1990s as an expanded and integrated version of MRP II.

ERP has been affected in various ways with Industry 4.0. At the data level, data can be collected directly from the source with tools such as IoT and RFID, and with Cloud computing, this data can be processed in real time. At the information level, artificial intelligence provides decision support mechanisms to ERP systems in areas such as forecasting, planning, and inventory management. At the knowledge level, smart robots and autonomous systems transform ERP systems into structures that can physically process data in the field. (Akyurt et al., 2020)

ERP systems are becoming more integrated, intelligent and agile with the new technologies offered by Industry 4.0. Thanks to this transformation:

- Data is collected more accurately and quickly,
- Analysis capacity increases with big data infrastructures,
- Decision-making processes are accelerated with artificial intelligence applications,
- ERP systems are turning into the nervous system of digital factories.

ERP systems enable seamless real-time data flow across departments. It is crucial for textile factories improving operational efficiency, reducing costs, and enhancing decision-making capabilities, enabling better material flow, minimizing waste, and ensuring faster response times to customer requirements (Ahmad et al., 2020) (Jeong, 2021). ERP solutions streamline workflows by automating repetitive tasks and providing greater transparency into the production cycle, which is essential for managing large-scale operations (Gokalp et al., 2018).

When sector-specific studies on ERP are examined, it is seen that technology is one of the basic building blocks for the digitalization of resource management. Altepost et al. (2024) conducted a compilation study examining ERP systems and digital transformation in the textile sector. Kohler et al. (2021) conducted an industrial analysis on the integration of ERP systems with IoT and AI. Aydoğmuş et al. (2021) conducted a study on the decision-making model for ERP selection.

Some SMEs in the sector still use ERP in a limited way. It is seen that the sector has not yet adopted some structures because it is a labor-intensive sector and has a more traditional structure. For this reason, ERP has been included among the Industry 4.0 IT investment alternatives in this study.

3.1.4 Image Processing (A_4)

Image processing is the name given to the mathematical and algorithmic operations that aim to analyze, improve or derive meaning from digital images by performing various operations on them. For example, noise reduction, edge detection, segmentation, color analysis, histogram equalization are the basic operations of image processing. It is a larger system that integrates processed images with the processes of perception, decision making and action. In addition to image processing tools, it is a system that includes decision support software and its control system (Javaid et al. 2022).

This study aims to evaluate image processing and machine vision studies. All evaluators were informed in detail about the subjects to be evaluated and the evaluation criteria.

Machine vision allows machines to perceive objects and make decisions through imaging technologies. The three main tasks here are: imaging, analysis and action. It is applied in many areas such as quality control, part recognition, pattern recognition, OCR (optical character recognition).

Computer vision, as one of the basic components of Industry 4.0, can work with IoT, artificial intelligence, robotics and cloud systems, thus digitizing the production environment. Real-time collection of visual data reduces error rates, increases efficiency, and minimizes human error. It directly contributes to the decision-making processes of machines in smart factories.

While machine vision is the basis of smart production in Industry 4.0, it plays a critical role in the formation of more sensitive and inclusive systems that work together with humans in Industry 5.0. This transition represents a change, development and evolution in production, not only with technology but also with a human-centered design approach. (Suma et al., 2024)

Image Processing technologies have emerged as a transformative tool in the textile industry by automating quality control processes, defect detection in fabrics. Image processing techniques, integrated with machine learning and artificial intelligence, further enhance defect detection capabilities by enabling real-time analysis and decision-making on the shop floor. In addition, these systems contribute to sustainable manufacturing goals by improving product quality and reducing defective output, which translates into material savings and greater customer satisfaction (Malik et al., 2024).

3.1.5 EMS (Energy Management System) (A_5)

Energy Management Systems are real-time energy monitoring and management systems created by using Industry 4.0 technologies (IoT, CPS, artificial intelligence, data analytics, etc.). They are designed to monitor energy consumption at specified points. They provide energy flexibility, perform load scheduling and energy consumption optimization. They have the ability to perform AI-supported energy planning. They provide energy optimization by integrating energy data with production. They are systems that contribute to sustainability by reducing energy costs.

Industry 4.0 can be effective not only in the production area but also in the entire value chain in terms of energy sustainability. Especially with EMS systems, real-time energy monitoring, predictive planning and optimized consumption become possible. This is seen as a contribution to sustainability (Javied et al., 2018).

EMS, together with Industry 4.0, is integrated with IoT, sensors, artificial intelligence and data analytics. It estimates energy usage with real-time data and prevents inefficiency. It not only reduces energy consumption, but also provides efficiency, production flexibility and sustainability. In tests conducted on a real robotic production line, it has been seen that with EMS, the robot's speed settings are estimated based on sub-cycle times, thus saving energy (Ferrero et al., 2020).

EMS enables manufacturers to monitor, analyze, and optimize energy consumption in real time, leading to significant cost savings and reduced environmental impacts. Additionally, EMS supports sustainable innovation by aligning energy optimization strategies with circular economy principles, fostering greener production processes (Altepost et al., 2024).

3.1.6 MES (Manufacturing Execution System) (A_6)

MES (Manufacturing Execution System) is a system that is used as a central software solution to ensure production performance, quality and agility and manages production processes in real time. With Industry 4.0, MES is not only a system that monitors processes, but also a structure that can make interactive and autonomous decisions (AlmadaLobo, 2015). In the context of Industry 4.0, MES has become not only a system that collects production line data, but also a platform that acts as a “digital twin”, providing a real-time digital representation of the production environment and contributing to data-driven decision-making processes. MES is a structure that acts as a bridge by providing data flow between ERP and the factory level (sensors, PLCs). It is a real-time system that provides instant information in all production management functions such as production, maintenance, quality and inventory. MES acts as a digital twin of production processes, facilitating system monitoring and optimization. The history of materials and equipment used in production can be tracked, and it contributes to the increase in quality and sustainability by providing visibility and traceability. MES systems have a modular and integrated structure that works by integrating both horizontally (with other systems) and vertically (with sub-control systems) in modern factories. Defined as the basic building block for Industry 4.0 by some studies, MES plays a central role in processes such as decision-making, automation and customization according to customer demands in smart factories. (Mantravadi & Møller, 2019)

MES provides real-time visibility and control over production processes, enabling manufacturers to track, monitor, and optimize workflows with greater accuracy and efficiency (Jia et al., 2024). MES plays a critical role in optimizing energy usage and material flow, contributing to sustainable and cost-effective manufacturing practices in the textile industry (Gokalp et al., 2018) (Jia et al., 2024) (Malik et al., 2024).

3.1.7 Smart Logistics & Inventory Management (A_7)

Smart Logistics & Inventory Management systems are designed to reduce time and labor losses caused by manual operations in warehouse and logistics processes, quickly determine product location, provide real-time visibility of inventory and thus prevent stoppages in the production line. It allows product movements and stock levels to be monitored with sensors and wireless data transmission. It works as a warning system by informing the user in real time when the material is low or when the system detects a malfunction. Product history and inventory data are stored remotely accessible with cloud-based data storage. It has an ergonomic and low-maintenance design with its simple structure, easy installation and sustainable material use. Smart Logistics & Inventory Management systems offer an accessible, scalable and intelligent solution, especially for SMEs, by digitizing traditional warehouse management. While reducing interruptions in production processes, they also facilitate stock tracking, order preparation and material recall. (Sakib et al., 2022).

Smart logistics is a fundamental building block for the success of Industry 4.0. Thanks to these systems, logistics becomes not only a supporting element but also a strategic element that creates value.

These systems leverage digital tools and real-time data to monitor inventory levels, streamline material flow, and ensure timely delivery of goods, which is particularly critical for textile manufacturers facing fluctuating demand (Jia et al., 2024). Through automation and predictive analytics, smart logistics solutions enhance resource management and reduce operational delays, enabling companies to maintain lean and responsive supply chains (Altepost et al. 2024). For small and medium-sized enterprises (SMEs), adopting these systems is a key driver of digital transformation, providing them with the agility to compete in a dynamic market while minimizing waste and inventory-related costs (Malik et al., 2024).

Applications specific to the textile supply chain can be exemplified as follows: Optimizing the quality of fabrics according to temperature and humidity conditions, use for end-to-end traceability from raw material supply to store shelves, inventory tracking with RFID, automatic re-order processes, automatic warning systems that reduce the risk of delays in logistics processes, monitoring compliance with sustainability standards such as OEKO-TEX and ISO 14001 (Luca, 2025).

This IT investment alternative, when combined with solutions that increase transparency such as blockchain, can provide solutions to the current problems of textile manufacturers such as low income for manufacturers, high commissions for intermediaries, lack of tracking of deliveries, poor quality products or counterfeiting, manual and slow management of orders (Bhuvaneshwarri & Ilango, 2023)

3.1.8 Blockchain (A_8)

Blockchain provides a decentralized and immutable data structure, allowing the entire life cycle of products to be recorded transparently and securely. It provides real-time information sharing between all actors (manufacturer, carrier, supplier, buyer) along the supply chain. In this way, the source of the product, its processing process and distribution steps become verifiable by everyone.

In Textile, where the components such as fabric, yarn, dyestuff come from and how they are processed can be recorded. Sustainability processes, especially supported by certificates such as OEKO-TEX and GOTS, can be made transparent. Digital tracking of original products increases brand security. Subsidiary products can be detected. Consumers can scan the product and learn whether it is ethical. This strengthens the concept of ethical fashion. Order, shipment and production data are shared securely among all stakeholders. Data such as carbon footprint and water usage can be stored securely on the blockchain (Nazam et al., 2022)

Blockchain technology is increasingly being adopted in the textile sector to enhance transparency, traceability, and sustainability within supply chains (Petrillo et al., 2024) This technology supports circular economy initiatives by enabling real-time tracking of material flows and promoting resource recycling efforts in textile manufacturing (Wiegand & Wynn, 2024). Additionally, its application in digital transformation aligns with the broader goals of textile manufacturers to optimize operations and reduce their environmental footprint and effective tool for managing supply chain risks while contributing to green and digital strategies (Orisadare et al., 2024) (Jeong, 2021).

3.1.9 Augmented Reality and Virtual Reality Applications (AR/VR) (A_9)

AR/VR technologies, when integrated with CAD systems in textile and ready-to-wear, provide interactive and immersive simulation of designs. Product design, analysis and presentation can be done by creating environments similar to real-world scenarios. In this way, the product development process is accelerated without the need for physical samples, waste is reduced, and production becomes more sustainable. Virtual try-on technologies allow consumers to try on clothes in a digital environment according to their own body measurements. These systems personalize the shopping experience and reduce environmental impact by reducing return rates. AR-supported mobile applications and retail solutions increase customer interaction and satisfaction. Brands can introduce their collections without the need for physical space with virtual fashion shows and product presentations. Store experiences created with AR/VR make online shopping more impressive and informative. AR-supported guidance and training modules at different stages of the production process can increase the efficiency and accuracy of workers. These technologies are also used in customer preference analysis and data-based product customization processes.

AR / VR technologies in the textile and fashion industries facilitate digital prototyping, 3D visualization, and virtual garment fitting, reducing the reliance on physical samples and support more sustainable production processes.

Many studies have been conducted to summarize the contribution of AR&VR systems to sustainability. These contributions include saving materials by reducing the need for physical prototypes. It helps reduce waste by simulating production errors in advance. It prevents overproduction by facilitating consumer-specific production (Glogar et al., 2025)

3.2 Key Criteria for Sustainable IT Investment Selection

The rapid development of information technologies offers organizations opportunities to gain competitive advantage and create sustainable value. However, the effective utilization of these opportunities requires a systematic and sustainability-oriented selection process.

In this study, IT investments are evaluated based on main criteria (provide the general framework) and their sub-criteria (detailed analysis of the technological, cost, security, strategic and environmental impacts of the projects). Thus, decision makers were able to consider investments not only in terms of their economic dimensions but also in terms of four pillars of the sustainability, which are; environmental, economic, social, cultural pillars.

In the next section, the main and sub-criteria used in the study are presented in tables and the main components of the evaluation process are explained

3.2.1 Technology Criteria (C_1)

The technology criterion evaluates the technical feasibility and operational potential of IT investments, focusing in particular on the level of compatibility of the proposed solutions with the existing infrastructure, how they support scalability and extensibility, how they maintain and support system integrity, and how they ensure transparency in data and processes. In this study, the "Technology" dimension is evaluated through four main sub-criteria which are below.

3.2.1.1 Compatibility (C_{11})

Compatibility refers to the ability of different systems to work seamlessly and continuously with each other and to ensure that the infrastructure is dynamically managed. Compatibility is one of the critical requirements for integrating IT systems. In IT, it is necessary to ensure that various components work together seamlessly. To achieve this, various challenges need to be addressed, including syntactic, semantic, and system heterogeneity. Syntactic heterogeneity is the difference in data formats and representation. Semantic heterogeneity is related to the difference in data interpretation and meaning. Systemic heterogeneity arises from the use of different hardware and software platforms. Overcoming these challenges is important for effective data integration and interoperability (George, 2005).

A compatible system reduces the need for major infrastructure changes and ensures seamless data exchange and system communication. It ensures that new technology is integrated into the business's digital ecosystem without causing operational disruptions.

3.2.1.2 Scalability (C_{12})

Scalability is the capability of the IT solution to accommodate growth and adapt to increasing demands or future technological advancements.

Scalability refers to the ability of an information technology solution to adapt to increasing operational needs, the number of users, or technological developments. This feature is a fundamental criterion for the future success of sustainable digital transformation investments.

The concept of scalability is a critical evaluation criterion, especially in digital transformation projects and long-term technology investments (Wu et al., 2020). While a system initially serves a small group of users, it should be able to integrate into a larger organizational structure, increasing data traffic, or new processes over time. If the system cannot respond to this growth, redesign, infrastructure investment, or replacement of the entire system may be required, which creates a significant burden in terms of time and cost.

3.2.1.3 Reliability (C_{13})

System reliability refers to the smooth operation of not only a machine or equipment, but also the entire production process, hardware (IoT devices, sensors), software (MES, ERP), communication setup (network protocols) and decision support systems (decision systems, AI models) as a whole. It is defined as the consistency and dependability of the IT system in performing its intended functions without frequent failures or interruptions. This concept has become more complex and critical with Industry 4.0 because more data is collected, decisions are made more automatically, and different systems and layers work in an integrated manner. Structures with high system reliability generally support pre-failure intervention, ensure production continuity, enable maintenance and inventory planning, and enable correct synchronization with ERP/MES. Low system reliability, on the other hand, leads to production stoppages, quality reductions, data losses or wrong decisions, and ultimately the failure of digital transformation projects (Souza, 2020).

3.2.1.4 Transparency (C_{14})

The ability of a digital system to provide clear, accessible, and real-time visibility into data, processes, and operations, ensuring that stakeholders can monitor and evaluate performance effectively.

Transparency can also be defined as the level of visibility and accessibility of data. Transparency is the situation where the right information is accessible to different stakeholders (manufacturers, customers, auditors, system providers) in an open and secure manner at the right time. The concept of Transparency is not only about the existence of data; it is about the data being encrypted, secure, contextual and shareable. When considered within the framework of Industry 4.0, it is supported by digital twin, semantic data processing and distributed ledger technologies; It aims to make production processes more traceable, reliable and sustainable.

With transparency, it is aimed that the data of the entire production process (e.g. production data, operator data, supply chain information) can be clearly monitored and accessed, and that they are visible; access to the data is provided not only within the company but also for external stakeholders such as external auditors, customers and suppliers. Thanks to technologies such as Blockchain (DLT), unchangeable but encrypted public data sharing can be done. This will be a feature that increases transparency while protecting data ownership. Transparent data flow is a feature that increases stakeholder confidence by providing the basis for external auditing, sustainability verification and product traceability. Not only access to data, but also meaningful access (data added to context with ontology) is provided. This enables correct interpretation between systems (Sun et al., 2020).

3.2.2 Cost (C_2)

The cost criterion refers to the financial aspects of implementing an IT investment. In this study, the cost dimension is structured under three main sub-criteria: Initial Investment Costs (C2.1), Operating Costs (C2.2) and Long-Term Savings (C2.3). These sub-dimensions aim to evaluate not only the initial expenses but also the ongoing financial impact of the investment over time and the long-term economic return. Another factor in investment decisions for textile companies is cost. For this reason, the cost concept was also focused on from a comprehensive perspective.

The explanation of this concept was shared in detail with the decision makers while making their evaluations.

3.2.2.1 Initial Investment Costs (C_{21})

Initial investment costs can be defined as the upfront expenditure required to procure, implement, and deploy the IT solution, including hardware, software, and setup costs.

According to a study conducted by Deloitte, cost effects are the determining factor in Industry 4.0 investments for all manufacturing companies, for big, SME or micro company, regardless of size (Finance, 2015).

Implementing Industry 4.0 technologies requires significant capital expenditure. These investments include high-cost steps such as restructuring production lines, installing robots and intelligent digital systems, and new infrastructure investments. Since the beginning of these studies requires significant investment costs, they can be considered at a level that can interrupt normal production in the short term (Bai et al., 2022).

3.2.2.2 Operational Costs (C_{22})

Operational costs are defined as the ongoing expenses associated with running the IT solution, such as energy usage, maintenance, and licensing fees. Operational costs are important cost items that arise during the operational phase of investment projects and directly affect the company's cash flow. These costs include expenses related to maintaining production processes, equipment maintenance, labor use and general operation (Yershova & Lynnyk 2021).

Factors affecting operational costs are personnel expenses and production labor, machinery and equipment maintenance costs, energy, raw material and auxiliary material usage, stock management and warehouse costs, and internal data processing and control systems expenses. Operational costs are the most critical cost group that occurs during the “activity” phase of the investment. Detailed management and analysis of these costs directly affects not only short-term profitability but also the overall return on investment (ROI). Net operational cash flow is an important indicator of how effectively these costs are managed.

3.2.2.3 Long-Term Savings (C_{23})

The potential for reducing costs over time through such as improved efficiency, resource optimization, and minimized downtime.

Long-term savings are cumulative financial gains achieved over the years after the investment becomes operational, thanks to factors such as lower operational costs, more efficient production processes, less maintenance and energy costs, and more efficient use of capital.

The results of the study by Bai et al. (2022), showed that a firm is more likely to obtain positive net benefits from Industry 4.0 technology investment when short-term disruption is small and long-term efficiency is high due to high initial investment costs. According to their research, the implementation of Industry 4.0 technologies provides increased efficiency in operational processes, especially through automation, predictive maintenance, robotics and digitalization. This increase in efficiency directly reduces operational costs through factors such as reduced labor costs, reduced waste and error rates, and reduced product waiting time in stock. In the study, an analysis of 111 companies that invested in Industry 4.0 over a 5-year period revealed a 2.72% decrease in average operational costs. This decrease is especially evident in early adopter companies.

3.2.3 Security (C_3)

Security is a factor that directly affects investment decisions. Especially in the implementation of Industry 4.0 technologies, data security and protection are among the main technical risks companies face. Security gaps can be a deterrent in companies' investment decision-making processes. It is emphasized that companies should also take security risks into account in their decision-making models.

3.2.3.1 Capacity (C_{31})

Capacity refers to the ability of a system to securely store, process, and access data for both current and anticipated future needs. It reflects how well an IT solution can manage large volumes of sensitive data without compromising security performance.

For example, an ERP or MES solution must be able to securely store and access expanding data such as production records, customer information, or quality logs with minimal risk of delay or loss.

This sub-criterion emphasizes the technical robustness of the IT solution investment in supporting secure growth and consistent system integrity.

3.2.3.2 Backup and Redundancy (C_{32})

Those are the mechanisms to create duplicate copies of data and systems to ensure recovery and continuity in case of data loss or system failure.

This criterion measures the existence of reliable backup mechanisms and redundant systems that prevent data loss or operational disruption in the event of a system failure. Redundancy involves creating duplicate system components or data storage paths that automatically take over if the primary one fails.

For example, a textile manufacturer using IoT-based machine monitoring systems should implement redundant data channels to ensure that real-time information is not lost during a network outage.

Effective backup and redundancy strategies are essential to ensure business continuity and protect critical operational data.

3.2.3.3 Disaster Recovery (C_{33})

Disaster recovery focuses on the organization’s readiness and capability level to restore system functionality after catastrophic events such as cyberattacks, natural disasters, or system crashes. It includes predefined protocols, recovery time objectives (RTO), and recovery point objectives (RPO).

A robust and essential disaster recovery plan for a digital manufacturing environment should be designed to ensure that systems can be quickly restored to continue operations with minimal data loss, even in the event of an earthquake or ransomware attack.

This sub-criterion reflects the resilience of IT systems and how the organization strategically manages risk for unforeseen events.

3.2.3.4 Cybersecurity (C_{34})

The system's ability to protect against internal and external threats. Cybersecurity is a factor that directly affects investment decisions. Especially in the implementation of Industry 4.0 technologies, data security is at the forefront of technical risks faced by companies. Cybersecurity vulnerabilities can be deterrents for companies in their decision-making process. It is emphasized that companies also take security risks into account in their decision-making model.

Cybersecurity assesses the ability of a system to defend against unauthorized access, data breaches, malware, phishing, and other cyber threats. It also includes encryption, access control, firewalls, user authentication, and compliance with standards such as ISO/IEC 27001.

Deloitte's report identified "cyber risk" as one of the biggest concerns of companies in digital transformation. 56% of the executives participating in the survey see cyber threats as the biggest operational risk in the process of implementing new technologies (Finance, 2015).

As textile companies increasingly adopt cloud-based platforms and IoT devices, protecting intellectual property, customer data, and manufacturing algorithms is increasingly important. Cybersecurity is particularly vital in multi-stakeholder environments where third-party integrations can increase exposure to security vulnerabilities.

3.2.4 Strategy (C_4)

The strategic dimension of IT investment evaluation focuses on how well a technology aligns with the organization's long-term goals, strengthens its market position, and supports sustainability-oriented transformation. This dimension is analyzed through three sub-criteria: Alignment with Vision, Contribution to Competitiveness, and Sustainability Goals.

3.2.4.1 Alignment with Vision (C_{41})

The extent to which the IT solution supports the organization's long-term strategic goals and sustainability objectives. This sub-criterion evaluates how well the IT alternative to be invested in aligns with the organization's strategic vision, digital roadmap, and long-term transformation goals. Investments that align with company goals are more likely to be supported, successfully adopted, and scaled across the organization.

For example, if a company's vision includes being a data-driven organization, investments in ERP systems with advanced analytics capabilities or centralized data warehouses are strongly aligned with this strategic direction.

In order for the investments to be long-term and sustainable, they must be compatible with the company's long-term strategy. The boards of directors of companies must align their sustainability and digitalization goals with strategic investments. Such alignment also ensures that IT efforts are integral parts of organizational growth, not isolated initiatives (Alkaraan et al., 2023).

3.2.4.2 Contribution to Competitiveness (C_{42})

The ability of the IT solution to enhance the company's market position, efficiency, and ability to compete effectively in the industry.

Studies emphasize that I4.0 technologies increase competitiveness by improving processes and increasing agility and efficiency (Alkaraan et al., 2023).

Industry 4.0 technologies provide competitive advantage in many dimensions, from workforce structure to product quality. Thanks to the trio of cost advantage, customized production and high quality, export increase, import decrease and total productivity increase are achieved. This creates a chance to rise in the global competitive ranking, especially for developing countries. The return on IT investments should be evaluated not only economically; but also through innovation capacity and foreign market expansion (Bal & Erkan, 2019).

3.2.4.3 Sustainability Goals (C_{43})

The extent to which the IT solution contributes to achieving the organization's environmental and sustainability targets, such as reducing emissions or conserving resources.

Alkaaran et al, in their study, explained that environmental sustainability, contribution to Sustainable Development Goals (SDGs), CE (circular economy) applications support strategic investment decisions. In particular, the successful integration of industry 4.0 technologies and solutions found for the circular economy are stated in the study as enabling companies to achieve sustainable performance and contributing to the SDGs.

3.2.5 Organizational culture (C_5)

Organizational culture refers to the shared values, beliefs, attitudes, and practices that shape how members of an organization interact with each other and approach technological change. In the context of IT investments, organizational culture plays a crucial role in facilitating or hindering successful adoption and integration of new technologies.

3.2.5.1 Adaptability (C_{51})

The ability of employees and processes to adjust to the implementation and integration of new IT systems.

In the study conducted by Divrik & Baykal (2024), it was emphasized that organizational culture must be flexible for digitalization to be successful. It was stated that organizations with flexible structures are more innovative and digital adaptation processes progress more successfully. In SMEs (small and medium-sized enterprises), the individual adaptability of decision makers was found to be decisive on the general adaptability of the organization. In the same study, it was reported that strategic flexibility and agility increase the success of digital transformation; especially the knowledge level of leaders and their openness to change directly affect adaptation.

3.2.5.2 Training Needs (C_{52})

The training and skills development required for employees to effectively use and manage the new IT solution.

According to Deloitte's report, the vast majority of employees in the Industry 4.0 transformation need to be retrained or receive additional training (upskilling) in order to use existing technologies effectively. This need is especially high in process-dependent areas such as production, purchasing and logistics.

Lack of education has been shown as one of the biggest obstacles to digital transformation; the importance of a skilled and digitally literate workforce has been emphasized. It has been stated that organizations should switch to a learning organization model in response to the need for education.

Glogar et al., (2025), on the other hand, clearly states that one of the biggest challenges in digital transformation, specific to the textile sector, is the lack of knowledge and skills of employees. For this reason, it is recommended to create skill development programs in industry-academia collaboration.

3.2.6 Management Support (C_6)

Management support refers to the degree of active involvement, commitment, and facilitation provided by organizational leaders during the selection, implementation, and integration of IT investments. Strong managerial backing is a critical success factor, especially in digital transformation initiatives that require significant behavioral and structural changes.

3.2.6.1 Leadership Support (C_{61})

The need of the leadership buy-in and support to facilitate the implementation and operationalization of IT investments. Deloitte research says No digital transformation project is feasible without leadership support. Without the vision and leadership of top management, digitalization projects will fail. Leader support is not only motivation, but also a prerequisite for structural transformation.

This sub-criterion assesses the extent to which the success of an IT project depends on visible and consistent support from senior management or key decision makers. In organizations with hierarchical cultures or centralized decision making, leadership buy-in directly impacts organizational motivation, prioritization, and resource mobilization.

For example, if a digital twin or MES project is supported by the CEO or facility manager, employees are more likely to collaborate, departments collaborate better, and the project gains strategic visibility.

A lack of leadership involvement often leads to poor project coordination, misalignment with strategic goals, and low employee engagement.

3.2.6.2 Willingness to Allocate Budget (C_{62})

The company's willingness to allocate resources to ensure the successful deployment and maintenance of the IT solution. Willingness to allocate budget is a critical parameter because the integration of systems like blockchain + edge computing requires high initial costs (Wu et al., 2020).

This criterion evaluates management's financial commitment to IT investments. It reflects whether leadership is willing to allocate sufficient and timely funds not only for initial deployment, but also for long-term maintenance, user training, updates, and integration.

For example, a company investing in AI-powered image processing for fabric quality control must allocate funds not only for software, but also for data infrastructure, pilot testing, and continuous model improvement.

Underfunded projects often face issues of scope reduction, implementation delays, and failure to realize their full potential.

3.2.7 Environmental impact (C_7)

Environmental impact refers to the extent to which an IT investment contributes to reducing the organization's ecological footprint. In the context of sustainable digital transformation, this could include minimizing energy consumption, material waste, emissions, and promoting environmentally friendly production systems. Environmental impact criteria reflect how IT investments support the organization's environmental/ecological sustainability goals. Energy efficiency focuses on reducing power consumption and optimizing energy use, while waste reduction evaluates the system's ability to minimize material and operational losses in processes—both parameters that are fundamental to achieving long-term environmental goals and complying with global sustainability standards.

3.2.7.1 Energy Efficiency (C_{71})

The IT solution's ability to optimize energy use, reducing overall consumption and associated costs.
This sub-criterion evaluates the extent to which the IT solution contributes to reducing energy consumption and improving energy use in production and operational processes. Technologies that enable real-time energy monitoring, predictive analysis, or automatic control of equipment can significantly improve energy performance.

For example, implementing an Energy Management System (EMS) integrated with IoT sensors can monitor machine usage, detect energy-intensive operations, and automatically adjust parameters to optimize energy use.

Additionally, ERP or MES platforms that enable efficient production planning can indirectly reduce energy use by reducing idle time, overproduction, or unnecessary machine starts.

3.2.7.2 Waste Reduction (C_{72})

The contribution of the IT solution to minimizing material and operational waste, aligning with sustainability goals.

Waste reduction refers to the capacity of IT investments to minimize material waste, defects, overproduction, and inefficient processes. Technologies such as AI-based quality control, digital twins, or blockchain-enabled traceability contribute to identifying and eliminating sources of waste throughout the value chain.

For example, image processing systems that detect print quality problems in real time prevent defective products from being passed on to later stages of the production process, reducing both material loss and rework costs.

3.2.8 Regulatory Compliance (C_8)

This metric assesses the extent to which IT investments are influenced or supported by external political, legal, and institutional factors. These factors include government policies, financial incentives, regulatory frameworks, and industry-specific directives that can encourage or hinder digital transformation efforts.

3.2.8.1 Availability of Incentives (C_{81})

The presence of governmental or regulatory programs, such as subsidies or tax credits, that support the adoption of IT investments.

This sub-criterion assesses whether government or institutional incentives (financial, tax or strategic) are available to support the proposed IT investment. These incentives could be in the form of:

- Investment grants
- Tax reductions or credits
- Low-interest loans
- R&D subsidies
- Public-private partnerships

For example, a textile company planning to invest in an Energy Management System (EMS) could benefit from national sustainability programmes or EU Green Deal funds aimed at reducing industrial energy consumption.

The availability of such incentives significantly increases the financial viability of the investment and can accelerate adoption timelines.

3.2.8.2 Alignment with Regulations and Directives (C_{82})

The IT solution's compliance with established industry social and environmental norms and guidelines such as Social Compliance (SC), Sustainability Development Goals (SDGs), European Union (EU) regulations, Digital Product Passport (DPP) etc.

This sub-criterion assesses the extent to which the IT investment is aligned with national and international regulatory requirements, sustainability goals, and industry compliance standards. It ensures that the proposed solution is not only internally beneficial, but also meets the expectations of regulatory bodies, trade agreements, and environmental or digital legislation.

For example, investing in blockchain-based supply chain tracking can help a company meet EU directives such as the Digital Product Passport on product traceability, ethical sourcing, or extended producer responsibility.

Compliance reduces legal risk, enhances brand reputation, and can even be a prerequisite for market access in certain regions or industries.

Table 3.1 shows a summary list for the criteria.

Table 3.1: The list of references for used criteria

#	Criteria	#	Sub-Criteria	Covered by
C_1	Technology	C_{11}	Compatibility	Petrillo et al., (2024), Wiegand & Wynn (2024), Jia et al., (2024), Sadeghi et al., (2024), Altepost et al., (2024), Orisadare et al., (2024), Gökalp et al., (2018)
		C_{12}	Scalability	Wiegand & Wynn (2024), Jia et al., (2024) Altepost et al., (2024), Orisadare et al., (2024), Akhtar et al., (2022), Küsters et al., (2017)
		C_{13}	Reliability	Petrillo et al., (2024), Wiegand & Wynn (2024), Jia et al., (2024), Orisadare et al., (2024), Malik et al., (2024), Gökalp et al., (2018)
		C_{14}	Transparency	Ahmad et al., (2020), Wiegand & Wynn (2024), Altepost et al. (2024), Orisadare et al., (2024), Gökalp et al., (2018)

C_2	Cost	C_{21}	Initial Investment Costs	Ahmad et al., (2020), Wiegand & Wynn (2024), Küsters et al., (2017), Altepost et al., (2024), Orisadare et al., (2024)
		C_{22}	Operational Costs	Wiegand & Wynn, (2024), Altepost et al., (2024) Orisadare et al., (2024), Malik et al., (2024), Gökalp et al., (2018)
		C_{23}	Long-Term Savings	Dal Forno et al., (2023), Ahmad et al., (2020), Küsters et al., (2017), Malik et al., (2024)
C_3	Security	C_{31}	Capacity	this study
		C_{32}	Backup and Redundancy	Altepost et al., (2024)
		C_{33}	Disaster recovery	Altepost et al., (2024)
		C_{34}	Cybersecurity	Petrillo et al., (2024), Dal Forno et al., (2023)
C_4	Strategic Fit	C_{41}	Alignment with Vision	Malik et al., (2024), Jia et al., (2024)
		C_{42}	Contribution to Competitiveness	Ahmad et al., (2020), Orisadare et al., (2024), Jia et al., (2024), Gökalp et al., (2018)
		C_{43}	Sustainability Goals	Akhtar et al., (2022), Altepost et al., (2024)
C_5	Organizational Culture	C_{51}	Adaptability	Dal Forno et al., (2023) Ahmad et al., (2020), Wiegand & Wynn (2024), Jia et al., (2024), Orisadare et al., (2024)
		C_{52}	Training Needs	Dal Forno et al., (2023), Ahmad et al., (2020), Wiegand & Wynn (2024), Küsters et al., (2017), Jia et al., (2024), Kulkarni et al., (2024)
C_6	Management Support	C_{61}	Dependency On Leader Support	Orisadare et al., (2024), Jia et al., (2024)
		C_{62}	Willingness to Allocate Budget	Orisadare et al., (2024), Jia et al., (2024)
C_7	Environmental Impact	C_{71}	Energy Efficiency	Petrillo et al., (2024), Ramos et al., (2023), Ahmad et al., (2020), Wiegand & Wynn, (2024), Jia et al., (2024), Altepost et al., (2024), Orisadare et al., (2024),
		C_{72}	Waste Reduction	Petrillo et al., (2024), Ramos et al., (2023), Ahmad et al., (2020), Wiegand et al., (2024), Jia et al., (2024), Altepost et al., (2024), Orisadare et al., (2024), Malik et al., (2024), Kulkarni et al., (2024)
C_8	Incentives & Politics	C_{81}	Availability of Incentives	Jia et al., (2024)
		C_{82}	Alignment with Regulations and Directives	Ahmad et al., (2020), Wiegand & Wynn, (2024), Orisadare et al., (2024)

3.3 Sustainable Development Goals (SDG's) and Criteria Alignment

The United Nations has declared 17 different sustainable development goals that are monitored with reports every year as of 2015. There are different targets under these goals. These goals, which include a total of 169 targets, have been created in a structure that covers all the legs of sustainability.

The compatibility of sustainable digital transformation in the textile sector with strategic goals is of critical importance in terms of concretizing the United Nations Sustainable Development Goals (SDGs). The eight main criteria and twenty-two sub-criteria defined in this study are directly or indirectly associated with the basic SDGs listed below:

- C_1: Technology - SDG 9: Industry, Innovation and Infrastructure

The technology criterion directly supports the "resilient infrastructure" and "sustainable industry" targets of SDG 9. In this context, four sub-criteria under C_1 define the basic competencies that will ensure the infrastructure strength and dissemination of digitalization applications in textile production processes.

Among the sub-criteria of C_1, scalability and compatibility in particular support the spread of innovative solutions and enable textile companies to rapidly implement Industry 4.0 applications. Reliability and transparency stand out as two key elements that strengthen operational excellence and sustainability reporting. Therefore, decision-makers should consider the balance in these four sub-criteria when planning technology investments and focus on solutions that will maximize contribution to SDG 9.

- C_2: Cost - SDG 8: Decent Work and Economic Growth & SDG 12: Responsible Consumption and Production

Balancing initial investment and operational costs ($C_{2.1}$, $C_{2.2}$) increases both macroeconomic stability and resource efficiency. Long-term savings ($C_{2.3}$) contribute to SDG 12's "waste reduction" and "sustainable supply chain" targets by encouraging more rational use of resources.

The capital expenditures incurred during the commissioning of a new system (such as hardware, licenses, integration services) directly shape the investment probability of SMEs and new market entrants in particular. Low initial costs reduce financial barriers and enable a wider range of businesses to adopt technology. This supports the strengthening of "micro, small and medium-sized enterprises" and the increase of employment opportunities within the scope of SDG 8. At the same time, capital-efficient choices contribute to SDG 12's responsible investment practices that minimize unnecessary resource consumption.

Effective management of operational costs directly determines the sustainability of digital transformation investments. Low operating expenses protect company profitability and competitiveness, while preventing excessive resource use and strengthening compliance with SDG 12's "waste reduction" and "resource efficiency" principles. In addition, cost optimization provides a business model that provides financial stability within the framework of SDG 8's "continuous and productive employment".

The saving potential that improves return on investment (ROI) and total cost of ownership (TCO) stems from factors such as energy efficiency, waste reduction and reduced maintenance frequency. High long-term savings opportunities stabilize companies' profitability and enable them to allocate resources to new sustainable projects with the savings gained. This directly contributes to SDG 12's "integration of resources into the circular economy" goal, while enabling businesses to finance their growth capacity in the context of SDG 8.

- C_3: Security - SDG 9: Build Resilient Infrastructure & SDG 11: Disaster Risk Reduction

Security criteria directly support SDG 9's "Build resilient infrastructure" goal by ensuring the continuity and resilience of digital infrastructure. The four sub-criteria under C_3—Capacity ($C_{3.1}$), Backup & Redundancy ($C_{3.2}$), Disaster Recovery ($C_{3.3}$), and Cybersecurity ($C_{3.4}$)—combine to strengthen infrastructure responsiveness to unexpected events and create a risk reduction spiral that aligns with SDG 11's "Disaster risk reduction" priorities.

Addressing these four sub-criteria together strengthens the ability of textile enterprises and urban infrastructures to withstand unexpected crises and systematically reduces the risks that may arise from natural disasters. When planning C_3 Security investments, decision-makers should consider infrastructure capacity, backup strategies, recovery plans and cyber defense with an integrated approach; thus, they can simultaneously contribute to both SDG 9's resilient industrial infrastructure and SDG 11's disaster risk management goals.

- C_4: Strategic Fit - SDG 8 – Decent Work and Economic Growth & SDG 17 – Partnerships for the Goals

Strategic Fit, which evaluates the extent to which investments align with the organization's long-term vision, competitive strategy and sustainability goals, covers not only the technical adequacy of the technology but also the support of senior management, stakeholder collaborations and the integrity of the corporate strategy. This holistic perspective simultaneously supports SDG 8's "sustainable economic growth and productive employment" goal and SDG 17's "partnerships for the goals" vision.

Alignment with Vision measures the extent to which IT investments align with the company's mission and sustainability roadmap. Multi-stakeholder initiatives within the scope of SDG 17, such as both public-private partnerships and university-industry joint projects, can be integrated into the digital transformation program to the extent that they align with the vision.

Contribution to Competitiveness evaluates the investment's contribution to the company's competitiveness. KPIs such as market share growth, process efficiency and innovative service/product development capacity are included in SDG 8, which supports economic growth and employment. Competitive advantage: creates sustainable employment models, thus reinforcing the goal of "decent work".

Sustainability Goals measure the contribution of the selected technology to environmental and social sustainability goals (carbon footprint, resource efficiency, social responsibility). It ensures compliance with SDG 12 ("responsible consumption and production") and indirectly with SDG 13 ("climate action") with internal ESG (Environmental, Social, Governance) reporting. At the same time, it paves the way for national and international collaborations within the framework of SDG 17 with stakeholder briefing and partnership models aimed at these goals.

In this way, C_4: Strategic Fit criteria; It ensures that digital transformation investments are placed in a sustainable and effective framework by simultaneously considering both internal strategic alignment and multi-stakeholder partnership and economic growth goals.

- C5: Operational Flexibility - SDG 8: Decent Work and Economic Growth

Operational resilience measures the ability of digital transformation investments to adapt to rapidly changing conditions and workforce dynamics. Taken together, the two sub-criteria of C_5—Adaptability (C5.1) and Training Needs (C5.2)—support the flexibility and continuous improvement of both systems and employees, contributing to SDG 8's "decent work and sustainable economic growth."

When adaptability remains low, systems run the risk of "locking in" in situations that require flexibility; when Training Needs is high, costs of staff absenteeism and time loss increase. Decision makers should create an agile transformation strategy in line with SDG 8 by integrating training programs and change management plans when planning C5 investments.

- C_6: Management Support - SDG 17: Partnerships for the Goals & SDG 8: Decent Work and Economic Growth

Managerial support is one of the most critical factors that directly affects the strategic success of digital transformation projects. Two sub-criteria within C_6—Leadership Commitment ($C_{6.1}$) and Budget Allocation ($C_{6.2}$)—ensure that both the vision of the senior management and resource planning are progressing on solid foundations. These criteria serve the goals of "partnerships for purpose" in SDG 17 and "sustainable economic growth" in SDG 8.

The support provided by senior managers to the project is the driving force of cultural transformation and internal ownership. High leadership commitment eliminates obstacles in change management, human resource motivation and stakeholder communication processes. Especially in multi-stakeholder platforms (public, private sector, university), SDG 17's "strategic partnerships" principle comes to life with the active participation and ownership of the project by leaders. Lack of commitment can lead to delays in decision-making processes and a gap between "sustainability intention" and implementation.

The budget allocation with the highest sub-criterion weight of C_6 creates the financial infrastructure that enables digital transformation to achieve realistic and measurable goals. Adequate and timely budget allocations facilitate contract negotiations with technology suppliers and enable rapid dissemination of pilot applications. This feeds into SDG 8's "sustainable economic growth and productive employment" goal, as unplanned financial constraints delay project actions and increase total costs and uncertainty. A robust budget allocation mechanism also supports "decent work" conditions through the contribution of projects to career development and employee engagement.

Taken together, the C_6 sub-criteria ensure that digital transformation initiatives go beyond being mere technological investments, and are implemented as programs that are aligned with corporate strategy, involve stakeholders, and create sustainable economic value. Decision makers should establish a robust governance model that is aligned with SDG 17 and SDG 8 by considering the balance between leadership and financing.

- C_7: Environmental Impact - SDG 7: Affordable and Clean Energy & SDG 13: Climate Action

The environmental impact criterion measures the direct results of digital transformation investments on energy consumption and waste management, serving both the "clean energy" goal of SDG 7 and the "climate action" priority of SDG 13. The two sub-criteria of C_7, Energy Efficiency ($C_{7.1}$) and Waste Reduction ($C_{7.2}$), provide critical mechanisms for minimizing the environmental footprint of textile production processes.

The Energy Efficiency sub-criterion contributes positively to SDG 13 by contributing to both the reduction of in-plant energy costs and the control of carbon emissions.

Waste reduction monitors the extent to which losses and process residues in raw material use are minimized and supports the reduction of waste rates and the sustainable consumption-production cycle (SDG 12). For example, with image processing and machine learning-based quality control systems, the number of defective products is reduced and the amount of rework or scrapped material is minimized.

- C_8: Regulatory Compliance - SDG 12: Responsible Consumption and Production; SDG 16: Peace, Justice and Strong Institutions

Compliance with regulations ensures that digital transformation projects operate within the legal framework and that an ecosystem based on trust is established with all stakeholders in the sector. Two sub-criteria under C_8 play a critical role in supporting sustainable production processes with both incentive mechanisms and reinforcing them with strong corporate governance.

State support, grant programs and tax incentives accelerate companies' sustainable technology investments. The availability of incentives sub-criterion enables businesses to more easily participate in the responsible consumption-production cycle within the framework of SDG 12's "resource efficiency and waste reduction" targets.

The Alignment with Standards and Directives sub-criterion increases compliance with international standards such as ISO 50001, ISO 27001, EU Digital Transformation and Sustainability Directives, and increases the transparency and accountability of corporate processes. This supports SDG 16's vision of "strong, accountable and transparent institutions" as it defines standards, traceability and reporting mechanisms.

Table 3.2 shows that which sub-criterion addresses which pillar of the sustainability.

Table 3.2: Summarized concept table on Sustainability Pillars and Sub-Criteria

Environmental Sustainability	**Economic Sustainability**
Compatibility (C11) Reliability (C13) Long-Term Savings (C23) Energy Efficiency (C71) Waste Reduction (C72) Sustainability Goals (C43) Alignment with Regulations & Directives (C82)	Compatibility (C11) Scalability (C12) Reliability (C13) Initial Investment Cost (C21) Operational Cost (C22) Long-Term Savings (C23) Contribution to Competitiveness (C42) Willingness to Allocate Budget (C62) Energy Efficiency (C71) Waste Reduction (C72) Availability of Incentives (C81)
Social Sustainability	**Cultural Sustainability**
Transparency (C14) Cybersecurity (C34) Disaster Recovery (C33) Training Needs (C52) Dependence on Leader Support (C61) Availability of Incentives (C81) Alignment with Regulations & Directives (C82)	Scalability (C12) Transparency (C14) Alignment with Vision (C41) Training Needs (C52) Adaptability (C51) Dependence on Leader Support (C61)

4 METHODOLOGY

When considering decision-making problems in general, it is seen that they contain too many different factors to be solved by considering a single criterion. When an evaluation effort is made by considering a single criterion, such decision-making problems are likely to lead to unrealistic outputs. One of the methods that can be useful is to evaluate these different criteria together.

This study uses a two-stage Multi-Criteria Decision Making (MCDM) approach to evaluate IT investment alternatives from a digital sustainability perspective. In the first stage, the Spherical Fuzzy Analytical Hierarchy Process (SF-AHP) is applied to determine the relative weights of the evaluation criteria considering the uncertainty and imprecision inherent in expert judgments. In the second stage, the Spherical Fuzzy Technique for Order Preference by Similarity to Ideal Solution (SF-TOPSIS) is used to rank the IT investment alternatives based on their performances with the weighted criteria. The procedure follows three main steps: (1) defining the hierarchical structure of the decision problem, (2) conducting the SF-AHP to obtain the criteria weights, and (3) applying the SF-TOPSIS to obtain the final ranking of the IT alternatives using the weights from the previous step.

In the Table 4.1 comparison of the latest Fuzzy Sets can be seen. According to those comparison, SF Sets integrated to AHP and TOPSIS is selected.

Table 4.1 Comparative Table of Advanced Fuzzy Set Models

Feature	Hesitant Fuzzy Set	Intuitionistic Fuzzy Set	Spherical Fuzzy Set
Membership value	A set of possible values	A single value	A single value
Non-membership value	Not defined	Explicitly defined	Explicitly defined
Indeterminacy (hesitation degree)	Implicitly captured through multiple membership values	Calculated as $1-\mu-\nu$	Explicitly provided as a separate component
Mathematical constraint	None	The sum of membership and non-membership must be ≤ 1	The squared sum of membership, non-membership, and indeterminacy must be ≤ 1
Flexibility in uncertainty modeling	High — captures hesitation in expert opinions	Moderate — structured representation of three aspects of uncertainty	High — more flexible and realistic representation of uncertainty
Primary use cases	Group decision-making, human-centric evaluations	Multi-criteria decision-making, risk and uncertainty modeling	Advanced decision support systems, digital sustainability, IT evaluation
Key advantage	Models indecision and hesitation directly	Considers both agreement and disagreement	Captures uncertainty with greater freedom and expressive power

Summary of those steps can be seen below:

Step 1. Defining the Hierarchical Structure of the Problem.

Step 2. SF-AHP execution to obtain the weights of the criteria

Step 3. By using criteria weights obtained from Step 2, SF-TOPSIS executed to rank the IT investment alternatives.

This section explains the methodological approach adopted in this study. This study creates a framework with the two-stage MCDM technique. The reasons for creating this framework with these techniques and the justifications for the selection of the techniques within the framework will be explained. Then, the Development of Spherical Fuzzy Sets will be explained chronologically and then the Theoretical Framework of Spherical AHP and Spherical TOPSIS will be explained in detail.

4.1 Selection Reason of Spherical Fuzzy AHP for Criteria Weighting

Analytical Hierarchy Process (AHP) is a widely used method to derive priority scales from pairwise comparisons between criteria. However, traditional AHP is limited in dealing with uncertainty and ambiguity in expert judgments. Traditional (crisp) AHP forces experts into exact judgments, which is unrealistic for qualitative sustainability criteria. To overcome this limitation, Spherical Fuzzy AHP approach is adopted in this study. Spherical fuzzy sets provide a broader representation of uncertainty by simultaneously addressing membership, non-membership and hesitation degrees under a global constraint.

Compared to traditional fuzzy and intuitive fuzzy AHP models, AHP with spherical fuzzy sets provides greater flexibility, higher expressiveness and better modeling of real-world uncertainty in decision making. This is particularly valuable in strategic IT investment contexts where decision makers often rely on subjective, imprecise and uncertain assessments limited by limited knowledge and experience.

By extending AHP with spherical fuzzy sets, which originally proposed by Gündogdu & Kahraman (2020), experts can express degrees of agreement, disagreement, and hesitation simultaneously. This means vague or uncertain opinions are captured explicitly, improving the accuracy of weight estimates. In fact, spherical fuzzy sets provide a “broad space of admissible triplets” for judgments, making them uniquely capable of handling the ambiguity and vagueness inherent in IT investment decisions. SF-AHP leads to more reliable criteria weights than traditional AHP or classical fuzzy AHP, because the partial confidence or doubts of experts are included rather than lost in translation. Therefore, SF-AHP was chosen to obtain robust, reliable weights for each criterion by acknowledging uncertainty upfront and aligning the weighting process with the fuzzy nature of digital sustainability assessments (Gündoğdu & Kahraman, 2020)

4.2 Selection Reason of Spherical Fuzzy TOPSIS for Ranking Alternatives

After setting the criteria weights, SF-TOPSIS is applied to rank the 9 IT investment alternatives. TOPSIS was chosen for this study for several reasons. It determines the best option by measuring the distance of each alternative from an ideal solution, and is used for cases where the alternative ratings on each criterion are given as fuzzy values. This means that it directly addresses any uncertainty. Compared to classical TOPSIS or simple scoring, SF-TOPSIS avoids information loss – no expert judgment is black and white, which increases the realism and consistency of the ranking. Another practical benefit is computational applicability: TOPSIS (even in spherical fuzzy form) is a less labor-intensive method than making pairwise comparisons between all 9 alternatives for the 22 sub-criteria. The method is easy to implement and interpret, and yields a clear proximity score for each alternative. SF-TOPSIS offers a suitable ranking in cases where the criteria are difficult to measure in the context of digital sustainability in textile manufacturing. By considering uncertainty, it ensures that the selected IT investment is truly the one closest to the “ideal” outcome, giving decision makers greater confidence (Gündoğdu & Kahraman, 2019)

By integrating SF-AHP and SF-TOPSIS, the study creates a flexible yet rigorous decision framework that accommodates expert uncertainty, increases assessment consistency, and remains practically applicable for real-world use, aligning well with the complex and forward-looking nature of digital sustainability decisions in the textile sector.

4.3 Theoretical Framework Spherical Fuzzy AHP and Spherical Fuzzy TOPSIS

4.3.1 Fuzzy Sets

Fuzzy set, introduced by Zadeh in 1965, is a class of objects whose membership degrees vary in a continuous range (between 0 and 1). Each element is assigned a value with a membership function. This value expresses the membership degree of that element in the set. While membership in classical sets is only 0 or 1, in fuzzy sets this value is assigned gradually.

Zadeh identifies the following problem while developing this concept: In the real world, objects often cannot be classified as “belonging to a set” or “not”. For example: Concepts such as “tall men” or “very large numbers” are defined with imprecise boundaries.

Therefore, fuzzy sets go beyond classical set theory and provide a model that is more suitable for human thought and uncertainty in the real world.

This study systematically demonstrates how the concept of fuzzy set is not only a definition but also how operations such as relations between sets (union, intersection, complement, subset), convexity, distance, difference and relations can be extended in the fuzzy context (Zadeh, 1965).

The history of fuzzy sets is explained: As of 1975, it was extended to new types of fuzzy sets by Zadeh and other researchers. These extensions are, respectively, Type 2 fuzzy sets by Zadeh in 1975, interval-valued fuzzy sets by Sambuc, Jahn in 1975 and Grattan Guinness in 1976, intuitionistic fuzzy sets by Atanassov in 1986, fuzzy multi-sets by Yager, neutrosophic fuzzy sets by Smarandache in 1998, non-stationary fuzzy sets developed by Garibaldi and Ozen in 2007, hesitant fuzzy sets by Torra and Narukawa in

2009, Pythagorean fuzzy sets by Yager and Abbasov in 2013, picture fuzzy sets developed by Cuong in 2014, orthopair fuzzy sets again by Yager in 2016, and spherical fuzzy sets by Kahraman and Gundogdu (Gündoğdu & Kahraman, 2021)

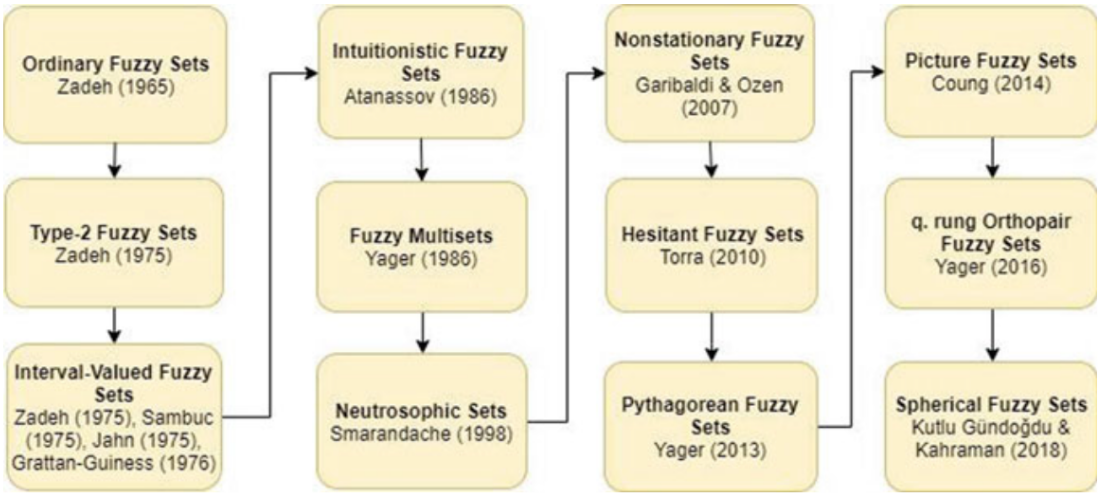

Figure 4.1: History of Fuzzy Sets is shown (Gündoğdu & Kahraman, 2021)

4.3.2 Spherical Fuzzy Sets (SFS)

It is an extension of fuzzy sets in 3D. It is named as such because it consists of membership degrees that can be expressed in the spherical plane. The distance between two SFS is measured by the spherical arc distance.

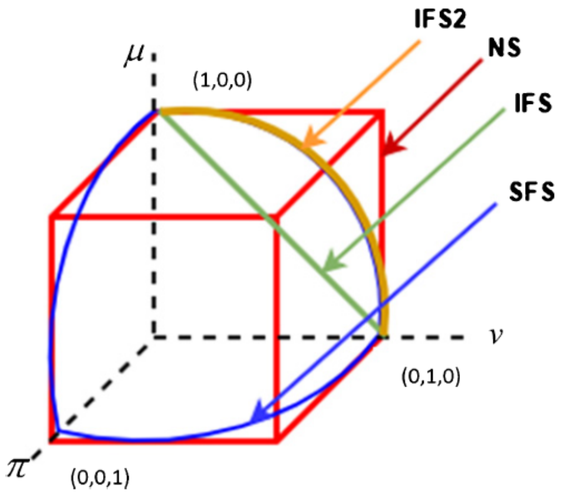

Figure 4.2: Geometric representation of SFS and Some Fuzzy Sets (Kahraman & Gündoğdu, 2018)

In spherical fuzzy sets, the values of the degrees μ, v, π can again be defined in the range [0,1], while the sum of the squares is between 0 and 1 (Gündoğdu and Kahraman, 2019).

Let U be a universe. A spherical fuzzy set A over U is defined by;

$$\tilde{A} = \{\langle u, (\mu_{\tilde{A}}(x), v_{\tilde{A}}(x), \pi_{\tilde{A}}(x)\rangle : x \in U\} \tag{1}$$

Where μ, v, π called membership function.

$$0 \leq \mu^2_{\tilde{A}_s}(x) + v^2_{\tilde{A}_s}(x) + \pi^2_{\tilde{A}_s}(x) \leq 1 \qquad \forall u \in U \tag{2}$$

The formulation of the distance between two spherical fuzzy sets is given in Equation (2).

$$\operatorname{dis}(\tilde{A}_s, \tilde{B}_s) = \frac{2}{\pi}\sum_{i=1}^{n} \arccos\left\{1 - \frac{1}{2}\begin{pmatrix} (\mu_{\tilde{A}_s} - \mu_{\tilde{B}_s})^2 \\ +(v_{\tilde{A}_s} - v_{\tilde{B}_s})^2 \\ +(\pi_{\tilde{A}_s} - \pi_{\tilde{B}_s})^2 \end{pmatrix}\right\} \tag{3}$$

SFS Arithmetic Operators defined as (Gündogdu and Kahraman, 2019):

1. $$\tilde{A}_S \otimes \tilde{B}_S = \left\{ \begin{matrix} \mu_{\tilde{A}_S}\mu_{\tilde{B}_S}, \left(v^2_{\tilde{A}_S} + v^2_{\tilde{B}_S} - v^2_{\tilde{A}_S}v^2_{\tilde{B}_S}\right)^{\frac{1}{2}}, \\ \left(\left(1 - v^2_{\tilde{B}_S}\right)\pi^2_{\tilde{A}_S} + \left(1 - v^2_{\tilde{A}_S}\right)\pi^2_{\tilde{B}_S} - \pi^2_{\tilde{A}_S}\pi^2_{\tilde{B}_S}\right)^{\frac{1}{2}} \end{matrix} \right\} \tag{4}$$

2. $$\tilde{A}_S \oplus \tilde{B}_S = \left\{ \begin{matrix} \left(\mu^2_{\tilde{A}_S} + \mu^2_{\tilde{B}_S} - \mu^2_{\tilde{A}_S}\mu^2_{\tilde{B}_S}\right)^{\frac{1}{2}}, v_{\tilde{A}_S}v_{\tilde{B}_S}, \\ \left(\left(1 - \mu^2_{\tilde{B}_S}\right)\pi^2_{\tilde{A}_S} + \left(1 - \mu^2_{\tilde{A}_S}\right)\pi^2_{\tilde{B}_S} - \pi^2_{\tilde{A}_S}\pi^2_{\tilde{B}_S}\right)^{\frac{1}{2}} \end{matrix} \right\} \tag{5}$$

3. $$\gamma \odot \tilde{A}_S = \left\{ \left((1 - \left(1 - \mu^2_{\tilde{A}_S}\right)^{\gamma} \right)^{\frac{1}{2}}, \; v_{\tilde{A}_S}{}^{\gamma} \;, \left((1 - \mu^2_{\tilde{A}_S})^{\gamma} - (1 - \mu^2_{\tilde{A}_S} - \pi^2_{\tilde{A}_S}{}^{\gamma}\right)^{1/2} \right\} \tag{6}$$

SWAM (Spherical Weighted Arithmetic Mean) and SWGM (Spherical Weighted Geometric Mean) are aggregation operators used in Spherical Fuzzy Set (SFS) theory to combine decision-makers' evaluations in multi-criteria decision-making (MCDM) methods like SF-AHP and SF-TOPSIS.

For definition of SWAM, let $w = (w_1, w_2, \dots, w_n); w_i \in [0,1]; \;\; \sum_{i=1}^{n} w_i = 1$, SWAM is calculated as

$$\begin{aligned} &\mathrm{SWAM}_w\left(A_{S_1}, \dots, A_{S_n}\right) = w_1 A_{S_1} + w_2 A_{S_2} + \cdots + w_n A_{S_n} \\ &= \left\{ \left[1 - \prod_{i=1}^{n} \left(1 - \mu^2_{A_{S_i}}\right)^{w_i}\right]^{\frac{1}{2}}, \right. \\ &\left. \prod_{i=1}^{n} v^{w_i}_{A_{S_i}}, \left[\prod_{i=1}^{n} \left(1 - \mu^2_{A_{S_i}}\right)^{w_i} - \prod_{i=1}^{n} \left(1 - \mu^2_{A_{S_i}} - \pi^2_{A_{S_i}}\right)^{w_i}\right]^{\frac{1}{2}} \right\} \end{aligned} \tag{7}$$

For definition SWGM, let $w = (w_1, w_2, \dots, w_n); w_i \in [0,1];\ \sum_{i=1}^{n} w_i = 1$, SWGM is calculated as

$$
\begin{gathered}
\mathrm{SWGM}_w\left(A_{S_1}, \dots, A_{S_n}\right) = A_{S_1}^{w1} + A_{S_2}^{w2} + \cdots + A_{S_n}^{wn} \\
= \left\{ \prod_{i=1}^{n} \mu_{A_{S_i}}^{w_i}, \left(1 - \prod_{i=1}^{n} \left(1 - v_{A_{S_i}}^2\right)^{w_i}\right)^{\frac{1}{2}}, \right. \\
\left. \left[\prod_{i=1}^{n} \left(1 - v_{A_{S_i}}^2\right)^{w_i} - \prod_{i=1}^{n} \left(1 - v_{A_{S_i}}^2 - \pi_{A_{S_i}}^2\right)^{w_i}\right]^{\frac{1}{2}} \right\}
\end{gathered}
\tag{8}
$$

Additionally, the Score and Accuracy Functions are defined. These functions can be utilized to assess the alternatives. Through this process, a precise numerical value is derived from a fuzzy number.

$$
\begin{gathered}
\mathrm{Score}(A_s) = \left(\mu_{A_s} - \pi_{A_S}\right)^2 - \left(v_{A_s} - \pi_{A_S}\right)^2 \\
\mathrm{Accurancy}(A_s) = \mu_{A_s}^2 + v_{A_S}^2 + \pi_{A_S}^2
\end{gathered}
\tag{9}
$$

Since fuzzy values are transformed into crisp values, it becomes possible to compare fuzzy numbers. The condition As<BsA_s < B_sAs<Bs holds true when the following criteria are met.

I. $\mathrm{Score}(A_s) < \mathrm{Score}\ (B_s)$ or

II. $\mathrm{Score}(A_s) = \mathrm{Score}\ (B_s)$ and $\mathrm{Accurancy}(A_s) < \mathrm{Accurancy}\ (B_s)$

Step 1. The assessments provided by decision-makers are expressed using linguistic terms. For this purpose, the scales presented in Tables 4.2 and 4.3 below can be utilized.

Table 4.2 Linguistic terms and their corresponding spherical fuzzy numbers (for criteria)

Linguistic Terms	(μ, v, π)	SI
Absolutely more Importance (AMI)	(0.9, 0.1, 0.0)	9
Very High Importance (VHI)	(0.8, 0.2, 0.1)	7
High Importance (HI)	(0.7, 0.3, 0.2)	5
Slightly More Importance (SMI)	(0.6, 0.4, 0.3)	3
Equally Importance (EI)	(0.5, 0.4, 0.4)	1
Slightly Low Importance (SLI)	(0.4, 0.6, 0.3)	1/3
Low Importance (LI)	(0.3, 0.7, 0.2)	1/5
Very Low Importance (VLI)	(0.2, 0.8, 0.1)	1/7
Absolutely Low Importance (ALI)	(0.1, 0.9, 0.0)	1/9

Table 4.3 Linguistic terms and their corresponding spherical fuzzy numbers (for projects)

Linguistic Terms	(μ, v, π)	SI
Superior(S)	(0.9, 0.1, 0.0)	9
Extremely Good (EG)	(0.8, 0.2, 0.1)	7
Very Good(VG)	(0.7, 0.3, 0.2)	5
Good(G)	(0.6, 0.4, 0.3)	3
Fair(F)	(0.5, 0.4, 0.4)	1
Poor(P)	(0.4, 0.6, 0.3)	1/3
Very Poor (VP)	(0.3, 0.7, 0.2)	1/5
Extremely Poor (EP)	(0.2, 0.8, 0.1)	1/7
Inferior(I)	(0.1, 0.9, 0.0)	1/9

4.3.3 Spherical Fuzzy AHP and Spherical Fuzzy TOPSIS

In this study, Spherical Fuzzy AHP Method and Spherical Fuzzy TOPSIS method, introduced by Gündoğdu & Kahraman (2019), has been selected as the methodology. In order to understand the notion, the relevant spherical fuzzy operations, SF-AHP and the SF-TOPSIS approach will be systematically explained in relation to one another.

This method is a Multi-Criteria Decision-Making (MCDM) method based on spherical fuzzy sets. In MCDM problems, as in the fuzzy TOPSIS method, decision matrices are constructed to represent the evaluation values of alternatives based on each criterion.

These matrices can also be structured within a spherical fuzzy framework. In this context, the alternatives (projects) can be defined as $A = \{ a_1, \ a_2 \ , \dots , a_m \mid m \geq 2 \}$ and criteria as $C = \{c_1, c_2, \dots , c_n \}$, weight vector as $w_1, w_2, \dots , w_n, 0 \leq w_j \leq 1$ provides the equation of $\sum_{j=1}^{n} w_j = 1$. In addition, let two Spherical fuzzy sets be $\tilde{A}_S = (\mu_{\tilde{A}_S}, \ v_{\tilde{A}_S} \ , \pi_{\tilde{A}_S})$ and $\tilde{B}_S = (\mu_{\tilde{B}_S}, \ v_{\tilde{B}_S} \ , \pi_{\tilde{B}_S})$.

Step 2. SF-AHP Model execution:

Step2.1. Conducting Consistency Analysis: At this stage, consistency is calculated before merging the matrices. In the SF-AHP consistency analysis, numerical values (SI) corresponding to spherical values are used instead of the spherical values themselves. For higher importance (i.e., criteria ranked above equal importance), the following formula is used (Gündoğdu & Kahraman, 2020):

$$SI = (|100 * ((\mu S - \pi S)\ 2 - (v S - \pi S)\ 2\ )|)\ ½ \qquad (10)$$

Similarly, for lower importance (i.e., criteria ranked below equal importance), the following formula is applied:

$$\frac{1}{SI} = \frac{1}{(|100 * ((\mu \tilde{S} - \pi \tilde{S})^{2} - (v\tilde{S} - \pi\tilde{S})^{2})|)^{1/2}} \tag{11}$$

Step 2.2. After ensuring the consistency of the matrices provided by the decision-makers, a pairwise comparison matrix is constructed using the spherical fuzzy set values.

Step 2.3. The evaluation from the decision-makers is aggregated using the SWGM operator, as defined in Equation 4.

Step 2.4. The spherical fuzzy weights of the criteria are calculated from the aggregated matrix using the SWAM operator, as defined in Equation 3.

Step 2.5. Defuzzification: the goal is to obtain crisp numerical values from the calculated spherical fuzzy weight coefficients. To achieve this, the score function equation provided below is applied.

$$S(\widetilde{w_j^s})\, S = \sqrt{\left|100 * \left[\left(3\mu_{\tilde{A}_S} - \frac{\pi\tilde{A}_S}{2}\right)^2 - \left(\frac{v_{\tilde{A}_S}}{2} - \pi\tilde{A}S\right)^2\right]\right|} \tag{12}$$

Step 2.6. Normalization is performed to obtain crisp values from the defuzzified criterion weights.

Step 2.7. Calculation of Global Net Weights: In the last step of SF-AHP, the global weights of criteria and sub-criteria are computed in this step.

Step 3. SF-TOPSIS Model execution:

Step 3.1. Decisions from three decision-makers aggregated with SWAM operator.

Step 3.2. After Step 2, the determined weight of each criterion and the evaluation degree of the alternatives, the spherical fuzzy matrix is constructed as follows, based on the matrix formed in the previous step.

$$D = \left(C_j(P_{iw})\right)_{m\times n} = \begin{bmatrix} (\mu_{11w}, v_{11w}, \pi_{11w}) & \cdots & (\mu_{1nw}, v_{1nw}, \pi_{1nw}) \\ \vdots & \ddots & \vdots \\ (\mu_{\mathrm{m}1w}, v_{m1w}, \pi_{m1w}) & \cdots & (\mu_{mnw}, v_{mnw}, \pi_{mnw}) \end{bmatrix} \tag{13}$$

The following formula should be used when calculating the weighted spherical fuzzy matrix, specifically for the multiplication of two Spherical Fuzzy Sets:

$$\tilde{A}_S \otimes \tilde{B}_S = \left\{ \begin{array}{c} \mu_{\tilde{A}_S}\mu_{\tilde{B}_S}\ , \left(v_{\tilde{A}_S}^2 + v_{\tilde{B}_S}^2 - v_{\tilde{A}_S}^2 v_{\tilde{B}_S}^2\right)^{\frac{1}{2}}, \\ \left(\begin{array}{c} (1 - v_{\tilde{B}_S}^2)\pi_{\tilde{A}_S}^2 + \\ (1 - v_{\tilde{B}_S}^2)\pi_{\tilde{A}_S}^2 - \pi_{\tilde{A}_S}^2 \pi_{\tilde{B}_S}^2 \end{array} \right)^{\frac{1}{2}} \end{array} \right\} \tag{14}$$

The weighted spherical fuzzy matrix is clarified, and score functions are determined for each alternative-criteria pair. Ideal solutions will be derived using the score values obtained by converting fuzzy values into crisp values.

$$\mathrm{Score}\left(C_j(P_{iw})\right) = \left(\mu_{ijw} - \pi_{ijw}\right)^2 - \left(v_{ijw} - \pi_{ijw}\right)^2 \tag{15}$$

Step 3.3. Using the score values, the Spherical Fuzzy Positive Ideal Solution (SF-PIS) and the Spherical Fuzzy Negative Ideal Solution (SF-NIS) are identified.

$$P^{*} = \left\{C_j, max_i \left\langle \text{Score}\left(C_j(P_{iw})\right)\right\rangle \mid j = 1,2 \dots n\right\}$$

$$P^{*} = \begin{Bmatrix} \langle C_1, (\mu_1^{*}, v_1^{*}, \pi_1^{*})\rangle, \\ \langle C_2, (\mu_2^{*}, v_2^{*}, \pi_2^{*})\rangle \dots \\ \langle C_n, (\mu_n^{*}, v_n^{*}, \pi_n^{*})\rangle \end{Bmatrix} \quad (16)$$

$$P^{-} = \left\{C_j, min_i \left\langle \text{Score}\left(C_j(P_{iw})\right)\right\rangle \mid j = 1,2 \dots n\right\}$$

$$P^{-} = \begin{Bmatrix} \langle C_1, (\mu_1^{-}, v_1^{-}, \pi_1^{-})\rangle, \\ \langle C_2, (\mu_2^{-}, v_2^{-}, \pi_2^{-})\rangle \\ \dots \dots \langle C_n, (\mu_n^{-}, v_n^{-}, \pi_n^{-})\rangle \end{Bmatrix} \quad (17)$$

For each A_i alternative, the distances to SF-PIS and SF-NIS are calculated. The Euclidean distance formula is used in the calculations.

The following equation is used to determine the Spherical Fuzzy Negative Ideal Solution (SF-NIS). By applying this formula, the distance of each criterion from the negative ideal solution is calculated. The greater this distance, the higher the likelihood of the alternative being selected.

$$D(P_i, P^{-}) = \sqrt{\frac{1}{2n}\sum_{i=1}^{n}\begin{pmatrix} \left(\mu_{p_i} - \mu_{p^-}\right)^2 + \\ \left(v_{p_i} - v_{p^-}\right)^2 + \left(\pi_{p_i} - \pi_{p^-}\right)^2 \end{pmatrix}} \quad (18)$$

The following equation is used to determine the Spherical Fuzzy Positive Ideal Solution (SF-PIS). By applying this formula, the distance of each criterion from the positive ideal solution is calculated. The smaller this distance, the higher the likelihood of the alternative being selected.

$$D(P_i, P^+) = \sqrt{\frac{1}{2n}\sum_{i=1}^{n}\begin{pmatrix}\left(\mu_{p_i} - \mu_{p^+}\right)^2 + \\ \left(v_{p_i} - v_{p^+}\right)^2 + \\ \left(\pi_{p_i} - \pi_{p^+}\right)^2\end{pmatrix}} \tag{19}$$

The minimum distance from the spherical fuzzy positive ideal solution and the maximum distance from the spherical fuzzy negative ideal solution are selected.

$$\begin{aligned} D_{\max}\,(P_i, P^-) &= \max_{1\le i\le m} D(P_i, P^-) \\ D_{\min}\,(P_i, P^+) &= \min_{1\le i\le m} D(P_i, P^+) \end{aligned} \tag{20}$$

The modified closeness ratio is calculated using the values determined.

$$\xi(P_i) = \frac{D(P_i, P^-)}{D_{max}(P_i, P^-)} - \frac{D(P_i, P^+)}{D_{min}(P_i, P^+)} \tag{21}$$

In this equation, the second element is always at least equal to the first, which results in a negative or zero outcome. To ensure positive or zero values, the equation is modified accordingly to compute the closeness ratio as follows:

$$\xi(P_i) = \frac{D(P_i, P^+)}{D_{min}(P_i, P^+)} - \frac{D(P_i, P^-)}{D_{max}(P_i, P^-)} \tag{22}$$

The alternatives are ranked based on their suitability, and the most suitable alternative is determined according to this ranking. One of the two calculation methods can be applied: If Equation 21 is used, the selection is made in decreasing order of closeness ratios. The alternative with the highest value is chosen as the most suitable. If Equation 22 is used, the selection is made in increasing order of closeness ratios. The alternative with the lowest value is considered the most suitable.

5 NUMERICAL ANALYSIS

SF-AHP for criteria weighting and SF-TOPSIS for IT investment alternative ranking is executed. Alternatives mentioned previously in detail. Assessed IT investments are A_1, A_2, A_3, A_4, A_5, A_6, A_7, A_8, A_9. The criteria for evaluating a project can vary based on the combination of qualitative and quantitative factors involved. A comprehensive review of the literature has led to the identification of numerous criteria and sub-criteria. In our study, 8 main and 22 sub-criteria are applied, which are detailed in Section 4. The evaluation process involves three decision-makers from textile professionals: DM1, Chief Operations Officer (COO) of a big sock production factory; DM2, Chairman of the Board of an apparel factory; and DM3, CDO of a big textile production factory. Each decision-maker is assigned an equal weight. Step 1 done by collecting judgments from decision-makers. Table 5.1 shows detailed information about DM's as a table.

Table 5.1 Decision Makers (DMs) Details

Decision Maker (DM)	Title	Factory Type	Experience (Years)	Assigned Weight
DM1	Chief Operations Officer (COO)	Sock Production Factory	17	1/3
DM2	Chairman of the Board	Apparel Factory	28	1/3
DM3	Chief Digital Officer (CDO)	Textile Production Factory	22	1/3

The linguistic judgments (by using Table 4.3) of the decision-makers regarding the sustainability level of the A_i IT investment alternative when assessed based on the $C_{i.i}$ sub-criterion are documented in Table 5.2, Table 5.3, Table 5.4.

Table 5.2 DM1 Judgments

	$C_{1.1}$	$C_{1.2}$	$C_{1.3}$	$C_{1.4}$	$C_{2.1}$	$C_{2.2}$	$C_{2.3}$	$C_{3.1}$	$C_{3.2}$	$C_{3.3}$	$C_{3.4}$	$C_{4.1}$	$C_{4.2}$	$C_{4.3}$	$C_{5.1}$	$C_{5.2}$	$C_{6.1}$	$C_{6.2}$	$C_{7.1}$	$C_{7.2}$	$C_{8.1}$	$C_{8.2}$
A_1	S	S	S	S	S	S	S	VG	S	S	S	S	S	EG	EG	EG	VG	EG	S	S	S	S
A_2	S	S	S	S	S	S	S	VG	S	S	S	S	S	EG	EG	EP	EP	VG	S	S	S	S
A_3	S	S	S	S	S	S	S	EG	EG	S	S	S	S	EG	S	F	F	S	VG	F	S	S
A_4	EP	S	S	S	S	S	S	EG	EG	S	S	S	S	VG	S	F	F	S	VG	I	S	S
A_5	EG	S	S	S	S	S	S	EG	EG	S	S	S	S	S	S	F	F	S	S	I	S	S
A_6	S	S	S	S	S	S	S	EG	S	S	S	S	S	S	S	F	EP	S	S	S	S	S
A_7	VG	VG	S	S	S	S	S	VG	S	S	S	S	S	VG	S	F	EP	S	S	VP	S	VG
A_8	F	G	S	S	VG	S	S	P	S	S	S	S	S	G	S	VP	EP	S	G	VG	VG	S
A_9	P	F	VG	VP	VG	G	VG	F	VG	VG	EG	G	VG	F	EP	VP	EP	P	S	EG	S	G

Table 5.3 DM2 Judgments

	$C_{1.1}$	$C_{1.2}$	$C_{1.3}$	$C_{1.4}$	$C_{2.1}$	$C_{2.2}$	$C_{2.3}$	$C_{3.1}$	$C_{3.2}$	$C_{3.3}$	$C_{3.4}$	$C_{4.1}$	$C_{4.2}$	$C_{4.3}$	$C_{5.1}$	$C_{5.2}$	$C_{6.1}$	$C_{6.2}$	$C_{7.1}$	$C_{7.2}$	$C_{8.1}$	$C_{8.2}$
A_1	S	S	G	S	EG	G	S	F	G	S	S	EG	S	S	VG	F	EG	S	S	S	S	S
A_2	S	S	VG	S	I	G	S	P	VG	S	P	VG	S	S	G	I	EP	VP	VP	VG	VG	EG
A_3	S	S	EG	EG	F	VG	S	G	S	S	S	S	S	G	VP	P	VP	EG	VG	G	S	S
A_4	G	VP	VG	S	S	S	S	S	EG	S	S	S	S	S	S	F	S	G	S	S	S	I
A_5	S	S	EG	S	VP	EG	S	F	F	F	VG	S	S	S	S	G	VP	S	S	F	S	S
A_6	S	S	EG	S	I	P	G	VG	VG	S	G	S	S	EG	P	P	VP	S	G	EG	S	S
A_7	VG	G	VG	S	VP	P	S	F	G	G	G	P	VG	G	EP	I	VP	VG	VP	P	S	S
A_8	G	G	S	S	VG	VG	S	VP	S	S	S	P	EG	S	VP	VP	VP	I	VP	S	S	S
A_9	VP	G	VG	G	G	G	F	VG	VG	VG	G	P	G	G	EP	P	G	EP	G	G	VG	I

Table 5.4 DM3 Judgments

	$C_{1.1}$	$C_{1.2}$	$C_{1.3}$	$C_{1.4}$	$C_{2.1}$	$C_{2.2}$	$C_{2.3}$	$C_{3.1}$	$C_{3.2}$	$C_{3.3}$	$C_{3.4}$	$C_{4.1}$	$C_{4.2}$	$C_{4.3}$	$C_{5.1}$	$C_{5.2}$	$C_{6.1}$	$C_{6.2}$	$C_{7.1}$	$C_{7.2}$	$C_{8.1}$	$C_{8.2}$
A_1	S	S	S	G	S	S	S	F	F	G	S	VG	S	S	G	VP	VG	S	F	G	G	S
A_2	VP	S	S	VG	S	F	S	F	F	VP	S	VG	S	S	G	I	VP	VP	F	VG	G	F
A_3	S	S	S	S	S	S	S	VP	S	S	S	S	G	G	S	S	I	S	VP	VP	S	F
A_4	F	VG	S	VP	VG	VG	VG	VP	I	F	F	F	S	F	F	VP	I	S	VP	VP	S	VP
A_5	VG	VG	S	VP	S	G	VG	VP	S	VP	VG	VG	F	S	VG	I	F	F	S	VG	F	VP
A_6	S	VG	S	VG	S	S	S	VG	S	S	S	S	S	VP	S	VG	I	S	I	VP	S	VP
A_7	VG	VG	S	F	S	VG	VG	F	S	S	VG	G	S	EP	VG	F	VP	VG	VP	I	VG	VP
A_8	VP	VP	S	S	I	EP	S	I	S	S	S	G	VP	I	S	S	I	VG	VP	I	I	S
A_9	VG	F	F	F	VP	F	F	I	F	VP	G	F	F	VP	P	F	VP	F	VP	VP	VP	VP

5.1 Application of SF-AHP: Weighting of the Criteria and Sub-Criteria

A pairwise comparison matrix is constructed using the global fuzzy set values. After ensuring the Step 2.1 done, consistency of the matrices provided by the decision makers, Step 2.2 applied by doing pairwise comparison.

Below at the following tables pairwise comparison matrices, their consistency ratios can be seen.

Table 5.5 Pairwise Comparison Matrix for the Sub-Criteria of the Main Criterion "Technology" (CR=0,06 – 0,06 – 0,07 Respectively)

DM1	$C_{1.1}$	$C_{1.2}$	$C_{1.3}$	$C_{1.4}$	DM2	$C_{1.1}$	$C_{1.2}$	$C_{1.3}$	$C_{1.4}$
$C_{1.1}$	1,00	EI	EI	SMI	$C_{1.1}$	1,00	SMI	SMI	VHI
$C_{1.2}$	EI	1,00	SMI	SMI	$C_{1.2}$	SLI	1,00	SLI	SMI
$C_{1.3}$	EI	SLI	1,00	SMI	$C_{1.3}$	SLI	SMI	1,00	SMI
$C_{1.4}$	SLI	SLI	SLI	1,00	$C_{1.4}$	VLI	SLI	SLI	1,00

DM3	$C_{1.1}$	$C_{1.2}$	$C_{1.3}$	$C_{1.4}$
$C_{1.1}$	1,00	SMI	SMI	HI
$C_{1.2}$	SLI	1,00	SLI	SMI
$C_{1.3}$	SLI	SMI	1,00	SMI
$C_{1.4}$	LI	SLI	SLI	1,00

Table 5.6 Pairwise Comparison Matrix for the Sub-Criteria of the Main Criterion "Cost" (CR=0,03 – 0,00 – 0,07 Respectively)

DM1	$C_{2.1}$	$C_{2.2}$	$C_{2.3}$	DM2	$C_{2.1}$	$C_{2.2}$	$C_{2.3}$	DM3	$C_{2.1}$	$C_{2.2}$	$C_{2.3}$
$C_{2.1}$	1,00	LI	EI	$C_{2.1}$	1,00	LI	EI	$C_{2.1}$	1,00	VLI	EI
$C_{2.2}$	HI	1,00	SMI	$C_{2.2}$	HI	1,00	HI	$C_{2.2}$	VHI	1,00	SMI
$C_{2.3}$	EI	SLI	1,00	$C_{2.3}$	EI	LI	1,00	$C_{2.3}$	EI	SLI	1,00

Table 5.7 Pairwise Comparison Matrix for the Sub-Criteria of the Main Criterion "Security" (CR=0,04 – 0,06 – 0,07 Respectively)

DM1	$C_{3.1}$	$C_{3.2}$	$C_{3.3}$	$C_{3.4}$	DM2	$C_{3.1}$	$C_{3.2}$	$C_{3.3}$	$C_{3.4}$
$C_{3.1}$	1,00	SMI	EI	HI	$C_{3.1}$	1,00	SMI	SMI	VHI
$C_{3.2}$	SLI	1,00	SLI	SMI	$C_{3.2}$	SLI	1,00	SLI	SMI
$C_{3.3}$	EI	SMI	1,00	SMI	$C_{3.3}$	SLI	SMI	1,00	SMI
$C_{3.4}$	LI	SLI	SLI	1,00	$C_{3.4}$	VLI	SLI	SLI	1,00

DM3	$C_{3.1}$	$C_{3.2}$	$C_{3.3}$	$C_{3.4}$
$C_{3.1}$	1,00	SMI	SMI	HI
$C_{3.2}$	SLI	1,00	SLI	SMI
$C_{3.3}$	SLI	SMI	1,00	SMI
$C_{3.4}$	LI	SLI	SLI	1,00

Table 5.8 Pairwise Comparison Matrix for the Sub-Criteria of the Main Criterion "Strategic Fit" (CR=0,00 – 0,02 – 0,07 Respectively)

DM1	$C_{4.1}$	$C_{4.2}$	$C_{4.3}$	DM2	$C_{4.1}$	$C_{4.2}$	$C_{4.3}$	DM3	$C_{4.1}$	$C_{4.2}$	$C_{4.3}$
$C_{4.1}$	1,00	LI	EI	$C_{4.1}$	1,00	LI	EI	$C_{4.1}$	1,00	VLI	EI
$C_{4.2}$	HI	1,00	HI	$C_{4.2}$	HI	1,00	SMI	$C_{4.2}$	VHI	1,00	SMI
$C_{4.3}$	EI	LI	1,00	$C_{4.3}$	EI	SLI	1,00	$C_{4.3}$	EI	SLI	1,00

Table 5.9 Pairwise Comparison Matrix for the Sub-Criteria of the Main Criterion " Organisational Culture" and "Management Support" (CR=0,00 – 0,00 – 0,00 / 0,00 – 0,00 – 0,00 Respectively), "Environmental Impact" and "Incentives and Policies" (CR=0,00 – 0,00 – 0,00 / 0,00 – 0,00 – 0,00 Respectively)

DM1	$C_{5.1}$	$C_{5.2}$	DM2	$C_{5.1}$	$C_{5.2}$	DM3	$C_{5.1}$	$C_{5.2}$
$C_{5.1}$	1,00	LI	$C_{5.1}$	1,00	SLI	$C_{5.1}$	1,00	EI
$C_{5.2}$	HI	1,00	$C_{5.2}$	SMI	1,00	$C_{5.2}$	EI	1,00

DM1	$C_{6.1}$	$C_{6.2}$	DM2	$C_{6.1}$	$C_{6.2}$	DM3	$C_{6.1}$	$C_{6.2}$
$C_{6.1}$	1,00	LI	$C_{6.1}$	1,00	LI	$C_{6.1}$	1,00	LI
$C_{6.2}$	HI	1,00	$C_{6.2}$	HI	1,00	$C_{6.2}$	HI	1,00

DM1	$C_{7.1}$	$C_{7.2}$	DM2	$C_{7.1}$	$C_{7.2}$	DM3	$C_{7.1}$	$C_{7.2}$
$C_{7.1}$	1,00	SLI	$C_{7.1}$	1,00	SLI	$C_{7.1}$	1,00	SLI
$C_{7.2}$	SMI	1,00	$C_{7.2}$	SMI	1,00	$C_{7.2}$	SMI	1,00

DM1	$C_{8.1}$	$C_{8.2}$	DM2	$C_{8.1}$	$C_{8.2}$	DM3	$C_{8.1}$	$C_{8.2}$
$C_{8.1}$	1,00	SMI	$C_{8.1}$	1,00	EI	$C_{8.1}$	1,00	AMI
$C_{8.2}$	SLI	1,00	$C_{8.2}$	EI	1,00	$C_{8.2}$	ALI	1,00

Table 5.10 Pairwise Comparison Matrix for the Main Criteria (CR=0,04 – 0,06 – 0,00 Respectively)

DM1	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
C_1	1,00	SLI	SMI	EI	EI	EI	VHI	SMI
C_2	SMI	1,00	HI	SMI	EI	EI	AMI	HI
C_3	SLI	LI	1,00	SLI	SLI	LI	SMI	EI
C_4	EI	SLI	SMI	1,00	EI	EI	VHI	SMI
C_5	EI	EI	SMI	EI	1,00	EI	VHI	SMI
C_6	EI	EI	HI	EI	EI	1,00	AMI	HI
C_7	VLI	ALI	SLI	VLI	VLI	ALI	1,00	SLI
C_8	SLI	LI	EI	SLI	SLI	LI	SMI	1,00

DM2	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
C_1	1,00	HI	HI	SMI	SMI	SLI	HI	SMI
C_2	LI	1,00	EI	SLI	SLI	ALI	EI	SLI
C_3	LI	EI	1,00	SLI	SLI	ALI	EI	SLI
C_4	SLI	SMI	SMI	1,00	SLI	SLI	SMI	EI
C_5	SLI	SMI	SMI	SMI	1,00	SLI	SMI	EI
C_6	SMI	AMI	AMI	SMI	SMI	1,00	AMI	SMI
C_7	LI	EI	EI	SLI	SLI	ALI	1,00	SLI
C_8	SLI	SMI	SMI	EI	EI	SLI	SMI	1,00

DM3	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
C_1	1,00	SMI	SMI	AMI	SMI	SMI	AMI	AMI
C_2	SLI	1,00	EI	SMI	EI	EI	SMI	SMI
C_3	SLI	EI	1,00	SMI	EI	EI	SMI	SMI
C_4	ALI	SLI	SLI	1,00	SLI	SLI	EI	EI
C_5	SLI	EI	EI	SMI	1,00	EI	SMI	SMI
C_6	SLI	EI	EI	SMI	EI	1,00	SMI	SMI
C_7	ALI	SLI	SLI	EI	SLI	SLI	1,00	EI
C_8	ALI	SLI	SLI	EI	SLI	SLI	EI	1,00

Step 2.3 is applied, the evaluations from the decision makers are aggregated using the SWGM operator given in Equation 4. Aggregated matrice can be seen at Appendices Table A1.

After this step, Step 2.4 is applied, aggregated matrices combined with SWAM operator. 2.5, defuzzification, 2.6, normalization and 2.7 calculation of their global weights steps applied. Table 5.11 shows all results for Criteria and and sub-criteria weights.

Table 5.11 Aggregation of criteria and sub-criteria normalized local weights based on SWAM operator

Criteria - Sub Criteria	μ	v	π	Defuzzified	Normalized Local Weights	Global Weights
C_1	**0,63**	**0,28**	**0,26**	**17,53**	**0,16**	**-**
$C_{1.1}$	0,59	0,38	0,32	16,10	0,29	0,05
$C_{1.2}$	0,50	0,47	0,34	13,45	0,38	0,06
$C_{1.3}$	0,52	0,45	0,34	13,90	0,23	0,04
$C_{1.4}$	0,41	0,57	0,32	10,61	0,10	0,02
C_2	**0,51**	**0,32**	**0,22**	**14,21**	**0,13**	**-**
$C_{2.1}$	0,44	0,48	0,22	12,12	0,16	0,02
$C_{2.2}$	0,64	0,34	0,26	17,83	0,66	0,08
$C_{2.3}$	0,46	0,46	0,24	12,65	0,19	0,02
C_3	**0,45**	**0,96**	**0,20**	**12,43**	**0,11**	**-**
$C_{3.1}$	0,61	0,36	0,30	16,87	0,40	0,04
$C_{3.2}$	0,49	0,48	0,33	12,96	0,16	0,02
$C_{3.3}$	0,54	0,43	0,34	14,55	0,36	0,04
$C_{3.4}$	0,40	0,56	0,31	10,51	0,08	0,01
C_4	**0,49**	**0,93**	**0,22**	**13,49**	**0,12**	**-**
$C_{4.1}$	0,44	0,48	0,22	12,12	0,14	0,02
$C_{4.2}$	0,64	0,34	0,26	17,84	0,71	0,09
$C_{4.3}$	0,46	0,46	0,24	12,65	0,14	0,02
C_5	**0,54**	**0,91**	**0,25**	**15,03**	**0,13**	**-**
$C_{5.1}$	0,45	0,48	0,23	12,36	0,17	0,02
$C_{5.2}$	0,55	0,38	0,26	15,24	0,83	0,11

C_6	**0,62**	**0,65**	**0,27**	**17,19**	**0,15**	**-**
$C_{6.1}$	0,42	0,52	0,19	11,55	0,17	0,03
$C_{6.2}$	0,62	0,34	0,26	17,23	0,83	0,13
C_7	**0,35**	**0,96**	**0,14**	**9,86**	**0,09**	**-**
$C_{7.1}$	0,45	0,48	0,23	12,50	0,25	0,02
$C_{7.2}$	0,55	0,39	0,26	15,31	0,75	0,07
C_8	**0,45**	**0,92**	**0,20**	**12,44**	**0,11**	**-**
$C_{8.1}$	0,58	0,36	0,26	16,19	0,75	0,08
$C_{8.2}$	0,41	0,54	0,21	11,19	0,25	0,03

5.2 Application of SF-TOPSIS: Ranking of the Alternatives

After determining the weights of the criteria, the evaluations of the alternatives from the decision makers were taken account using, Step 3, the SF-TOPSIS method. The evaluations were combined at Step 3.1, with SWAM operator. Shown in Table A5.

Then the combined matrices and the global fuzzy weights of the criteria were multiplied using the multiplication function given in Equation 4. The global fuzzy matrix calculation is performed based on the matrix created in the previous step, which determines the weight of each criterion and the evaluation degree of the alternatives. Table A6 shows the resulting matrix of Step 3.2. Table 5.12 shows defuzzification with score function based on SWAM operator. Equation 15 used.

Table 5.12 Defuzzification with Score function based on SWAM Operator

	$C_{1.1}$	$C_{1.2}$	$C_{1.3}$	$C_{1.4}$	$C_{2.1}$	$C_{2.2}$	$C_{2.3}$	$C_{3.1}$	$C_{3.2}$	$C_{3.3}$	$C_{3.4}$	$C_{4.1}$	$C_{4.2}$	$C_{4.3}$	$C_{5.1}$	$C_{5.2}$	$C_{6.1}$	$C_{6.2}$	$C_{7.1}$	$C_{7.2}$	$C_{8.1}$	$C_{8.2}$
A_1	0,13	-0,02	-0,01	-0,06	-0,05	0,04	-0,05	0,05	0,02	0,00	-0,19	-0,03	0,21	-0,03	0,01	0,03	-0,02	0,09	-0,01	0,01	-0,16	-0,16
A_2	0,03	-0,02	-0,01	-0,08	-0,14	-0,01	-0,05	0,05	0,00	-0,01	-0,07	-0,02	0,21	-0,03	0,03	-0,41	-0,14	0,00	0,00	0,00	-0,01	-0,01
A_3	0,13	-0,02	-0,01	-0,11	-0,01	0,06	-0,05	0,00	-0,04	0,05	-0,19	-0,09	0,04	0,03	-0,05	0,01	0,12	0,09	0,00	0,10	-0,03	-0,03
A_4	0,09	-0,03	-0,01	-0,11	-0,04	0,06	-0,03	0,02	-0,07	0,00	-0,04	-0,01	0,21	0,01	-0,01	0,15	0,00	0,03	0,00	-0,06	-0,12	-0,12
A_5	0,02	-0,02	-0,01	-0,11	-0,06	0,02	-0,03	0,02	-0,01	0,01	-0,05	-0,04	0,02	-0,05	-0,04	0,10	0,20	0,02	0,13	0,06	-0,09	-0,09
A_6	0,13	-0,02	-0,01	-0,08	-0,14	0,04	-0,02	0,00	-0,03	0,05	-0,06	-0,09	0,21	-0,04	-0,03	0,07	-0,18	0,18	-0,01	-0,01	-0,09	-0,09
A_7	0,00	0,02	-0,01	-0,04	-0,06	0,01	-0,03	0,05	-0,02	0,00	-0,02	0,01	0,06	0,04	-0,04	0,15	-0,07	0,01	-0,02	0,00	-0,05	-0,05
A_8	0,09	0,07	0,01	-0,19	-0,01	0,01	-0,05	0,00	-0,05	0,05	-0,19	0,01	0,03	-0,02	-0,05	-0,03	-0,18	0,00	0,04	-0,02	-0,16	-0,16
A_9	0,03	0,14	0,04	0,15	0,05	0,05	0,11	0,04	0,05	0,00	0,03	0,15	0,02	0,13	-0,02	0,13	0,04	0,11	0,00	0,01	0,03	0,03

The weighted matrices were clarified using the score function given in Equation 9 and the points with positive ideal solutions (PIS) and negative ideal solutions were found.

Table 5.13 SF-PIS and SF-NIS Points Connected to SWAM Operator

	$C_{1.1}$	$C_{1.2}$	$C_{1.3}$	$C_{1.4}$	$C_{2.1}$	$C_{2.2}$	$C_{2.3}$	$C_{3.1}$	$C_{3.2}$	$C_{3.3}$	$C_{3.4}$	$C_{4.1}$	$C_{4.2}$	$C_{4.3}$	$C_{5.1}$	$C_{5.2}$	$C_{6.1}$	$C_{6.2}$	$C_{7.1}$	$C_{7.2}$	$C_{8.1}$	$C_{8.2}$
MAX	0,13	0,14	0,04	0,15	0,05	0,06	0,11	0,05	0,05	0,05	0,03	0,15	0,21	0,13	0,03	0,15	0,20	0,18	0,13	0,10	0,03	0,03
MIN	0,00	-0,03	-0,01	-0,19	-0,14	-0,01	-0,05	0,00	-0,07	-0,01	-0,19	-0,09	0,02	-0,05	-0,05	-0,41	-0,18	0,00	-0,02	-0,06	-0,16	-0,16

Table 5.14 Distances to positive and negative ideal solutions

Project Alternatives	**D(Xi,X∗)**	**D(Xi,X−)**
A_1	0,1765	0,3141
A_2	0,2303	0,2693
A_3	0,1819	0,3143
A_4	0,2267	0,2524
A_5	0,2150	0,2547
A_6	0,1596	0,3202
A_7	0,2625	0,1878
A_8	0,2406	0,2836
A_9	0,3743	0,0946

Table 5.15 Closeness ratio of each alternative

Project Alternatives	Closeness Ratio	Rank
A_1	0,13	2
A_2	0,60	5
A_3	0,16	3
A_4	0,63	7
A_5	0,55	4
A_6	0,00	1
A_7	1,06	8
A_8	0,62	6
A_9	2,05	9

5.3 Results

The global weight of the Technology (C1) criterion is seen as the highest. Under this criterion, Scalability (C1.2 – 0.06) is the sub-criterion with the highest local importance of technology. Whether the technology is suitable for the growing data volume, number of users and operational expansion is a determining factor for decision makers. Compatibility (C1.1 – 0.05) and Reliability (C1.3 – 0.04) Integration with existing systems and stability of the system were also found to be important. However, Transparency (C1.4 – 0.02) was evaluated as less important than the others, but transparency of information sharing is important in terms of sustainability.

Management Support (C6) criterion was ranked as the second level of importance. While one of the most critical determining factors for decision makers is Willingness to Allocate Budget (C6.2 – 0.13), Dependence on Leader Support (C6.1 – 0.03) sub-criterion, Leadership determination, gained less weight in the shadow of budget support. However, managers need to take an active role in this process.

The total global weight of Organizational Culture (C5) is in the 3rd place, and the Training Needs (C5.2 – 0.11) sub-criterion has the highest weight. The need for training is of strategic importance for the effective use of new technologies. The Adaptability (C5.1 – 0.02) criterion remained relatively low.

The total global weight of the Cost (C2) criterion is seen as the fourth priority. Operational Costs (C2.2 – 0.08) under this criterion has the highest priority. The impact of the investment on daily operations is seen as critical for long-term success. While start-up costs are important in the Long-Term Savings (C2.3 – 0.02) and Initial Investment Costs (C2.1 – 0.02) criteria, it is understood that decision makers evaluate the short-term operational burden more critically.

Strategic Alignment (C4) is seen as the fifth priority when making investment decisions. Contribution to Competitiveness (C4.2 – 0.09) One of the most important criteria is that the investment provides a competitive advantage to the company. Alignment with Vision (C4.1 – 0.02) and Sustainability Goals (C4.3 – 0.02) Although integration with corporate vision and sustainability goals is important, direct competitive advantage has been evaluated as a priority.

Regulatory Compliance (C8) is in sixth place. The Availability of Incentives (C8.1 – 0.08) sub-criterion clearly shows that government support is one of the factors that directly affects the investment decision.

When the Alignment with Standards (C8.2 – 0.03) sub-criterion is examined, compliance with regulations is evaluated within the scope of sustainability, but it is a secondary priority.

Capacity (C3.1 – 0.04) and Disaster Recovery (C3.3 – 0.04) under the Security (C3) criterion: It reflects that preparation for disasters and data recovery capability are prominent. Cybersecurity (C3.4 – 0.01) Although it has a relatively lower score, the literature draws attention to the increasing importance of cybersecurity. Backup and Redundancy (C3.2 – 0.02): Secure backup of data is the basic building block for decision support systems.

Environmental Impact (C7) criterion remains at the lower ranks compared to other factors in purchasing decisions. Waste Reduction (C7.2 – 0.07): It stands out in terms of resource efficiency and environmentally friendly production. Energy Efficiency (C7.1 – 0.02): Although energy saving is strategically important, it carries relatively less weight in the decision process.

Manufacturing Execution Systems (MES) stand out as the top priority alternative thanks to the real-time monitoring, automatic data backup and alarm mechanisms it offers; it has an effect that greatly increases process reliability. While the capacity management functions of MES detect bottlenecks in lines in advance and optimize resource usage, the integrated maintenance planning and backup infrastructure minimize downtimes caused by unexpected failures. In addition, considering the high budget allocation assessment (C6.2), MES investment promises a fast and measurable return on investment (ROI) for decision makers; this offers a critical advantage in terms of both reducing operational costs and aligning with the strategic vision.

MES, IoT, ERP systems and EMS took the first four places in the ranking. While IoT sensors provide countless data points to the business by instantly collecting production and energy data, MES matches this raw data with production scheduling, maintenance and quality control processes. Data collected with IoT sensors optimizes production processes in real time through MES. Data and production outputs produced by MES are analyzed in the ERP system and support strategic decisions towards sustainable goals. EMS and IoT-based systems comply with international standards in reporting energy consumption and emissions.

Digital Twin, Blockchain and Image Processing were determined as medium priority investment alternatives. Although these systems provide additional benefits, they were seen as lower priority compared to basic operational needs. Sensitivity analysis conducted on Image Processing systems revealed that improving the compatibility sub-criterion (e.g., from evaluations like “EP”, “G”, “F” to “S”) significantly enhanced its performance, raising its rank to fourth place. This shows that it can be an alternative that can be preferred and contribute to sustainability as its integration ability with other systems increases. The analysis of the opinions shows that Blockchain is a system that can be used in the coming years in terms of sustainability declaration in EU regulations such as Digital Product Passport (DPP) thanks to its high level of transparency, and that its level of use and priority in production in the textile and ready-to-wear sector is still behind, but it is recognized. For digital twins more research and application is needed for modeling, system integration and reliable artificial intelligence solutions for widespread industrial use.

Smart Logistics and Storage and AR/VR solutions are ranked as the lowest priority. This indicates that the benefits that companies will currently receive from logistics optimization and augmented reality applications are perceived as more limited compared to other systems.

5.4 Sensitivity Analysis

To test the robustness and reliability of the proposed decision-making framework, three types of sensitivity analyses were conducted. These analyses aim to observe how variations in specific parameters affect the final ranking of IT investment alternatives.

As seen in the sensitivity analysis of the model, its stability in small changes shows the applicability of the proposed framework in SMEs and its usability in strategic decision-making processes.

5.4.1 Sensitivity Analysis of C_{11} (Compatibility for Image Processing)

This analysis examined the impact of changing the weight of the "Compatibility" criterion (C11) for Image Processing, which showed significant influence in the initial model. Incremental increases and decreases (±10%, ±20%) in the weight of C11 were applied while keeping the total weight sum normalized. The results revealed that while minor changes did not significantly alter the final ranking, large variations could cause a shift between closely ranked alternatives (e.g., MES and IoT). This demonstrates that C11 is a moderately sensitive criterion and should be carefully assessed in real-life decision environments.

Boosting the compatibility score for Image Processing significantly raised its closeness ratio—moving it from 7th to 4th place—highlighting how critical seamless integration is to its overall appeal.

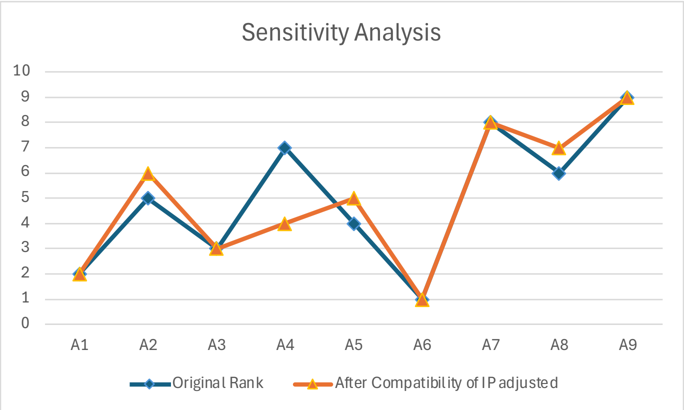

Figure 5.1: The results of the sensitivity analysis of C_{11}'s weight in line chart

5.4.2 Sensitivity Analysis of DM Weightages

This analysis focused on altering the influence ratios of decision makers to evaluate how individual perspectives affect overall results. Scenarios with equal weightings, single-dominant DM, and weighted average settings were simulated. Changing the weightage sensitivity calculated. From (0,33-0,33-0,33) to (0,5-0,3-0,2) and (0,1-0,8-0,1). The resulting rankings showed that although the absolute closeness scores varied, the top-ranked alternative remained consistent, indicating the framework's resistance to interpersonal bias and its robustness in multi-expert settings.

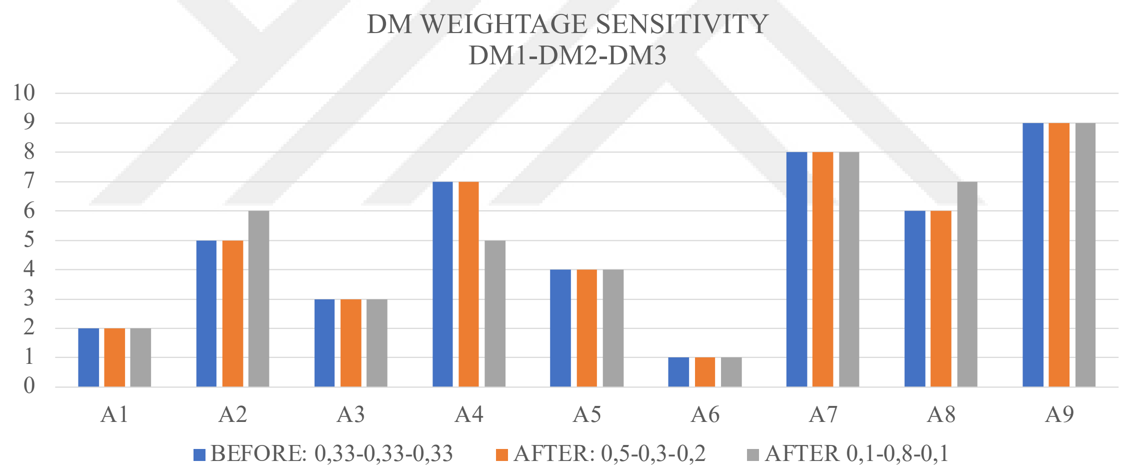

Figure 5.2: The results of the sensitivity analysis of DM's weightages in bar chart

5.4.3 Sensitivity Analysis of Closeness Ratio Proximity

This test identified the alternatives with minimal closeness score differences—particularly those with rankings that could reverse under slight perturbations. Alternatives with closeness ratios differing by less than 0.05 were flagged as sensitive pairs. In these cases, even small modifications in weightings or inputs could change their order. Recognizing such borderline cases helps decision makers prioritize further evaluation or scenario analysis before finalizing investment decisions. Changing Cybersecurity criterion's weight from 1 to 9 affects as Figure 5.3.

Project Alternatives	Closeness Ratio	Rank	Closeness Ratios After	Ranks After
A1	0,1251	2	0,1212	2
A2	0,6018	5	0,5987	5
A3	0,1581	3	0,1553	3
A4	0,6319	7	0,6332	7
A5	0,5515	4	0,5504	4
A6	0,0000	1	0,0000	1
A7	1,0584	8	1,0589	8
A8	0,6218	6	0,6090	6
A9	2,0500	9	2,0516	9

Figure 5.3: The results of the sensitivity analysis of closeness ratio proximity related the most important criterion.

In summary, the sensitivity analyses validate that the proposed model is methodologically stable, while also highlighting specific points of sensitivity that decision makers should be aware of. This enhances both the transparency and the strategic applicability of the framework in real-world textile investment scenarios.

6 CONCLUSION

The assessment integrated comprehensive criteria across economic, environmental, social and cultural dimensions, drawing on insights collected from decision makers in Türkiye's textile industry.

The complementary integration of IoT, MES and ERP solutions is the catalyst for digital transformation. These technologies, when used in an integrated manner, form the backbone of a digitally sustainable production environment. Textile companies that prioritize IoT, MES, ERP and EMS systems use their resources effectively, optimize production processes and develop a sustainable business model. Companies that use these systems together gain permanent competitive advantage by better adapting to future market conditions and customer expectations. Transferring the outputs to the ERP system enables competitive contribution (C4.2) and long-term savings (C2.3) analyses to be transferred to the upper-level strategy layer. Thus, decision-makers can build a sustainable and flexible management model based on data flow throughout the entire supply chain.

Energy Management Systems (EMS) and IoT-based solutions stand out as two important components that balance each other in terms of sustainability. EMS increases energy efficiency and long-term savings rates thanks to ISO 50001-compliant reporting capabilities and access to incentive mechanisms (C8.1), while IoT sensors reduce environmental impacts by detecting waste and waste amounts in production processes in real time. This combination creates a strong synergy in terms of both financial sustainability and environmental performance goals; however, if the initial cost (C2.1) and training needs (C5.2) are not balanced, optimal impact can be challenging.

Innovative technologies such as Digital Twin, Blockchain, Image Processing (Machine Vision), Smart Logistics and AR/VR have the potential to be the infrastructure of the future, but are currently in the pilot application phase due to high training requirements and start-up costs. These solutions less likely climb to the top ranks in closeness ratio scores due to complex expertise requirements and insufficient regulatory support (C8.2). Therefore, in order for these technologies to become sustainable and scalable, infrastructure maturity must first increase, standardization processes must be completed, and application training models must become widespread. When these conditions are met, these alternatives can become the locomotive of the second wave of digital transformation.

Decision makers should prioritize MES, IoT, ERP and EMS technologies while simultaneously planning training and infrastructure preparation for the implementation of these investments. Phased deployment with planned pilot applications minimizes system compatibility (Compatibility, C1.1) and scalability (Scalability, C1.2) risks, while ensuring predictability of operational costs (Operational Costs, C2.2). Furthermore, since management support and budget allocation (C6.1–C6.2) are critical success factors, a strong governance model should be established through senior sponsorship and project management offices (PMOs).

The effectiveness of state-supported incentive mechanisms (Availability of Incentives, C8.1) should be emphasized to accelerate digital and sustainable transformation in the textile sector. Grants and tax exemptions allocated for EMS and IoT projects reduce investor risk perception. In addition, integration with regulatory compliance (C8.2) and standard certification programs (ISO 50001, ISO 27001, etc.) facilitates the sustainability motto of all stakeholders in the supply chain. In this context, public-private partnerships and sectoral tailor-made digital transformation incentives are recommended.

Ultimately, this study underlines the strategic importance of prioritizing core production technologies to support digital sustainability in the textile sector. The findings suggest that companies should focus their investments on integrated systems like MES, IoT, ERP, and EMS.

6.1 Thesis Contribution

The most important innovation of this study is the use of Spherical Fuzzy AHP in criteria weighting and Spherical Fuzzy TOPSIS in ranking the alternatives to the Textile industry investment choice. Compared to traditional fuzzy AHP approaches, spherical fuzzy values produce more consistent decision support outputs by simultaneously addressing both membership and uncertainty degrees. In addition, the selection of SWGM (geometric mean) and SWAM (arithmetic mean) operators in distance calculations between positive and negative ideal solutions has ensured that different expert opinions are integrated into a single result in a balanced manner. In this respect, the study offers both a practical model for the theoretical literature and a transparent framework that can be directly applied to field practitioners.

Study's textile industry context: this study is not considered specific to the textile sector, as it includes contributions from only three industry professionals. Rather, a sector-specific structure is embedded in the framework's design, particularly in the selection of evaluation criteria, decision context, and investment alternatives. The criteria were developed based on a comprehensive literature review focused on textile manufacturing, covering topics such as digital transformation in manufacturing, sectoral sustainability pressures (e.g., the EU Green Deal), and the adoption of technologies such as IoT, ERP, and MES, which are particularly important for the textile industry.

Furthermore, the expert assessments were not arbitrary; they represented different roles within the textile ecosystem, such as digital transformation manager, sustainability, and production investment decision maker. This diversity contributed to a comprehensive reflection of sectoral priorities and decision dynamics.

While the MCDM methods (Global Fuzzy AHP and SF-TOPSIS) are transferable, the input structure, weighting logic, and sustainability focus were tailored to the textile sector's challenges and transformation needs. Adapting the model to other sectors would require a complete redefinition of the criteria set and contextual assumptions.

6.2 Limitations and Future Work

Since the closeness ratio values obtained are based on expert surveys, the geographical and institutional diversity of the participant pool should be expanded. In addition, dynamic MCDM models that take into account the interactions between criteria (e.g. fuzzy DEMATEL or ANP integrations) can be examined in future studies to increase the robustness of the results. The context-specific effects observed during the data collection phase (infrastructure maturity varying from firm to firm) should also be carefully considered when making sectoral generalizations.

In the next step, "success criteria" (KPIs) can be determined based on the pilot application results, and the financial-operational-environmental impacts of the systems can be measured in real usage scenarios. In addition, with the addition of AI-supported optimization modules (e.g. machine learning maintenance prediction, energy consumption prediction), the performance of dynamic and autonomous decision support systems can be evaluated. Thus, the study will continue to provide both theoretical and applied results to the digital sustainability literature in the textile industry.

Future research could further explore the integration dynamics among these technologies and expand empirical applications, thereby strengthening the industry's path toward sustainable digital transformation.

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APPENDICES

Appendix A.

Table A1: SWGM Aggregated matrices for pairwise comparison of all Criteria

	C1: Technology			C2: Cost			C3: Security			C4: Strategic Fit			C5: Operational Flexibility			C6: Management Support			C7: Environmental Impact			C8: Regulatory Compliance		
	μ	ν	π	μ	ν	π	μ	ν	π	μ	ν	π	μ	ν	π	μ	ν	π	μ	ν	π	μ	ν	π
C1: Technology	0,50	0,33	0,40	0,55	0,43	0,28	0,63	0,33	0,27	0,64	0,25	0,30	0,56	0,33	0,34	0,49	0,33	0,34	0,80	0,13	0,13	0,69	0,25	0,25
C2: Cost	0,42	0,43	0,27	0,50	0,33	0,40	0,56	0,29	0,35	0,52	0,33	0,30	0,46	0,33	0,37	0,29	0,33	0,26	0,65	0,24	0,30	0,55	0,29	0,28
C3: Security	0,36	1,00	0,27	0,42	0,91	0,33	0,50	0,89	0,40	0,46	0,99	0,30	0,43	0,99	0,33	0,25	1,00	0,20	0,56	0,89	0,34	0,49	0,99	0,34
C4: Strategic Fit	0,27	0,99	0,23	0,46	0,91	0,30	0,52	0,90	0,30	0,50	0,89	0,40	0,43	0,99	0,33	0,43	0,99	0,33	0,62	0,88	0,30	0,53	0,89	0,37
C5: Operational Flexibility	0,43	0,99	0,33	0,53	0,89	0,37	0,56	0,89	0,34	0,56	0,89	0,34	0,50	0,89	0,40	0,46	0,99	0,37	0,66	0,88	0,26	0,56	0,89	0,34
C6: Management Support	0,49	0,89	0,34	0,61	0,42	0,34	0,68	0,40	0,27	0,56	0,88	0,34	0,53	0,88	0,37	0,50	0,88	0,40	0,79	0,36	0,19	0,63	0,88	0,27
C7: Environmental Impact	0,18	1,00	0,11	0,27	0,94	0,23	0,43	0,91	0,33	0,34	0,99	0,26	0,32	0,99	0,23	0,16	1,00	0,12	0,50	0,89	0,40	0,43	0,99	0,33
C8: Regulatory Compliance	0,25	0,99	0,20	0,41	0,92	0,27	0,49	0,90	0,34	0,46	0,90	0,36	0,43	0,91	0,33	0,36	0,99	0,27	0,56	0,89	0,34	0,50	0,89	0,40

Table A2: Spherical Fuzzy Set Correspondences of DM 1 Evaluation of Alternatives

	$C_{1.1}$	$C_{1.2}$	$C_{1.3}$	$C_{1.4}$	$C_{2.1}$	$C_{2.2}$	$C_{2.3}$	$C_{3.1}$	$C_{3.2}$	$C_{3.3}$	$C_{3.4}$
A_1	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.7, 0.3, 0.2)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)
A_2	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.7, 0.3, 0.2)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)
A_3	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.8, 0.2, 0.1)	(0.8, 0.2, 0.1)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)
A_4	(0.2, 0.8, 0.1)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.8, 0.2, 0.1)	(0.8, 0.2, 0.1)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)
A_5	(0.8, 0.2, 0.1)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.8, 0.2, 0.1)	(0.8, 0.2, 0.1)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)
A_6	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.8, 0.2, 0.1)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)
A_7	(0.7, 0.3, 0.2)	(0.7, 0.3, 0.2)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.7, 0.3, 0.2)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)
A_8	(0.5, 0.5, 0.4)	(0.6, 0.4, 0.3)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.7, 0.3, 0.2)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.4, 0.6, 0.3)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)
A_9	(0.4, 0.6, 0.3)	(0.5, 0.5, 0.4)	(0.7, 0.3, 0.2)	(0.3, 0.7, 0.2)	(0.7, 0.3, 0.2)	(0.6, 0.4, 0.3)	(0.7, 0.3, 0.2)	(0.5, 0.5, 0.4)	(0.7, 0.3, 0.2)	(0.7, 0.3, 0.2)	(0.8, 0.2, 0.1)

$C_{4.1}$	$C_{4.2}$	$C_{4.3}$	$C_{5.1}$	$C_{5.2}$	$C_{6.1}$	$C_{6.2}$	$C_{7.1}$	$C_{7.2}$	$C_{8.1}$	$C_{8.2}$
(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.8, 0.2, 0.1)	(0.8, 0.2, 0.1)	(0.8, 0.2, 0.1)	(0.7, 0.3, 0.2)	(0.8, 0.2, 0.1)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)
(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.8, 0.2, 0.1)	(0.8, 0.2, 0.1)	(0.2, 0.8, 0.1)	(0.2, 0.8, 0.1)	(0.7, 0.3, 0.2)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)
(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.8, 0.2, 0.1)	(0.9, 0.1, 0.0)	(0.5, 0.5, 0.4)	(0.5, 0.5, 0.4)	(0.9, 0.1, 0.0)	(0.7, 0.3, 0.2)	(0.5, 0.5, 0.4)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)
(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.7, 0.3, 0.2)	(0.9, 0.1, 0.0)	(0.5, 0.5, 0.4)	(0.5, 0.5, 0.4)	(0.9, 0.1, 0.0)	(0.7, 0.3, 0.2)	(0.1, 0.9, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)
(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.5, 0.5, 0.4)	(0.5, 0.5, 0.4)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.1, 0.9, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)
(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.5, 0.5, 0.4)	(0.2, 0.8, 0.1)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)
(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.7, 0.3, 0.2)	(0.9, 0.1, 0.0)	(0.5, 0.5, 0.4)	(0.2, 0.8, 0.1)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.3, 0.7, 0.2)	(0.9, 0.1, 0.0)	(0.7, 0.3, 0.2)
(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.6, 0.4, 0.3)	(0.9, 0.1, 0.0)	(0.3, 0.7, 0.2)	(0.2, 0.8, 0.1)	(0.9, 0.1, 0.0)	(0.6, 0.4, 0.3)	(0.7, 0.3, 0.2)	(0.7, 0.3, 0.2)	(0.9, 0.1, 0.0)
(0.6, 0.4, 0.3)	(0.7, 0.3, 0.2)	(0.5, 0.5, 0.4)	(0.2, 0.8, 0.1)	(0.3, 0.7, 0.2)	(0.2, 0.8, 0.1)	(0.4, 0.6, 0.3)	(0.9, 0.1, 0.0)	(0.8, 0.2, 0.1)	(0.9, 0.1, 0.0)	(0.6, 0.4, 0.3)

Table A3: Spherical Fuzzy Set Correspondences of DM 2 Evaluation of Alternatives

	$C_{1.1}$	$C_{1.2}$	$C_{1.3}$	$C_{1.4}$	$C_{2.1}$	$C_{2.2}$	$C_{2.3}$	$C_{3.1}$	$C_{3.2}$	$C_{3.3}$	$C_{3.4}$
A_1	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.6, 0.4, 0.3)	(0.9, 0.1, 0.0)	(0.8, 0.2, 0.1)	(0.6, 0.4, 0.3)	(0.9, 0.1, 0.0)	(0.5, 0.5, 0.4)	(0.6, 0.4, 0.3)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)
A_2	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.7, 0.3, 0.2)	(0.9, 0.1, 0.0)	(0.1, 0.9, 0.0)	(0.6, 0.4, 0.3)	(0.9, 0.1, 0.0)	(0.4, 0.6, 0.3)	(0.7, 0.3, 0.2)	(0.9, 0.1, 0.0)	(0.4, 0.6, 0.3)
A_3	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.8, 0.2, 0.1)	(0.8, 0.2, 0.1)	(0.5, 0.5, 0.4)	(0.7, 0.3, 0.2)	(0.9, 0.1, 0.0)	(0.6, 0.4, 0.3)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)
A_4	(0.6, 0.4, 0.3)	(0.3, 0.7, 0.2)	(0.7, 0.3, 0.2)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.8, 0.2, 0.1)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)
A_5	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.8, 0.2, 0.1)	(0.9, 0.1, 0.0)	(0.3, 0.7, 0.2)	(0.8, 0.2, 0.1)	(0.9, 0.1, 0.0)	(0.5, 0.5, 0.4)	(0.5, 0.5, 0.4)	(0.5, 0.5, 0.4)	(0.7, 0.3, 0.2)
A_6	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.8, 0.2, 0.1)	(0.9, 0.1, 0.0)	(0.1, 0.9, 0.0)	(0.4, 0.6, 0.3)	(0.6, 0.4, 0.3)	(0.7, 0.3, 0.2)	(0.7, 0.3, 0.2)	(0.9, 0.1, 0.0)	(0.6, 0.4, 0.3)
A_7	(0.7, 0.3, 0.2)	(0.6, 0.4, 0.3)	(0.7, 0.3, 0.2)	(0.9, 0.1, 0.0)	(0.3, 0.7, 0.2)	(0.4, 0.6, 0.3)	(0.9, 0.1, 0.0)	(0.5, 0.5, 0.4)	(0.6, 0.4, 0.3)	(0.6, 0.4, 0.3)	(0.6, 0.4, 0.3)
A_8	(0.6, 0.4, 0.3)	(0.6, 0.4, 0.3)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.7, 0.3, 0.2)	(0.7, 0.3, 0.2)	(0.9, 0.1, 0.0)	(0.3, 0.7, 0.2)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)
A_9	(0.3, 0.7, 0.2)	(0.6, 0.4, 0.3)	(0.7, 0.3, 0.2)	(0.6, 0.4, 0.3)	(0.6, 0.4, 0.3)	(0.6, 0.4, 0.3)	(0.5, 0.5, 0.4)	(0.7, 0.3, 0.2)	(0.7, 0.3, 0.2)	(0.7, 0.3, 0.2)	(0.6, 0.4, 0.3)

$C_{4.1}$	$C_{4.2}$	$C_{4.3}$	$C_{5.1}$	$C_{5.2}$	$C_{6.1}$	$C_{6.2}$	$C_{7.1}$	$C_{7.2}$	$C_{8.1}$	$C_{8.2}$
(0.8, 0.2, 0.1)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.7, 0.3, 0.2)	(0.5, 0.5, 0.4)	(0.8, 0.2, 0.1)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)
(0.7, 0.3, 0.2)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.6, 0.4, 0.3)	(0.1, 0.9, 0.0)	(0.2, 0.8, 0.1)	(0.3, 0.7, 0.2)	(0.3, 0.7, 0.2)	(0.7, 0.3, 0.2)	(0.7, 0.3, 0.2)	(0.8, 0.2, 0.1)
(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.6, 0.4, 0.3)	(0.3, 0.7, 0.2)	(0.4, 0.6, 0.3)	(0.3, 0.7, 0.2)	(0.8, 0.2, 0.1)	(0.7, 0.3, 0.2)	(0.6, 0.4, 0.3)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)
(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.5, 0.5, 0.4)	(0.9, 0.1, 0.0)	(0.6, 0.4, 0.3)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.1, 0.9, 0.0)
(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.6, 0.4, 0.3)	(0.3, 0.7, 0.2)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.5, 0.5, 0.4)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)
(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.8, 0.2, 0.1)	(0.4, 0.6, 0.3)	(0.4, 0.6, 0.3)	(0.3, 0.7, 0.2)	(0.9, 0.1, 0.0)	(0.6, 0.4, 0.3)	(0.8, 0.2, 0.1)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)
(0.4, 0.6, 0.3)	(0.7, 0.3, 0.2)	(0.6, 0.4, 0.3)	(0.2, 0.8, 0.1)	(0.1, 0.9, 0.0)	(0.3, 0.7, 0.2)	(0.7, 0.3, 0.2)	(0.3, 0.7, 0.2)	(0.4, 0.6, 0.3)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)
(0.4, 0.6, 0.3)	(0.8, 0.2, 0.1)	(0.9, 0.1, 0.0)	(0.3, 0.7, 0.2)	(0.3, 0.7, 0.2)	(0.3, 0.7, 0.2)	(0.1, 0.9, 0.0)	(0.3, 0.7, 0.2)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)
(0.4, 0.6, 0.3)	(0.6, 0.4, 0.3)	(0.6, 0.4, 0.3)	(0.2, 0.8, 0.1)	(0.4, 0.6, 0.3)	(0.6, 0.4, 0.3)	(0.2, 0.8, 0.1)	(0.6, 0.4, 0.3)	(0.6, 0.4, 0.3)	(0.7, 0.3, 0.2)	(0.1, 0.9, 0.0)

Table A4: Spherical Fuzzy Set Correspondences of DM 3 Evaluation of Alternatives

	$C_{1.1}$	$C_{1.2}$	$C_{1.3}$	$C_{1.4}$	$C_{2.1}$	$C_{2.2}$	$C_{2.3}$	$C_{3.1}$	$C_{3.2}$	$C_{3.3}$	$C_{3.4}$
A_1	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.6, 0.4, 0.3)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.5, 0.5, 0.4)	(0.5, 0.5, 0.4)	(0.6, 0.4, 0.3)	(0.9, 0.1, 0.0)
A_2	(0.3, 0.7, 0.2)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.7, 0.3, 0.2)	(0.9, 0.1, 0.0)	(0.5, 0.5, 0.4)	(0.9, 0.1, 0.0)	(0.5, 0.5, 0.4)	(0.5, 0.5, 0.4)	(0.3, 0.7, 0.2)	(0.9, 0.1, 0.0)
A_3	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.3, 0.7, 0.2)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)
A_4	(0.5, 0.5, 0.4)	(0.7, 0.3, 0.2)	(0.9, 0.1, 0.0)	(0.3, 0.7, 0.2)	(0.7, 0.3, 0.2)	(0.7, 0.3, 0.2)	(0.7, 0.3, 0.2)	(0.3, 0.7, 0.2)	(0.1, 0.9, 0.0)	(0.5, 0.5, 0.4)	(0.5, 0.5, 0.4)
A_5	(0.7, 0.3, 0.2)	(0.7, 0.3, 0.2)	(0.9, 0.1, 0.0)	(0.3, 0.7, 0.2)	(0.9, 0.1, 0.0)	(0.6, 0.4, 0.3)	(0.7, 0.3, 0.2)	(0.3, 0.7, 0.2)	(0.9, 0.1, 0.0)	(0.3, 0.7, 0.2)	(0.7, 0.3, 0.2)
A_6	(0.9, 0.1, 0.0)	(0.7, 0.3, 0.2)	(0.9, 0.1, 0.0)	(0.7, 0.3, 0.2)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.7, 0.3, 0.2)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)
A_7	(0.7, 0.3, 0.2)	(0.7, 0.3, 0.2)	(0.9, 0.1, 0.0)	(0.5, 0.5, 0.4)	(0.9, 0.1, 0.0)	(0.7, 0.3, 0.2)	(0.7, 0.3, 0.2)	(0.5, 0.5, 0.4)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.7, 0.3, 0.2)
A_8	(0.3, 0.7, 0.2)	(0.3, 0.7, 0.2)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.1, 0.9, 0.0)	(0.2, 0.8, 0.1)	(0.9, 0.1, 0.0)	(0.1, 0.9, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)
A_9	(0.7, 0.3, 0.2)	(0.5, 0.5, 0.4)	(0.5, 0.5, 0.4)	(0.5, 0.5, 0.4)	(0.3, 0.7, 0.2)	(0.5, 0.5, 0.4)	(0.5, 0.5, 0.4)	(0.1, 0.9, 0.0)	(0.5, 0.5, 0.4)	(0.3, 0.7, 0.2)	(0.6, 0.4, 0.3)

$C_{4.1}$	$C_{4.2}$	$C_{4.3}$	$C_{5.1}$	$C_{5.2}$	$C_{6.1}$	$C_{6.2}$	$C_{7.1}$	$C_{7.2}$	$C_{8.1}$	$C_{8.2}$
(0.7, 0.3, 0.2)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.6, 0.4, 0.3)	(0.3, 0.7, 0.2)	(0.7, 0.3, 0.2)	(0.9, 0.1, 0.0)	(0.5, 0.5, 0.4)	(0.6, 0.4, 0.3)	(0.6, 0.4, 0.3)	(0.9, 0.1, 0.0)
(0.7, 0.3, 0.2)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.6, 0.4, 0.3)	(0.1, 0.9, 0.0)	(0.3, 0.7, 0.2)	(0.3, 0.7, 0.2)	(0.5, 0.5, 0.4)	(0.7, 0.3, 0.2)	(0.6, 0.4, 0.3)	(0.5, 0.5, 0.4)
(0.9, 0.1, 0.0)	(0.6, 0.4, 0.3)	(0.6, 0.4, 0.3)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.1, 0.9, 0.0)	(0.9, 0.1, 0.0)	(0.3, 0.7, 0.2)	(0.3, 0.7, 0.2)	(0.9, 0.1, 0.0)	(0.5, 0.5, 0.4)
(0.5, 0.5, 0.4)	(0.9, 0.1, 0.0)	(0.5, 0.5, 0.4)	(0.5, 0.5, 0.4)	(0.3, 0.7, 0.2)	(0.1, 0.9, 0.0)	(0.9, 0.1, 0.0)	(0.3, 0.7, 0.2)	(0.3, 0.7, 0.2)	(0.9, 0.1, 0.0)	(0.3, 0.7, 0.2)
(0.7, 0.3, 0.2)	(0.5, 0.5, 0.4)	(0.9, 0.1, 0.0)	(0.7, 0.3, 0.2)	(0.1, 0.9, 0.0)	(0.5, 0.5, 0.4)	(0.5, 0.5, 0.4)	(0.9, 0.1, 0.0)	(0.7, 0.3, 0.2)	(0.5, 0.5, 0.4)	(0.3, 0.7, 0.2)
(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.3, 0.7, 0.2)	(0.9, 0.1, 0.0)	(0.7, 0.3, 0.2)	(0.1, 0.9, 0.0)	(0.9, 0.1, 0.0)	(0.1, 0.9, 0.0)	(0.3, 0.7, 0.2)	(0.9, 0.1, 0.0)	(0.3, 0.7, 0.2)
(0.6, 0.4, 0.3)	(0.9, 0.1, 0.0)	(0.2, 0.8, 0.1)	(0.7, 0.3, 0.2)	(0.5, 0.5, 0.4)	(0.3, 0.7, 0.2)	(0.7, 0.3, 0.2)	(0.3, 0.7, 0.2)	(0.1, 0.9, 0.0)	(0.7, 0.3, 0.2)	(0.3, 0.7, 0.2)
(0.6, 0.4, 0.3)	(0.3, 0.7, 0.2)	(0.1, 0.9, 0.0)	(0.9, 0.1, 0.0)	(0.9, 0.1, 0.0)	(0.1, 0.9, 0.0)	(0.7, 0.3, 0.2)	(0.3, 0.7, 0.2)	(0.1, 0.9, 0.0)	(0.1, 0.9, 0.0)	(0.9, 0.1, 0.0)
(0.5, 0.5, 0.4)	(0.5, 0.5, 0.4)	(0.3, 0.7, 0.2)	(0.4, 0.6, 0.3)	(0.5, 0.5, 0.4)	(0.3, 0.7, 0.2)	(0.5, 0.5, 0.4)	(0.3, 0.7, 0.2)	(0.3, 0.7, 0.2)	(0.3, 0.7, 0.2)	(0.3, 0.7, 0.2)

Table A5: Expert Opinions Combined with SWAM

	$C_{1.1}$			$C_{1.2}$			$C_{1.3}$			$C_{1.4}$			$C_{2.1}$			$C_{2.2}$			$C_{2.3}$			$C_{3.1}$			$C_{3.2}$			$C_{3.3}$			$C_{3.4}$		
	μ	v	π	μ	v	π	μ	v	π	μ	v	π	μ	v	π	μ	v	π	μ	v	π	μ	v	π	μ	v	π	μ	v	π	μ	v	π
A_1	0,90	0,10	0,00	0,90	0,10	0,00	0,85	0,16	0,12	0,85	0,16	0,12	0,87	0,13	0,05	0,85	0,16	0,12	0,90	0,10	0,00	0,58	0,36	0,34	0,74	0,25	0,23	0,85	0,16	0,12	0,90	0,10	0,00
A_2	0,82	0,19	0,07	0,90	0,10	0,00	0,86	0,14	0,08	0,86	0,14	0,08	0,82	0,21	0,00	0,74	0,25	0,23	0,90	0,10	0,00	0,56	0,42	0,30	0,76	0,23	0,21	0,82	0,19	0,07	0,83	0,18	0,11
A_3	0,90	0,10	0,00	0,90	0,10	0,00	0,87	0,13	0,05	0,87	0,13	0,05	0,84	0,16	0,15	0,86	0,14	0,08	0,90	0,10	0,00	0,64	0,38	0,21	0,87	0,13	0,05	0,90	0,10	0,00	0,90	0,10	0,00
A_4	0,48	0,50	0,31	0,74	0,28	0,14	0,86	0,14	0,08	0,82	0,19	0,07	0,86	0,14	0,08	0,86	0,14	0,08	0,86	0,14	0,08	0,78	0,24	0,10	0,70	0,33	0,10	0,84	0,16	0,15	0,84	0,16	0,15
A_5	0,82	0,18	0,11	0,86	0,14	0,08	0,87	0,13	0,05	0,82	0,19	0,07	0,82	0,19	0,07	0,80	0,20	0,14	0,86	0,14	0,08	0,61	0,38	0,25	0,79	0,20	0,18	0,70	0,30	0,21	0,80	0,21	0,14
A_6	0,90	0,10	0,00	0,86	0,14	0,08	0,87	0,13	0,05	0,86	0,14	0,08	0,82	0,21	0,00	0,83	0,18	0,11	0,85	0,16	0,12	0,74	0,26	0,17	0,86	0,14	0,08	0,90	0,10	0,00	0,85	0,16	0,12
A_7	0,70	0,30	0,20	0,67	0,33	0,23	0,86	0,14	0,08	0,84	0,16	0,15	0,82	0,19	0,07	0,75	0,26	0,17	0,86	0,14	0,08	0,58	0,36	0,34	0,85	0,16	0,12	0,85	0,16	0,12	0,78	0,23	0,17
A_8	0,49	0,48	0,32	0,53	0,48	0,28	0,90	0,10	0,00	0,90	0,10	0,00	0,60	0,43	0,18	0,74	0,29	0,12	0,90	0,10	0,00	0,30	0,72	0,22	0,90	0,10	0,00	0,90	0,10	0,00	0,90	0,10	0,00
A_9	0,52	0,50	0,24	0,54	0,40	0,37	0,65	0,33	0,27	0,49	0,48	0,32	0,58	0,44	0,24	0,57	0,40	0,33	0,58	0,36	0,34	0,53	0,48	0,27	0,65	0,33	0,27	0,62	0,40	0,20	0,69	0,32	0,24

$C_{4.1}$			$C_{4.2}$			$C_{4.3}$			$C_{5.1}$			$C_{5.2}$			$C_{6.1}$			$C_{6.2}$			$C_{7.1}$			$C_{7.2}$			$C_{8.1}$			$C_{8.2}$		
μ	v	π	μ	v	π	μ	v	π	μ	v	π	μ	v	π	μ	v	π	μ	v	π	μ	v	π	μ	v	π	μ	v	π	μ	v	π
0,82	0,18	0,11	0,90	0,10	0,00	0,87	0,13	0,05	0,71	0,29	0,20	0,61	0,38	0,25	0,74	0,26	0,17	0,87	0,13	0,05	0,84	0,16	0,15	0,85	0,16	0,12	0,85	0,16	0,12	0,90	0,10	0,00
0,80	0,21	0,14	0,90	0,10	0,00	0,87	0,13	0,05	0,69	0,32	0,24	0,14	0,87	0,06	0,24	0,77	0,14	0,50	0,53	0,20	0,70	0,30	0,21	0,80	0,21	0,14	0,78	0,23	0,17	0,79	0,20	0,18
0,90	0,10	0,00	0,85	0,16	0,12	0,69	0,32	0,24	0,82	0,19	0,07	0,71	0,29	0,23	0,35	0,63	0,28	0,87	0,13	0,05	0,62	0,40	0,20	0,49	0,48	0,32	0,90	0,10	0,00	0,84	0,16	0,15
0,84	0,16	0,15	0,90	0,10	0,00	0,76	0,23	0,21	0,84	0,16	0,15	0,45	0,48	0,36	0,69	0,33	0,20	0,85	0,16	0,12	0,74	0,28	0,14	0,67	0,40	0,09	0,90	0,10	0,00	0,67	0,40	0,09
0,86	0,14	0,08	0,84	0,16	0,15	0,90	0,10	0,00	0,86	0,14	0,08	0,47	0,52	0,31	0,45	0,48	0,36	0,84	0,16	0,15	0,90	0,10	0,00	0,53	0,48	0,27	0,84	0,16	0,15	0,82	0,19	0,07
0,90	0,10	0,00	0,90	0,10	0,00	0,78	0,24	0,10	0,83	0,18	0,11	0,56	0,42	0,30	0,22	0,80	0,13	0,90	0,10	0,00	0,71	0,33	0,16	0,78	0,24	0,10	0,90	0,10	0,00	0,82	0,19	0,07
0,73	0,29	0,20	0,86	0,14	0,08	0,57	0,46	0,23	0,74	0,29	0,12	0,42	0,52	0,35	0,27	0,73	0,17	0,80	0,21	0,14	0,68	0,37	0,13	0,30	0,72	0,22	0,86	0,14	0,08	0,74	0,28	0,14
0,73	0,29	0,20	0,78	0,24	0,10	0,71	0,33	0,16	0,82	0,19	0,07	0,68	0,37	0,13	0,22	0,80	0,13	0,74	0,30	0,11	0,44	0,58	0,25	0,74	0,30	0,11	0,74	0,30	0,11	0,90	0,10	0,00
0,51	0,46	0,34	0,61	0,36	0,30	0,49	0,48	0,32	0,29	0,73	0,20	0,41	0,55	0,32	0,42	0,61	0,23	0,39	0,58	0,31	0,72	0,30	0,17	0,64	0,38	0,21	0,74	0,28	0,14	0,41	0,63	0,23

Table A6: Combined Matrix with Weights of Criteria Dependent on SWAM Operator

	$C_{1.1}$			$C_{1.2}$			$C_{1.3}$			$C_{1.4}$			$C_{2.1}$			$C_{2.2}$			$C_{2.3}$			$C_{3.1}$			$C_{3.2}$			$C_{3.3}$			$C_{3.4}$		
	μ	v	π	μ	v	π	μ	v	π	μ	v	π	μ	v	π	μ	v	π	μ	v	π	μ	v	π	μ	v	π	μ	v	π	μ	v	π
A_1	0,53	0,39	0,00	0,45	0,48	0,00	0,44	0,47	0,34	0,34	0,58	0,34	0,39	0,50	0,20	0,54	0,37	0,34	0,42	0,47	0,00	0,36	0,49	0,61	0,36	0,53	0,49	0,46	0,45	0,34	0,36	0,57	0,00
A_2	0,49	0,42	0,25	0,45	0,48	0,00	0,45	0,47	0,28	0,35	0,58	0,28	0,36	0,52	0,00	0,47	0,41	0,49	0,42	0,47	0,00	0,34	0,53	0,58	0,37	0,52	0,46	0,45	0,46	0,25	0,33	0,58	0,32
A_3	0,53	0,39	0,00	0,45	0,48	0,00	0,45	0,47	0,20	0,36	0,58	0,20	0,37	0,50	0,38	0,55	0,36	0,28	0,42	0,47	0,00	0,39	0,51	0,46	0,43	0,50	0,20	0,49	0,44	0,00	0,36	0,57	0,00
A_4	0,28	0,60	0,58	0,38	0,53	0,36	0,45	0,47	0,28	0,34	0,59	0,25	0,38	0,50	0,28	0,55	0,36	0,28	0,40	0,48	0,28	0,48	0,42	0,30	0,34	0,56	0,30	0,45	0,45	0,38	0,34	0,58	0,38
A_5	0,48	0,41	0,32	0,43	0,48	0,28	0,45	0,47	0,20	0,34	0,59	0,25	0,36	0,51	0,25	0,51	0,39	0,37	0,40	0,48	0,28	0,37	0,51	0,51	0,39	0,51	0,42	0,38	0,51	0,47	0,32	0,59	0,37
A_6	0,53	0,39	0,00	0,43	0,48	0,28	0,45	0,47	0,20	0,35	0,58	0,28	0,36	0,52	0,00	0,53	0,38	0,32	0,39	0,48	0,34	0,45	0,43	0,41	0,42	0,50	0,28	0,49	0,44	0,00	0,34	0,58	0,34
A_7	0,41	0,47	0,45	0,34	0,55	0,49	0,45	0,47	0,28	0,34	0,58	0,38	0,36	0,51	0,25	0,48	0,42	0,40	0,40	0,48	0,28	0,36	0,49	0,61	0,41	0,50	0,34	0,46	0,45	0,34	0,31	0,59	0,41
A_8	0,29	0,58	0,59	0,27	0,63	0,55	0,47	0,46	0,00	0,37	0,57	0,00	0,27	0,61	0,43	0,47	0,43	0,33	0,42	0,47	0,00	0,18	0,76	0,47	0,44	0,49	0,00	0,49	0,44	0,00	0,36	0,57	0,00
A_9	0,31	0,60	0,50	0,27	0,59	0,65	0,34	0,54	0,54	0,20	0,69	0,59	0,25	0,62	0,50	0,36	0,51	0,61	0,27	0,56	0,61	0,32	0,57	0,54	0,32	0,56	0,54	0,33	0,56	0,45	0,28	0,62	0,49

$C_{4.1}$			$C_{4.2}$			$C_{4.3}$			$C_{5.1}$			$C_{5.2}$			$C_{6.1}$			$C_{6.2}$			$C_{7.1}$			$C_{7.2}$			$C_{8.1}$			$C_{8.2}$		
μ	v	π	μ	v	π	μ	v	π	μ	v	π	μ	v	π	μ	v	π	μ	v	π	μ	v	π	μ	v	π	μ	v	π	μ	v	π
0,36	0,51	0,32	0,57	0,35	0,00	0,40	0,47	0,20	0,32	0,54	0,45	0,34	0,52	0,51	0,31	0,57	0,41	0,54	0,36	0,20	0,38	0,50	0,38	0,47	0,42	0,34	0,49	0,39	0,34	0,37	0,54	0,00
0,35	0,52	0,37	0,57	0,35	0,00	0,40	0,47	0,20	0,31	0,56	0,49	0,08	0,89	0,23	0,10	0,84	0,37	0,31	0,60	0,45	0,41	0,47	0,47	0,44	0,44	0,37	0,45	0,42	0,41	0,32	0,56	0,42
0,40	0,49	0,00	0,54	0,37	0,34	0,32	0,54	0,49	0,37	0,51	0,25	0,39	0,46	0,49	0,15	0,75	0,55	0,54	0,36	0,20	0,36	0,53	0,45	0,27	0,59	0,59	0,52	0,37	0,00	0,34	0,55	0,38
0,37	0,50	0,38	0,57	0,35	0,00	0,35	0,50	0,46	0,38	0,50	0,38	0,25	0,59	0,64	0,29	0,59	0,45	0,52	0,37	0,34	0,44	0,46	0,36	0,37	0,54	0,29	0,52	0,37	0,00	0,27	0,63	0,29
0,38	0,50	0,28	0,53	0,37	0,38	0,41	0,47	0,00	0,39	0,50	0,28	0,26	0,62	0,58	0,19	0,66	0,64	0,52	0,37	0,38	0,53	0,39	0,00	0,29	0,59	0,54	0,49	0,39	0,38	0,34	0,56	0,25
0,40	0,49	0,00	0,57	0,35	0,00	0,36	0,51	0,30	0,37	0,51	0,32	0,31	0,54	0,58	0,09	0,86	0,36	0,56	0,35	0,00	0,42	0,49	0,39	0,43	0,45	0,30	0,52	0,37	0,00	0,34	0,56	0,25
0,32	0,55	0,45	0,55	0,36	0,28	0,26	0,61	0,49	0,33	0,54	0,33	0,23	0,62	0,63	0,11	0,81	0,42	0,49	0,39	0,37	0,40	0,51	0,35	0,17	0,77	0,47	0,50	0,38	0,28	0,30	0,58	0,36
0,32	0,55	0,45	0,50	0,41	0,30	0,33	0,55	0,39	0,37	0,51	0,25	0,37	0,51	0,35	0,09	0,86	0,36	0,45	0,44	0,32	0,26	0,66	0,51	0,41	0,48	0,32	0,43	0,46	0,32	0,37	0,54	0,00
0,23	0,63	0,61	0,39	0,48	0,57	0,23	0,63	0,59	0,13	0,80	0,45	0,23	0,64	0,59	0,18	0,74	0,49	0,24	0,64	0,58	0,43	0,47	0,42	0,35	0,53	0,46	0,43	0,44	0,36	0,17	0,76	0,49

BIOGRAPHICAL SKETCH

Elif Can Edge KURTUL received a Bachelor’s degree in Automotive Engineering from Karabuk University. Following graduation, seven years of professional experience were acquired in the automotive industry, in roles including Methods Engineering, Project Engineering, and Digital Transformation Engineering. These roles involved process optimization, project management, and the implementation of digital manufacturing solutions.

Currently, the candidate is employed at the IHKIB Digital Transformation Center as a Digital Process Development Engineer. In this capacity, efforts are focused on supporting textile and apparel companies in adopting lean methodologies and digital tools to improve operational efficiency and enable sustainable transformation.

The candidate’s interdisciplinary experience across engineering, digitalization, and industrial transformation provides a strong foundation for research in smart manufacturing and technology-driven improvement strategies.