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Ranking of Criteria Affecting the Implementation Readiness of Internet of Things in Industries Using TISM and Fuzzy TOPSIS Analysis

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ABSTRACT

The Internet of Things (IoT) technology has emerged as a vital driver across various fields, engaging businesses, platforms, and industries. IoT involves a holistic ecosystem and a value chain that necessitates the evaluation of impactful dimensions for successful implementation. This research employs the TISM method to identify driver and dependent criteria regarding IoT implementation readiness and uses the fuzzy TOPSIS method to rank these criteria. In the initial step, 15 criteria were identified through a review of previous studies. The TISM results reveal five levels reflecting the driver power and dependence of the criteria. Based on these results, “Implementation Knowledge and Expertise (C2)”, “Technical and Infrastructural Readiness (C9)” and “Financial and Investment Readiness (C12)” were placed at level 5, marking them as the most driver criteria. Additionally, “Implementation Roadmap (C8)” was identified as the most dependent criterion at level one. According to the fuzzy TOPSIS results, “Senior Management Support (C6)”, “IoT Usage Culture (C1)”, “Business Model Development Capability (C15)”, “Financial and Investment Readiness (C12)” and “Technical and Infrastructural Readiness (C9)” ranked first to fifth, respectively. The combined results provide valuable insights for decision-makers and stakeholders involved in IoT implementation. By determining driver and dependent levels and ranking the criteria, industries can effectively prepare for the successful implementation of IoT.

1. Introduction

The Internet of Things (IoT) has recently garnered substantial attention, often referred to as the fourth industrial revolution. IoT is more than just a technology; it’s a concept centered on creating

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interconnections among various objects [1]. Recognized as a disruptive innovation, IoT is expanding swiftly, serving as a widely adopted technological platform, particularly within networks of diverse intelligent devices, autonomous vehicles, IoT-based automation, robots, and other connected devices [2,3]. The IoT ecosystem has seen rapid growth, with expectations for further significant surges. For instance, CISCO predicts that by 2030, 500 billion IoT devices will be internet-connected [4], and the IoT market cap is projected to reach 771 billion USD by 2026 [5]. IoT applications are associated with pervasive systems that offer small and medium enterprises (SMEs) the chance to transition into digital businesses. Through the analysis of collected data, these enterprises can make well-informed decisions that affect their business models, thereby boosting their competitiveness [6]. By utilizing IoT solutions, companies can collect data to support decision-making, customize their products or services, strengthen customer relationships, and compete in both local and global markets through innovation and technological progress [7].

The Industrial Internet of Things (IIoT) is one of the most widely adopted smart technologies among manufacturers. IIoT refers to the application of IoT technology within manufacturing processes and is expected to influence future integration and optimization of information technology (IT). The rise of IIoT technology is affecting all industries, affecting both large corporations and small to medium enterprises in ways that are becoming increasingly unavoidable. Manufacturing companies are guided by various strategies across different technologies [8]. Additionally, IIoT offers a dynamic platform that enables real-time interactions between stakeholders [9].

Leveraging data from IIoT systems provides decision-makers with critical insights that aid in creating and delivering value, virtualizing supply chains, enhancing customer engagement, and promoting efficient policies and practices [3,10]. IIoT enables continuous data collection, analysis, and seamless sharing across production and supply chain processes [11,12]. This data-driven approach not only enhances customer value but also transforms supply chains into adaptable, data-centric ecosystems that can meet shifting market demands [13-15]. Additionally, insights from IIoT data enable companies to build stronger customer relationships by customizing products and services according to changing preferences, fostering sustainable growth and competitive edge [3], [10,16,17]. The widespread adoption of IIoT technology has an extensive impact across all sectors, influencing both large corporations and small and medium-sized enterprises (SMEs) [13,18,19]. IIoT has the potential to benefit a variety of sectors, including supply chains across different industries. With IIoT, companies can reduce uncertainty and increase profits. Traditionally, supply chains are valued for their product-tracking capabilities, and now the industry aims to outperform competitors by integrating advanced IoT technology [13]. In today’s environment, industry stakeholders are increasingly aware of the numerous benefits that IIoT brings to supply chain processes, driving proactive readiness for its adoption [2,20,21].

Implementing IIoT in supply chains and operations offers benefits such as reduced risks and costs, improved transparency, visibility, flexibility, smoother operations, and virtualization [10,22]. The main goal of IIoT adoption is to enhance productivity, operational efficiency, and the management of manufacturing processes and assets through product customization, smart inspections, and predictive maintenance. IIoT leverages technologies like cloud computing, machine-to-machine communication, machine learning, artificial intelligence, and distributed computing. This shift not only transforms manufacturing but also creates new corporate opportunities [8]. However, the high costs, complexity, and risks of IIoT adoption necessitate a thorough readiness assessment before implementation [9,23].

Technology readiness is defined as the inclination of individuals to accept and use new technologies to achieve their objectives [24-26]. Successfully deploying IIoT solutions requires assessing readiness in three key areas: technology, organizational structure, and workforce competency. Evaluating current technology capabilities, organizational effectiveness, and workforce skills is essential for ensuring readiness for IIoT advancements, which is vital for sustainable implementation [27].

According to the aforementioned points, assessing the readiness of an organization to deploy industrial Internet of Things (IIoT) technology is imperative for the success of such initiatives. The objective of this study is to systematically identify and prioritize the various criteria that significantly impact the readiness of industries for effective IIoT implementation. Utilizing a combination of the Total Interpretive Structural Modeling (TISM) approach alongside fuzzy Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) analysis, this research aims to provide a comprehensive understanding of the elements that play a crucial role in determining IIoT readiness. By illuminating the criteria that most profoundly influence an organization's readiness to adopt IIoT technologies, this study offers essential insights that will benefit not only industry stakeholders but also researchers in the field. Additionally, the findings will equip organizations with a structured methodology that enables them to evaluate their current position regarding IIoT adoption and identify areas for improvement. Ultimately, this research is vital for formulating effective strategies that facilitate the adoption of IIoT solutions, which are essential for fostering sustainable growth and driving technological advancements within industrial ecosystems.

2. Literature Review

The rapid evolution of the Internet of Things (IoT) and its application in industrial settings, known as the Industrial Internet of Things (IIoT), has attracted significant scholarly attention in recent years. In various fields such as supply chain management [28,29], banking and financial markets [30-33], urban management [34], and educational administration [35], leveraging digital technologies like the Internet of Things (IoT) and artificial intelligence (AI) is increasingly essential for enhancing productivity and improving competitiveness.

Numerous studies have been conducted to explore various dimensions of IoT readiness and its implications for implementation across different sectors, particularly in manufacturing and supply chain management. These studies highlight the critical importance of understanding and addressing the challenges associated with IIoT adoption. In this section, we will review the most significant research efforts in this field, examining key findings and methodologies utilized to assess IoT and IIoT readiness. Furthermore, we will identify existing gaps in the literature, emphasizing the need for further exploration into specific dimensions that influence successful implementation. This comprehensive literature review aims to provide a foundational understanding of the current state of research on IIoT readiness and underscore the importance of developing effective strategies for its adoption, particularly for small and medium-sized enterprises (SMEs) striving to remain competitive in a digitalized economy.

In recent years, the use of Multi-Criteria Decision-Making (MCDM) methods, especially those involving different fuzzy environments, has gained substantial attention within the IoT and IIoT domains. MCDM methods provide a structured approach to evaluate and prioritize multiple, often conflicting, criteria—an essential feature in contexts where numerous factors must be considered simultaneously [36,37]. This methodical framework enables decision-makers to comprehensively analyze various elements of IoT and IIoT systems, ultimately supporting more informed and effective decisions that improve system performance and operational efficiency.

Khan et al. [10] conducted a study on the application of the Internet of Things (IoT) in advancing cars, smart homes, and educational institutions. Their research particularly emphasizes how IoT technology is enhancing student learning, digitalizing traditional education methods, and improving overall academic performance by transforming schools into modern, smart, and safe environments. They proposed a hybrid multi-criteria decision-making (MCDM) approach. Specifically, they utilized two MCDM-based techniques—Entropy and TOPSIS—to rank different smart school systems and evaluate essential parameters. Entropy was employed to determine the weight of each criterion, while TOPSIS facilitated the ranking process to identify the most suitable IoT-based school system in terms of intelligence and safety.

In another study, Qi et al. [38] proposed an integrated method that combines multi-objective optimization through ratio analysis plus the full multiplicative form (MULTIMOORA) and criteria interaction via inter-criteria correlation (CRITIC), utilizing q-rung orthopair fuzzy sets (q-ROFSs). In their method, CRITIC determines attribute weights, while MULTIMOORA ranks the options within the q-ROFSs framework. They applied this approach in a case study on the challenges of BDA in advancing intelligent IIoT systems within the Industry 4.0 context. Through comparative and sensitivity analyses, they demonstrated the effectiveness of their framework in prioritizing elements crucial to intelligent IIoT system development.

Li et al. [39] investigated the integration of blockchain technology (BT) with digital twins (DT) to enhance transparency, data immutability, and secure peer-to-peer communication within industrial IoT sectors. They highlighted that blockchain could help DTs provide secure, compliant, and traceable manufacturing processes. Despite the potential, significant barriers exist in implementing BT and DT within IIoT. To analyze these barriers, they proposed a decision-making framework based on q-rung orthopair fuzzy sets (q-ROFS), combining subjective and objective weights (SOWIA) with WASPAS. Their study further validated this approach through a case study on IIoT adoption in Industry 4.0, emphasizing its utility in overcoming adoption barriers.

Hosseini Dehshiri and Amiri [40] carried out a study on the integration of the Internet of Things (IoT) within Renewable Energy Systems (RES), focusing on the benefits of IoT in energy planning and demand management to create a sustainable balance between energy supply and demand. Their study aimed to evaluate significant risks associated with implementing IoT in RES using a hybrid Multi-Criteria Decision-Making (MCDM) approach under uncertain conditions in Iran. The Fuzzy Stepwise Weight Assessment Ratio Analysis (F-SWARA) method was employed to determine the importance of various criteria, and the Fuzzy Combined Compromise Solution (F-CoCoSo) method was applied to assess the risks of IoT integration. Their approach was validated through sensitivity analysis and comparison with fuzzy WASPAS, fuzzy ARAS, and fuzzy TOPSIS methods. Heidary Dahooie et al. [41] performed a study addressing the challenges of decision-making for disruptive technologies like the Internet of Things (IoT) in public sector organizations. They introduced a novel portfolio matrix for selecting IoT applications in urban transportation based on their impact on sustainable development (SD) and implementation feasibility. Seventeen IoT applications were identified for urban transport through a systematic literature review. The authors employed an improved Fuzzy Cognitive Map (FCM) with the Best Worth Method (BWM) to determine the significance of SD criteria and IoT challenges and used the Additive Ratio Assessment (ARAS) method to rank IoT applications accordingly.

Ali et al. [42] conducted a study examining the essential drivers for adopting the Internet of Things (IoT) in supply chain management (SCM), particularly in the post-COVID-19 era. The researchers used an integrated approach combining rough set theory and DEMATEL, known as the rough strength relation analysis (RSRA) method, to evaluate drivers of IoT adoption in SCM based on expert insights from industry and academia. They identified and assessed 14 drivers from an extensive literature review, with results indicating that “Efficient logistics systems,” “Business knowledge acumen,” and

"Information safety assurance" are the top three critical factors. Kumar et al. [28] conducted a study to analyze and prioritize various enablers for the adoption of blockchain-IoT in managing logistics and supply chains. To facilitate this examination, the researchers employed the Diffusion of Innovation and the Technology-Organization-Environment theories as a framework for identifying adoption enablers. The identification of these enablers was confirmed using the Fuzzy-Delphi technique, and their interrelationships were analyzed with the fuzzy Decision-Making Trial and Evaluation Laboratory (DEMATEL) tool. Furthermore, their study proposed a framework based on the Graph Theory Matrix Method to measure the extent of a firm's readiness to adopt blockchain-IoT, illustrated through a real-life case.

Seker [43] evaluated smart waste collection systems based on IoT, focusing on uncertain parameters by applying a modified Entropy measure and a Multi-Criteria Decision-Making (MCDM) method for local municipalities in Istanbul. To address the uncertainty and vagueness associated with the decision-making process, the research employs Interval-valued q-rung orthopair fuzzy sets (IVq-ROFSs). The findings indicate that the waste collection system developed using RFID, GIS, and GPRS is identified as the most suitable smart waste collection system based on IoT for municipal use. Additionally, sensitivity and comparative analyses were conducted at the end of the study to validate the results and demonstrate the robustness of the proposed method in the decision-making process. In another study, Yu et al. [44] address the strategic advantages many industrial firms gain from IoT in supply chain (SC) and operations, while noting the hesitation some firms still experience in adopting this technology. The study seeks to identify and analyze significant barriers that firms encounter when implementing IoT for sustainable SC. Using the Analytical Hierarchy Process (AHP) within a spherical fuzzy set framework, this research assesses these barriers, which are unique to the sustainable SC context. Unlike previous fuzzy set extensions like Intuitionistic and Pythagorean sets, the spherical fuzzy set employs three-dimensional membership functions, enhancing its capacity to handle uncertainty and decision-maker preferences. The barriers are divided into economic, organizational, environmental, and technological categories. Through spherical fuzzy AHP with the Spherical Fuzzy Geometric Mean, the study finds that economic factors, particularly operational costs and budget constraints, are the most influential in hindering IoT implementation.

Asadi et al. [45] identify and rank key factors influencing IoT adoption and examines its impact on manufacturing company performance. Employing a hybrid approach that combines the adaptive neuro-fuzzy inference system with the decision-making trial and evaluation laboratory (DEMATEL), this research provides a novel perspective on critical adoption factors, specifically in technological, environmental, and organizational dimensions. Data were collected from industrial managers involved in IT decision-making in Malaysian manufacturing firms. The findings aim to guide IoT adoption in manufacturing, supporting improved efficiency for industries, service providers, and policymakers. Hejazi Dehaghani et al. [1] explore the transformative role of the Internet of Things (IoT) in healthcare, focusing on its potential to improve patient care and optimize health information management. This study identifies key indicators for IoT implementation readiness in healthcare facilities affiliated with Isfahan University of Medical Sciences. Using a practical, descriptive survey methodology, the researchers developed a model based on expert insights to evaluate preparedness across five critical areas. The findings reveal that the most significant factor is "specialized staff training at the university", while the least impactful is "acquisition of technical knowledge from universities and affiliated institutions".

Sumrit [46] proposes a hybrid multi-criteria decision-making (MCDM) approach to improve readiness for Industrial Internet of Things (IIoT) adoption in manufacturing firms. To tackle uncertainty in decision-making, a Pythagorean fuzzy approach is incorporated, with the framework integrating both the Technology-Organization-Environment (TOE) and Human-Organization-Technology (HOT) fit models to identify barriers. Additionally, a triple helix model (THM), which highlights the collaboration between universities, industries, and government, is used to develop practical strategies. This framework is applied in a case study within Thailand's agro-food processing industry, where identified barriers are confirmed via the Delphi method. The SWARA method prioritizes barriers, revealing “lack of digital culture”, “lack of knowledge and expertise”, and “job displacement concerns” as the top challenges. COBRA is employed to rank strategies under THM, indicating that universities' role in enhancing human capital is critical, followed by government support in ICT infrastructure and investment incentives. Also Sumrit [9] addresses the transformative impact of Industrial Internet of Things (IIoT) technology on global manufacturing, highlighting the need for careful readiness assessment due to the high costs, complexity, and risks involved. This study introduces an evaluation framework employing the interval-valued Pythagorean fuzzy set (IVPFS) method to manage uncertainty in human decision-making. An extensive literature review, complemented by expert validation, identifies twelve critical readiness criteria. Using IVPF-AHP, the study calculates the relative weights of these criteria and assesses readiness through IVPFS. This approach helps manufacturers make informed decisions on IIoT adoption readiness or identify necessary preparatory actions to enhance adoption success. A case study involving a prominent Thai agro-food processing company illustrates the framework's practical application.

Zahedian Nezhad et al. [47] evaluate key dimensions critical to implementation readiness. Using Fuzzy DEMATEL and Fuzzy AHP methods, the authors prioritize dimensions that influence IoT readiness, identifying organizational factors, hard infrastructures, and soft infrastructures as the most significant. Though less central, environmental factors, security, privacy, data analytics, and customer training also play a role in readiness. Parra-Sanchez et al. [48] assess the effectiveness of information and communication technology (ICT) policies in promoting digital transformation and technology readiness for Internet of Things (IoT) adoption among Colombian SMEs in the trading sector. Using the ICT module from Colombia’s Annual Trade Survey (2017–2018), the study analyzes the relationship between ICT application adoption and policy enforcement, applying a chi-square test for independence and descriptive analysis to understand factors influencing SMEs’ adoption decisions. The findings emphasize the critical role of technology readiness in IoT adoption, suggesting that Colombian SMEs require supportive IoT policies to enhance e-commerce capabilities.

Nurika and Jung [49] evaluate Malaysia's IoT deployment using the CREATE-IoT standard, a benchmarking tool established in Europe, to assess both technical and business perspectives of IoT readiness. Their findings reveal that 84% of Malaysia’s IoT Key Performance Indicators (42 out of 50 KPIs) are in an advanced state, indicating strong IoT readiness. However, areas needing improvement include setting clear timelines for IoT service transaction completion to enhance customer satisfaction and developing local capacity for IoT sensor and device production. These enhancements could support more sustainable, scalable, and cost-effective IoT deployments in Malaysia. Yahaya et al. [50] examine the factors influencing user readiness for IoT adoption in Malaysia's education sector. The study focuses on smart devices and applications in higher education, identifying key factors such as ICT infrastructure, knowledge, skills, societal impact, cost, trust, and political aspects. A survey of 335 students from a Northern Malaysian university shows significant correlations between these factors and user readiness, with high application use ranking highly. The findings underscore the importance of user preparedness for IoT integration in education to progress toward smart universities.

In another study, Fagbola and Venter [5] analyze the challenges posed by shadow IoT devices—physical objects that connect to networks without IT knowledge. Their study emphasizes the urgent need for a forensic readiness model tailored for networks with shadow devices, as their concealed nature impedes traditional digital and IoT forensic methods for evidence capture and preservation. To address this, the paper proposes a conceptual model to enhance digital forensic readiness in organizations using shadow IoT devices, focusing on improving device identification, monitoring, and the preservation of digital evidence to effectively respond to security or privacy breaches.

Negm [51] examines the technology readiness level of higher education students regarding their intention to adopt educational Internet of Things (IoT) solutions for online learning. Utilizing a quantitative deductive research approach, the study employs a technology readiness index theory and gathers data through an online questionnaire distributed via social media platforms targeting Generation Z students. Path coefficient analysis of structural equation modeling (SEM) is used to test the hypotheses. The findings reveal that students' technological optimism, discomfort, and insecurity significantly influence their adoption intentions toward IoT products and services for online learning, while innovativeness appears insignificant. Hasan et al. [24] investigate the challenges faced by logistics companies in Malaysia, particularly regarding tracking and tracing within their networks, which negatively impacts last-mile service quality. The study highlights the potential of the Internet of Things (IoT) to optimize outbound logistics operations, specifically in last-mile delivery. Despite its perceived benefits, the adoption rate of IoT technology in Malaysia remains low. Therefore, the research aims to assess the readiness of logistics companies for IoT implementation and to propose best practices for its adoption. Utilizing qualitative methods and case studies of various courier companies, the preliminary findings indicate that IoT can significantly enhance productivity and efficiency in parcel delivery services. This research aims to identify the factors affecting organizations' readiness to adopt IoT and provide recommendations for effective implementation in the logistics sector.

Rizal et al. [4] address the challenges posed by the increasing versatility of Internet of Things (IoT) devices, which heightens the risk of continuous cyber-attacks. The limited processing capabilities and memory of these devices complicate security and forensic analysis, making it difficult to collect and document attacks during investigations. This research emphasizes the need for a comprehensive understanding of the complex consequences of IoT device attacks, highlighting vulnerabilities and potential threats while proposing strategies to enhance the resilience of the IoT ecosystem. To address these challenges, the study proposes an improved IoT forensic readiness framework that leverages artificial intelligence to automatically collect and analyze digital evidence from various IoT devices, functioning as an early warning system. This enhanced framework, based on ISO/IEC 27043, aims to facilitate the effective detection and documentation of attacks, ultimately contributing to more robust forensic investigations.

Radenković et al. [52] examine consumer readiness to adopt new business models for demand response in electricity markets, highlighting the need to align these models with consumer interests. Their study seeks to create a business model that encourages customer participation in demand response services, utilizing the Internet of Things (IoT) for easier access. It assesses customer attitudes toward various incentives, such as green energy, environmental protection, financial benefits, and trust in market operators. The results indicate that customized service packages can be developed based on individual consumer traits, with a significant interest in environmental conservation and a preference for state institutions as service providers. Martínez et al. [53] highlight the significant energy consumption of non-residential buildings in Europe, which represents about 20% of total energy use and is on the rise. To address this issue, they propose a "measure-analyze-decide and act" methodology for quantifying the Smart Readiness Indicator (SRI) in university buildings, underscoring the value of smart building initiatives, especially regarding Nearly Zero Energy

Buildings (NZEB) and COVID-19 prevention. They outline a three-level IoT model encompassing information acquisition, interoperable communication, and data-driven decision-making, and present the sensoriZAR IoT ecosystem deployed at the University of Zaragoza, Spain, focused on monitoring CO2 and energy consumption. Their findings demonstrate the effectiveness of real installations and the potential of IoT technologies to support Sustainable Development Goals (SDGs).

Table 1
Summary of Previous Studies

Author	Journal	Year	Context	Main Objectives	Methodology
Cui et al. [54]	Technological Forecasting and Social Change	2021	IoT	To determine the major barriers to IoT adoption in the circular economy within the manufacturing sector.	SWARA-CoCoSo under Pythagorean fuzzy
Seker [43]	Technology in Society	2022	IoT	To evaluate smart waste collection systems using IoT technology.	BWM, FCM and ARAS
Yu et al. [44]	Computers & Industrial Engineering	2022	IoT	To identify and examine the barriers to IoT adoption in sustainable supply chains.	Entropy and CODAS under interval-valued under qROFSs
Asadi et al. [45]	Technovation	2022	IIoT	To investigate the impact of IoT adoption on the performance of manufacturing companies.	DEMATEL and ANFIS
Ali et al. [42]	Computers & Industrial Engineering	2023	IoT	To examine the key factors behind the adoption of IoT in supply chain management.	DEMATEL under rough set theory
Dahooie et al. [41]	Technology in Society	2023	IoT	To design a novel portfolio matrix for decision-making aimed at identifying IoT applications in sustainable urban transportation.	CoCoSo under Triangular fuzzy set
Qi et al. [38]	Technological Forecasting and Social Change	2023	IIoT	To assess, prioritize, and evaluate the challenges of big data analytics in the development of IIoT systems.	CRITIC and MULTIMOORA under q-ROFSs
Li et al. [39]	Technological Forecasting and Social Change	2023	IIoT	To create a decision support system model for analyzing the barriers to the implementation of digital twin, blockchain, and IIoT technologies in the context of Industry 4.0.	MEREC and WASPAS under q-ROFSs
Kumar et al. [55]	Technological Forecasting and Social Change	2023	IoT	To perform a thorough analysis of the enablers for leveraging blockchain-IoT in logistics and supply chain management.	Fuzzy DEMATEL and Graph Theory
Dehshiri and Amiri [40]	Energy	2023	IoT	To create risk assessments for the integration of IoT in renewable energy systems.	SWARA
Khan et al. [10]	Computers in Human Behavior Reports	2024	IoT	To introduce a hybrid MCDM approach for ranking various smart school systems within the IoT framework.	Entropy and TOPSIS approaches

Despite extensive research on the readiness for implementing the Internet of Things (IoT) in various industries, significant gaps remain in the literature. Table 1 shows a summary of previous studies. While many studies have examined factors influencing IoT adoption, they often overlook the distinction between driving and dependent criteria, failing to establish a clear hierarchy among them. Notably, none has utilized the Total Interpretive Structural Modeling (TISM) technique, which could clarify the relationships between factors affecting IoT readiness. By integrating TISM with fuzzy TOPSIS analysis, this study seeks to fill these gaps and provide a comprehensive methodology for ranking and analyzing the dimensions influencing IoT readiness, thereby offering valuable insights for both academia and industry practitioners. To this end, the most influential criteria affecting IoT implementation readiness were extracted from previous studies. Table 2 presents a list of these criteria along with references associated with each criterion. Subsequently, these criteria were examined and analyzed using both the TISM and fuzzy TOPSIS methods.

Table 2
Key criteria for IoT implementation readiness

	Criteria	Reference
C1	IoT Usage Culture	[2], [16], [18], [46], [48]
C2	Implementation Knowledge and Expertise	[5], [6], [8], [51], [56]
C3	Technology Acceptance	[39], [43], [44], [45]
C4	Regulation and Standardization	[49], [51], [52], [54]
C5	Cyber Security and Privacy	[10], [14], [44], [57]
C6	Top Management Support	[1], [3], [18], [24], [41]
C7	System Monitoring Capability	[4], [9], [16], [46], [58]
C8	Implementation Roadmap	[10], [20], [44], [57]
C9	Technical and Infrastructure Readiness	[6], [24], [53], [59], [60]
C10	Change Management Capability	[5], [41], [42], [44]
C11	Internet Access Quality and Speed	[9], [46], [52], [61]
C12	Financial and Investment Readiness	[24], [45], [53], [54]
C13	Network Strength	[14], [16], [18], [49], [50]
C14	Research Readiness	[1], [7], [18], [39]
C15	Capability of Business Model Development	[3], [8], [38], [49], [54]

3. Methodology

This part of the study explains the methods used. First, the steps of the TISM method are explained, and then the explanations related to the Fuzzy TOPSIS method are presented. Figure 1 shows the methodological structure of the present study.

3.1 Steps in the TISM Methodology

The comprehensive interpretive structural modeling (TISM) method identifies hierarchical levels among categories, where a category with a higher level number and located in lower layers exerts greater influence over other categories. This process is based on the model presented in the study by Sushil [62], which is illustrated diagrammatically in Figure 1, with the following explanation.

3.1.1 Identify and Define Elements

The initial step in any structural modeling process is to identify and define the elements whose relationships are to be modeled. This can be achieved through any idea-generation method, such as a small group exercise, or by applying grounded theory. Additionally, if relevant information from prior studies is available, the identified elements can be linked to previous research.

3.1.2 Define Contextual Relationship

To build a model of the structure connecting the elements, it is essential to define the contextual relationships between them. These relationships depend on the type of structure being considered, such as intent, priority, attribute enhancement, process, or mathematical dependency.

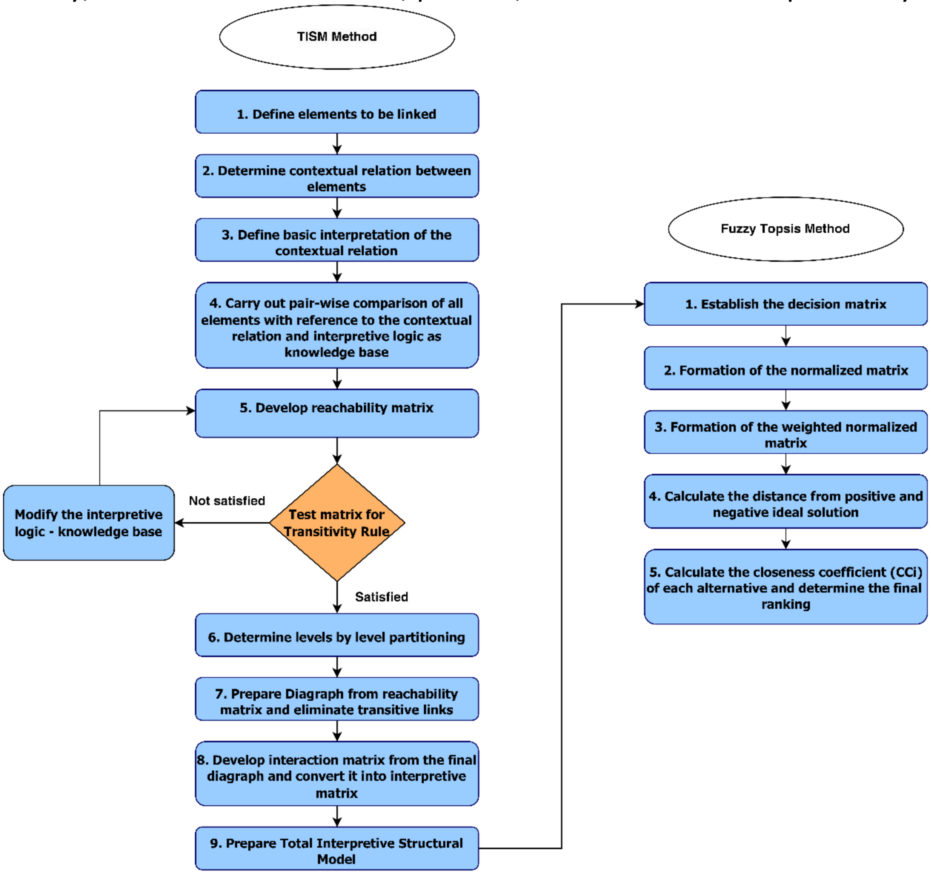

Fig. 1. Methodological Structure of the Study

3.1.3 Interpretation of Relationship

While the contextual relationship clarifies the nature of connections based on the type of structure, it provides limited insight into how those relationships function in practice. To fully understand the relationship between each pair of elements, it is necessary to address the interpretive question, thereby revealing underlying, detailed knowledge.

3.1.4 Interpretive Logic of Pair-wise Comparison

In a paired comparison, the $i\,th$ element is individually compared with each element from $(i+1)th$ to the $n\,th$ element. Given n elements, there will be a total of $n(n\;-\;1)/2$ paired comparisons. Since each pair of elements (i, j) can have two potential directional links—either $(i\text{–}j)$ or $(j\text{–}i)$—the Knowledge Base will contain $n(n\;-\;1)$ rows. For each $(i\text{–}j)$ link, the entry can be marked as 'Yes (Y)' or 'No (N),' and if marked 'Yes', it will require further interpretation. This process reveals the interpretive logic of paired relationships, forming the 'Interpretive Logic—Knowledge Base'.

3.1.5 Reachability Matrix and Transitivity Check

In the interpretive logic—knowledge base, paired comparisons are translated into a reachability matrix by entering a 1 in the $(i\;-\;j)$ cell if the corresponding knowledge base entry is 'Y'; otherwise, a 0 is entered for each 'N' entry. This matrix is then checked for transitivity, updating it until full transitivity is achieved. For each newly established transitive link, the Knowledge Base is also updated. Each 'No' entry is converted to 'Yes', and 'Transitive' is noted in the interpretation column. If the transitive relationship can be meaningfully explained, the logic is added alongside the 'Transitive' entry; otherwise, it is left as-is.

3.1.6 Level Partition on Reachability Matrix

In this step, we need to identify the reachability and antecedent sets for each element. Elements at the top level of the hierarchy do not reach any elements beyond their own level. Therefore, the reachability set for a top-level element includes the element itself and any other elements within the same level that it can reach, such as those in a strongly connected subset. The antecedent set for a top-level element consists of the element itself, elements from lower levels that reach it, and any elements in a strongly connected subset at the top level. Consequently, if an element is at the top level, the intersection of its reachability and antecedent sets will be identical to its reachability set. Top-level elements satisfying this condition should then be removed from the element set, and this process is repeated iteratively until all levels are identified.

3.1.7 Developing Diagraph

The elements are organized graphically by levels, with directed links drawn according to the relationships indicated in the reachability matrix. A simplified version of the initial digraph is then created by progressively removing transitive relationships, examining each for its interpretative value from the knowledge base. Only those transitive relationships with essential interpretations are retained.

3.1.8 Interaction Matrix

The final digraph is converted into a binary interaction matrix, where each interaction is represented by a 1 entry. These cells with 1 entries are then interpreted by selecting the corresponding interpretations from the knowledge base, forming what is known as the Interpretive Matrix.

3.1.9 Total Interpretive Structural Model

The connective and interpretive details within the interpretive direct interaction matrix and digraph are used to construct the TISM. In this process, the nodes in the digraph are replaced by interpretations of the elements, each enclosed in boxes. The interpretations in the cells of the interpretive direct interaction matrix are displayed beside the corresponding links in the structural model. This approach provides a complete interpretation of the structural model.

3.2 Steps in the Fussy TOPSIS Methodology

TOPSIS, an effective Technique for Order of Preference by Similarity to Ideal Solution is a foundational method in multi-criteria decision-making developed by Hwang and Yoon [63]. This method operates on the principle that the selected alternative should be closest to the positive ideal solution (PIS) and farthest from the negative ideal solution (NIS). Traditionally, TOPSIS represents individual judgments with precise, crisp values; however, in practice, such exact measurement may not be feasible. Instead, linguistic values, represented through fuzzy set theory, can offer a more accurate approach. Consequently, fuzzy TOPSIS is particularly well suited for addressing real-life decision-making problems in uncertain, fuzzy environments.

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Fuzzy-TOPSIS is a powerful approach in multicriteria decision-making [64]. It tackles the uncertainties and imprecision common in decision-making by incorporating fuzzy logic principles [65,66]. Using fuzzy sets allows for the assessment and comparison of various alternatives across multiple criteria, creating a dependable structure for decision-making amidst ambiguity [67].

A pairwise comparison matrix is developed using a triangular fuzzy number mentioned by (a,b,c). Figure 2 shows a schematic diagram of the intersection among fuzzy numbers. The expert scores were taken on the linguistic scale, as shown in Table 3.

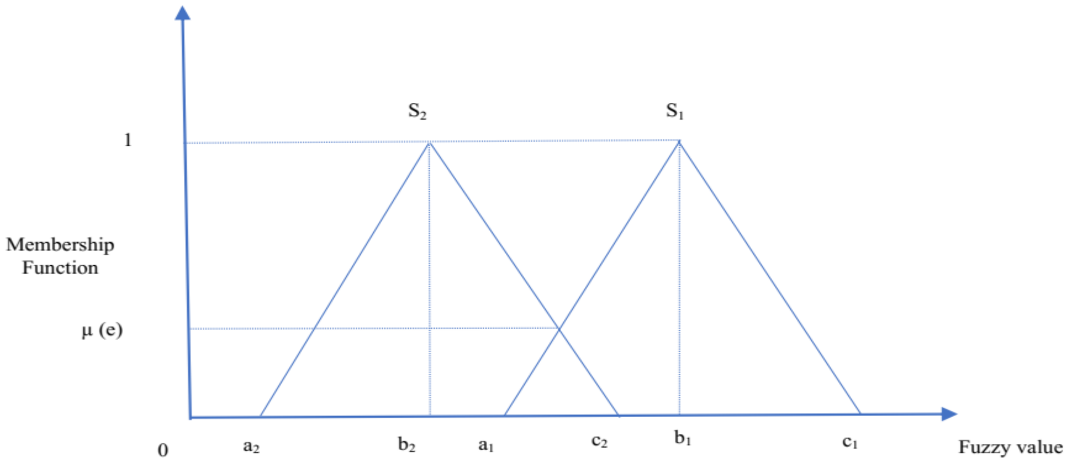

Fig. 2. Intersection among fuzzy numbers [68]

Table 3
Linguistic scale [28]

Linguistic term	Triangular fuzzy number
Very low (VL)	(1, 1, 3)
Low (L)	(1, 3, 5)
Medium (M)	(3, 5, 7)
High (H)	(5, 7, 9)
Very high (VH)	(7, 9, 9)

3.2.1 Establish the decision matrix

In the initial step of the fuzzy TOPSIS method, the decision matrix ($\widetilde{D}$) is constructed based on expert opinions. In this stage, the relevant experts and specialists are first identified, and then their insights are gathered through a structured questionnaire. These perspectives are entered into the decision matrix as both quantitative and qualitative data. Each cell in this matrix represents the significance of the research criteria, illustrated by fuzzy numbers or symbols ($\tilde{X}_{ij}$). If the total number of experts is k, the final decision matrix is formed by averaging their opinions.

$$\widetilde{D} = \begin{bmatrix} \tilde{X}_{11} & \tilde{X}_{1j} & \tilde{X}_{1m} \\ \vdots & \ddots & \vdots \\ \tilde{X}_{n1} & \tilde{X}_{nj} & \tilde{X}_{nm} \end{bmatrix} \quad (1)$$

$$\tilde{X}_{ij} = \frac{1}{k}\left[\tilde{X}_{ij}^{1} + \tilde{X}_{ij}^{r} + \cdots + \tilde{X}_{j}^{k}\right] \quad (2)$$

3.2.2 Formation of the normalized matrix

In the second step of the fuzzy TOPSIS method, normalization is applied to standardize fuzzy numbers and convert them into a dimensionless format. This process enables more precise analysis and facilitates comparison and decision-making among fuzzy variables. In other words, the defined fuzzy values are transformed to a standardized range between 0 and 1. Normalization helps constrain the fuzzy values, making them comparable by eliminating measurement units and simplifying the fuzzy numbers. The normalized matrix is denoted by R.

$$\begin{aligned} &\tilde{R} = [\tilde{r}_{ij}]_{m\times n} \\ &\tilde{r}_{ij} = \left(\frac{l_{ij}}{u_j^+}, \frac{m_{ij}}{u_j^+}, \frac{u_{ij}}{u_j^+}\right) \; and \; u_j^+ = max_i u_{ij} \; (benefit\ criteria) \\ &\tilde{r}_{ij} = \left(\frac{l_j^-}{u_{ij}}, \frac{l_j^-}{m_{ij}}, \frac{l_j^-}{l_{ij}}\right) \; and \; l_j^- = max_i l_{ij} \; (cost\ criteria) \end{aligned} \tag{3}$$

3.2.3 Formation of the weighted normalized matrix

In this step, fuzzy weights are used to measure the importance of each criterion, reflecting their relative significance. The output is a matrix where the criteria are combined with fuzzy weights to capture the precise impact of each criterion. This process enhances accuracy and improves decision-making aligned with the issue at hand.

$$\begin{aligned} &\tilde{v}_{ij} = \tilde{r}_{ij} \otimes \tilde{w}_j, \\ &where \; \tilde{v} = [\tilde{v}_{ij}]_{m\times n}, i = 1, 2, \dots, m; j = 1, 2, \dots, n. \end{aligned} \tag{4}$$

3.2.4 Calculate the distance from positive and negative ideal solution

In the fourth step of the fuzzy TOPSIS method, the positive ideal solution (PIS) and negative ideal solution (NIS) are first defined according to Equation 5. Then, according to Equation 6 the distance from PIS and NIS is evaluated, denoted by $d_i^+$and d_i^- ,respectively.The positive ideal serves as the representative of the desirable value, while the negative ideal represents the undesirable or least preferred value in fuzzy TOPSIS. These distances are used to assess the quality and importance of each fuzzy variable in the decision-making process. Variables that are closer to the positive ideal, with shorter distances, are considered key factors in decision-making as they are nearer to optimal values and exert greater influence. Conversely, variables closer to the negative ideal, with shorter distances, have a lesser impact on decision-making. Equation 7 illustrates how to calculate the distance between two fuzzy numbers.

$$\begin{aligned} &A^+ = \{\tilde{v}_1^+, \tilde{v}_2^+, \dots, \tilde{v}_n^+\} \qquad A^- = \{\tilde{v}_1^-, \tilde{v}_2^-, \dots, \tilde{v}_n^-\} \\ &where \; \tilde{v}_j^+ = (1,1,1) \qquad \tilde{v}_j^- = (0,0,0) \end{aligned} \tag{5}$$

$$\begin{aligned} d_i^+ &= \sum_{j=1}^{n} d\left(\tilde{v}_{ij}, \tilde{v}_j^+\right), i = 1, 2, \dots, m; j = 1, 2, \dots, n. \\ d_i^- &= \sum_{j=1}^{n} d\left(\tilde{v}_{ij}, \tilde{v}_j^-\right), i = 1, 2, \dots, m; j = 1, 2, \dots, n. \end{aligned} \tag{6}$$

$$d\left(\tilde{A}, \tilde{B}\right) = \sqrt{\frac{1}{3}[(a_1 - b_1)^2 + (a_2 - b_2)^2 + (a_3 - b_3)^2]} \tag{7}$$

3.2.5 5. Calculate the closeness coefficient (CCi) and determine the final ranking

The closeness coefficient (CCi) represents the distances to the fuzzy positive ideal solution (A^+) and the fuzzy negative ideal solution (A^-) simultaneously. The closeness coefficient of each alternative is calculated according to Equation 8. Then the different alternatives are ranked according to CCi in decreasing order.

$$CC_i = \frac{d_i^-}{d_i^+ + d_i^-} \tag{8}$$

4. Results

First, the criteria influencing the readiness for IoT implementation were extracted from related studies, as previously presented in Table 2. Subsequently, the relationships between these criteria and how they affect each other were determined based on expert opinions. The reachability matrix was developed according to the frequency of expert responses. In this matrix, the number 1 indicates that the row element influences the column element, while the number 0 indicates that there is no influence from the row element on the column element (Table 4).

Table 4
Initial reachability matrix

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15
C1	0	1	1	1	1	0	1	1	0	1	0	1	0	1	1
C2	0	0	1	1	1	1	1	1	0	1	1	1	1	1	1
C3	0	0	0	1	0	0	0	1	0	1	0	0	0	1	1
C4	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1
C5	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1
C6	1	1	1	0	1	0	0	1	1	1	1	1	0	1	1
C7	0	0	1	0	1	1	0	0	0	0	0	0	0	0	0
C8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C9	1	1	1	1	1	1	1	1	0	1	1	0	1	1	1
C10	1	0	1	0	1	0	0	1	0	0	0	0	0	0	1
C11	0	0	1	0	0	0	1	0	0	0	0	0	0	1	0
C12	0	1	1	1	0	1	1	1	1	1	1	0	1	1	1
C13	0	0	1	0	1	0	1	0	0	1	0	0	0	0	0
C14	0	1	0	0	0	0	0	1	0	1	0	0	0	0	1
C15	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0

After aligning the reachability matrix, the final reachability matrix was obtained. The numbers that are 0 in the reachability matrix but 1 in the final reachability matrix are marked with (*1). In this matrix, the numbers (1) indicate direct relationships, while the numbers (*1) signify indirect relationships. Table 5 shows the final reachability matrix.

The penetration rate and the degree of dependence are derived from the 1s in the final reachability matrix. The sum of the 1s in each row and column is calculated, with the total number of 1s in a row representing the penetration rate and the total number of 1s in a column indicating the degree of dependence. The penetration rate reflects the impact of the criteria, while the degree of dependence shows the level of susceptibility (see Table 6).

The results obtained from the fuzzy TOPSIS method reveal the ranking of 15 critical criteria related to the Internet of Things (IoT) across various industries. These criteria have been evaluated and prioritized based on their distances from the positive and negative ideals, and they are arranged in order of importance. Table 7 below displays the ranking results which provide decision-makers and researchers with a deeper understanding of the key factors influencing the implementation and utilization of IoT in industrial environments. These findings can serve as a practical guide for developing and refining IoT-based strategies within industries.

Table 5
Final reachability matrix

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	Sum
C1		1	1	1	1	1*	1	1	1*	1	1*	1	1*	1	1	14
C2	1*		1	1	1	1	1	1	1*	1	1	1	1	1	1	14
C3	1*	1*		1	1*	1*	1*	1	1*	1	1*	1*	1*	1	1	14
C4	1	1	1		1	1	1	1	1	1	1	1	1	1	1	14
C5	0	0	1	1		0	0	1*	0	1*	0	0	0	1*	1	6
C6	1	1	1	1*	1		1*	1	1	1	1	1	1*	1	1	14
C7	1*	1*	1	1*	1	1		1*	1*	1*	1*	1*	0	1*	1*	13
C8	0	0	0	0	0	0	0		0	0	0	0	0	0	0	0
C9	1	1	1	1	1	1	1	1		1	1	1*	1	1	1	14
C10	1	1*	1	1*	1	0	1*	1	0		0	1*	0	1*	1	10
C11	0	1*	1	1*	1*	1*	1	1*	0	1*		0	0	1	1*	10
C12	1*	1	1	1	1*	1	1	1	1	1	1		1	1	1	14
C13	1*	0	1	1*	1	1*	1	1*	0	1	0	0		1*	1*	10
C14	1*	1	1*	1*	1*	1*	1*	1	0	1	1*	1*	1*		1	13
C15	1*	0	1*	0	1*	0	0	1	0	1	0	0	0	0		
Sum	11	10	13	12	13	10	11	14	7	13	9	9	8	12	13	

Table 6
penetration rate and the degree of dependence

Criteria	Penetration rate	Degree of dependence
C1	14	11
C2	14	10
C3	14	13
C4	14	12
C5	6	13
C6	14	10
C7	13	11
C8	0	14
C9	14	7
C10	10	13
C11	10	9
C12	14	9
C13	10	8
C14	13	12
C15	5	13

Table 7
Fuzzy TOPSIS Results

Code	Criteria	D (Si, S-)	D (Si, S+)	cci	Final Ranking
C1	IoT Usage Culture	8.68	7.89	0.5238	2
C2	Implementation Knowledge and Expertise	8.75	8.37	0.5111	8
C3	Technology Acceptance	7.9	7.6	0.5097	9
C4	Regulation and Standardization	8.45	7.8	0.5200	6
C5	Cyber Security and Privacy	7.65	8.45	0.4752	13
C6	Top Management Support	8.67	7.49	0.5365	1
C7	System Monitoring Capability	7.56	8.3	0.4767	12
C8	Implementation Roadmap	7.65	8.05	0.4873	10

Code	Criteria	D (Si, S-)	D (Si, S+)	cci	Final Ranking
C9	Technical and Infrastructure Readiness	8.64	7.96	0.5205	5
C10	Change Management Capability	8.23	7.76	0.5147	7
C11	Internet Access Quality and Speed	7.65	8.96	0.4606	15
C12	IoT Usage Culture	8.65	7.96	0.5208	4
C13	Implementation Knowledge and Expertise	7.68	8.95	0.4618	14
C14	Technology Acceptance	7.78	8.32	0.4832	11
C15	Regulation and Standardization	8.34	7.59	0.5235	3

Figure 3 shows the combined results of TISM and Fuzzy TOPSIS methods.

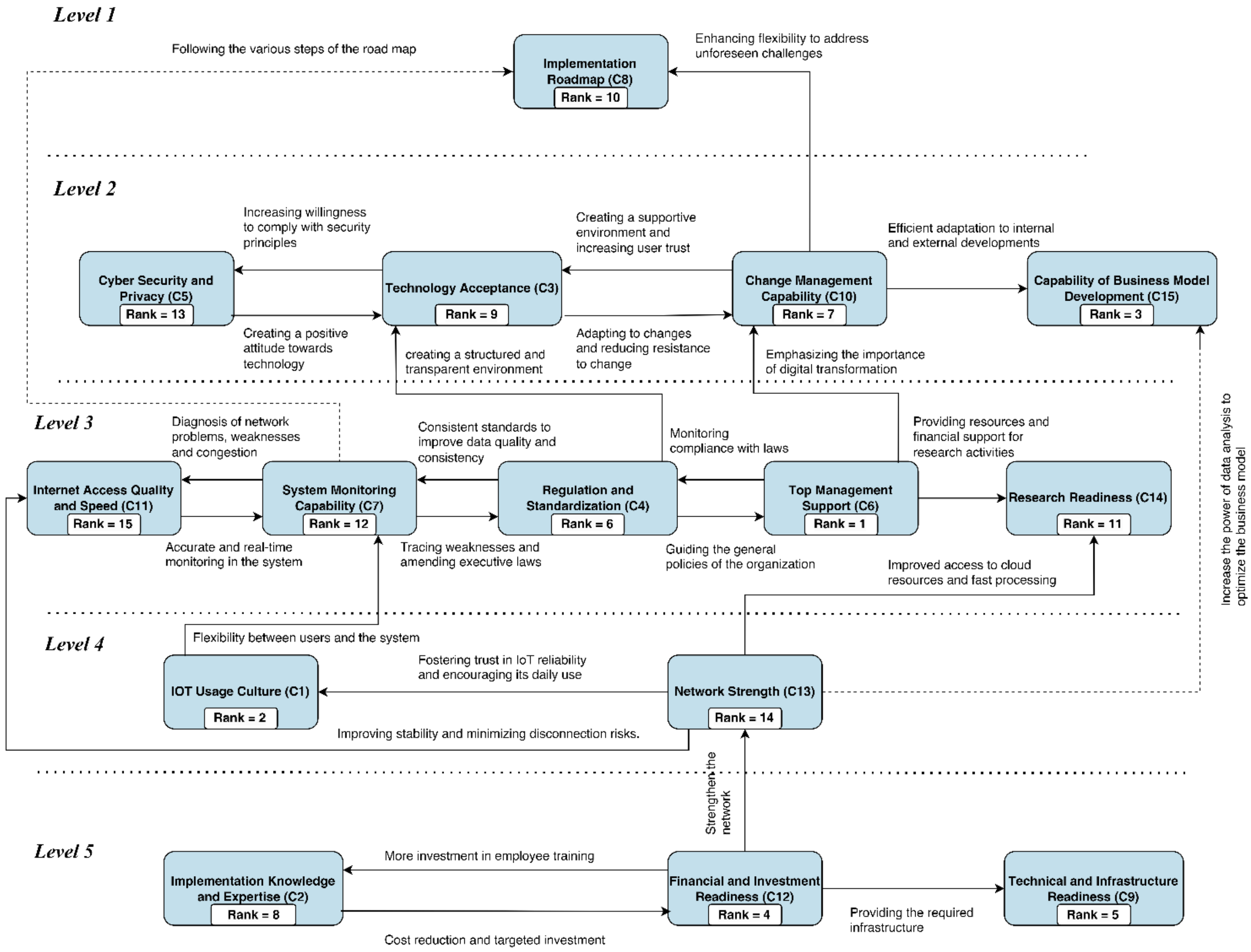

Fig. 3. Combined results of TISM and Fuzzy TOPSIS

5. Conclusions

This study aimed to rank factors influencing the implementation readiness of the Internet of Things in industries using fuzzy TISM and TOPSIS analysis. These methods were applied in two interconnected steps. TISM helped identify complex relationships among the criteria and organized them into five levels. Level 5 represents the most influential criteria which have driver power, while Level 1 indicates the most susceptible. As one moves closer to Level 1, the criteria's driver power decreases, and their dependency increases.

Level 1 establishes "Implementation Roadmap (C8)" as the foundation for successfully executing IoT technology projects. Level 2 identifies critical criteria like “Technology Acceptance (C3)”, “Privacy

Capability (C5)", "Change Management Capability (C10)" and "Business Model Development Capability (C15)" essential for technology adoption and implementation. Level 3 emphasizes necessary elements such as "Required Legislation and Standards (C4)", "Senior Management Support (C6)", "System Monitoring Capability (C7)", "Internet Access Quality and Speed (C11)" and "Research Readiness (C14)" for facilitating execution. Level 4 focuses on "IoT Usage Culture (C1)" and "Network Strength (C13)", reflecting cultural and infrastructural influences on technology adoption. Lastly, Level 5 incorporates "Implementation Knowledge and Expertise (C2)", "Technical and Infrastructural Readiness (C9)" and "Financial and Investment Readiness (C12)" as critical factors for the successful implementation of contemporary systems and technologies.

Following the initial analysis and determination of the influence and susceptibility of the criteria using the TISM method, the fuzzy TOPSIS method was also applied for a more precise and comprehensive ranking of the criteria. This approach allowed for prioritizing the criteria based on quantitative and qualitative evaluations. The results obtained from fuzzy TOPSIS indicate that the criteria "Senior Management Support (C6)", "IoT Usage Culture (C1)", "Business Model Development Capability (C15)", "Financial and Investment Readiness (C12)" and "Technical and Infrastructural Readiness (C9)" achieved ranks 1 through 5, respectively.

Integrating the TISM and fuzzy TOPSIS methods offers a precise understanding of key criteria. TISM identifies influence levels and interconnections among criteria, while fuzzy TOPSIS establishes clear priorities through quantitative and qualitative assessments. This combination aids decision-makers and project implementers in grasping the priorities and essential requirements for IoT implementation. Ultimately, the study highlights that focusing on key criteria and selecting suitable strategies based on these priorities is crucial for enhancing project efficiency and impact in IoT implementation.

The criterion "Financial and Investment Readiness (C12)" is ranked 4th by fuzzy TOPSIS and positioned at Level 5 using the TISM method, underscoring its crucial role in enhancing IoT efficiency and development in industries. To improve "Financial and Investment Readiness (C12)" and boost IoT productivity, targeted investment strategies should be implemented. These include allocating budgets for essential infrastructure, such as high-speed communication networks and data security systems, to meet IoT requirements. Furthermore, forming strategic partnerships with financial institutions and investors can attract necessary funding for IoT projects, enabling companies to pursue innovative initiatives. Additionally, developing financial and economic skills is vital for financial and managerial personnel, who must adeptly analyze costs and returns on IoT investments.

Developing long-term investment strategies can help industries secure the financial resources needed for sustainable IoT implementation, thereby enhancing profitability and productivity. Additionally, applying financial risk management techniques to mitigate market fluctuations and technology risks bolsters financial stability, enabling companies to invest in new technologies with greater resilience against economic and technical challenges.

The "Technical and Infrastructural Readiness (C9)" criterion is a key factor in the successful implementation of IoT in industries. The TISM method places it at Level 5 and highlights its crucial role in providing the technological infrastructure needed for IoT development. In the TOPSIS ranking, it holds the 5th position, which emphasizes its substantial influence on the efficiency and effectiveness of IoT technologies. Therefore, developing and enhancing technical infrastructure is crucial for the successful deployment of IoT in industrial settings.

To improve technical readiness and infrastructure in industries, organizations are advised to make ongoing investments in updating advanced communication equipment and technologies, including 5G networks and fiber optics, to enhance data transmission speed and capacity. Establishing distributed data centers and adopting cloud computing technologies can also provide greater security and efficiency for managing large volumes of data. Additionally, training and developing a skilled workforce in areas related to advanced networking, data storage, and processing will boost technical readiness. By strengthening these infrastructures, industries can effectively leverage IoT's potential to enhance efficiency and adaptability.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

[1] Hejazi Dehaghani, S. A., Hajrahimi, B., & Dehaghani Hejazi, S. M. (2020). Providing a model for assessing the readiness of hospitals affiliated to Isfahan University of Medical Sciences in using the Internet of Things (IoT) Technology. Journal of Education and Health Promotion, 9, 201. https://doi.org/10.4103/jehp.jehp_429_19

[2] Majeed, A. A., & Rupasinghe, T. D. (2017). Internet of Things (IoT) Embedded Future Supply Chains for Industry 4.0: An Assessment from an ERP-based Fashion Apparel and Footwear Industry. International Journal of Supply Chain Management, 6(1), Article 1. https://doi.org/10.59160/ijscm.v6i1.1395

[3] Kamble, S. S., Gunasekaran, A., & Sharma, R. (2018). Analysis of the driving and dependence power of barriers to adopt industry 4.0 in Indian manufacturing industry. Computers in Industry, 101, 107–119. https://doi.org/10.1016/j.compind.2018.06.004

[4] Rizal, R., Selamat, S. R., Mas'ud, M. Z., & Rahmatulloh, A. (2024, September 1). AResNet Model Using Deep Learning Approach for Enhancing the Internet of Things (IoT) Forensic Readiness Framework. | EBSCOhost. https://doi.org/10.22266/ijies2024.1031.71

[5] Fagbola, F. I., & Venter, H. S. (2022). Smart Digital Forensic Readiness Model for Shadow IoT Devices. Applied Sciences, 12(2), Article 2. https://doi.org/10.3390/app12020730

[6] Abazi, B. (2016). An approach to the impact of transformation from the traditional use of ICT to the Internet of Things: How smart solutions can transform SMEs. IFAC-PapersOnLine, 49(29), 148–151. https://doi.org/10.1016/j.ifacol.2016.11.091

[7] Neagu, G., Ianculescu, M., Alexandru, A., Florian, V., & Rădulescu, C. Z. (2019). Next generation IoT and its influence on decision-making. An illustrative case study. Procedia Computer Science, 162, 555–561. https://doi.org/10.1016/j.procs.2019.12.023

[8] Kiel, D., Arnold, C., & Voigt, K.-I. (2017). The influence of the Industrial Internet of Things on business models of established manufacturing companies – A business level perspective. Technovation, 68, 4–19. https://doi.org/10.1016/j.technovation.2017.09.003

[9] Sumrit, D. (2022). Evaluating readiness degree for Industrial Internet of Things adoption in manufacturing enterprises under interval-valued Pythagorean fuzzy approach. Production & Manufacturing Research. https://www.tandfonline.com/doi/abs/10.1080/21693277.2022.2064931

[10] Khan, M. A., & Salah, K. (2018). IoT security: Review, blockchain solutions, and open challenges. Future Generation Computer Systems, 82, 395–411. https://doi.org/10.1016/j.future.2017.11.022

[11] Aazam, M., Zeadally, S., & Harras, K. A. (2018). Deploying Fog Computing in Industrial Internet of Things and Industry 4.0. IEEE Transactions on Industrial Informatics, 14(10), 4674–4682. IEEE Transactions on Industrial Informatics. https://doi.org/10.1109/TII.2018.2855198

[12] Choo, K.-K. R., Gritzalis, S., & Park, J. H. (2018). Cryptographic Solutions for Industrial Internet-of-Things: Research Challenges and Opportunities. IEEE Transactions on Industrial Informatics, 14(8), 3567–3569. IEEE Transactions on Industrial Informatics. https://doi.org/10.1109/TII.2018.2841049

[13] Civerchia, F., Bocchino, S., Salvadori, C., Rossi, E., Maggiani, L., & Petracca, M. (2017). Industrial Internet of Things monitoring solution for advanced predictive maintenance applications. Journal of Industrial Information Integration, 7, 4–12. https://doi.org/10.1016/j.jii.2017.02.003

[14] Latif, S., Idrees, Z., Ahmad, J., Zheng, L., & Zou, Z. (2021). A blockchain-based architecture for secure and trustworthy operations in the industrial Internet of Things. Journal of Industrial Information Integration, 21, 100190. https://doi.org/10.1016/j.jii.2020.100190

[15] Ahmadirad, Z. (2024). The Banking and Investment in the Future: Unveiling Opportunities and Research Necessities for Long-Term Growth. International Journal of Applied Research in Management, Economics and Accounting, 1(2), Article 2. https://doi.org/10.63pahi053/ijmea.7

[16] Malik, P. K., Sharma, R., Singh, R., Gehlot, A., Satapathy, S. C., Alnumay, W. S., Pelusi, D., Ghosh, U., & Nayak, J. (2021). Industrial Internet of Things and its Applications in Industry 4.0: State of The Art. Computer Communications, 166, 125–139. https://doi.org/10.1016/j.comcom.2020.11.016

[17] Haseli, G., Sheikh, R., & Sana, S. S. (2020). Base-criterion on multi-criteria decision-making method and its applications. International Journal of Management Science and Engineering Management, 15(2), 79–88. https://doi.org/10.1080/17509653.2019.1633964

[18] Kumar, R., Sindhwani, R., & Singh, P. L. (2021). IIoT implementation challenges: Analysis and mitigation by blockchain. Journal of Global Operations and Strategic Sourcing, 15(3), 363–379. https://doi.org/10.1108/JGOSS-08-2021-0056

[19] Haseli, G., & Sheikh, R. (2022). Base criterion method (BCM). In Multiple criteria decision making: Techniques, Analysis and Applications (pp. 17–38). Springer. https://doi.org/10.1007/978-981-16-7414-3_2

[20] Sodhro, A. H., Pirbhulal, S., Muzammal, M., & Zongwei, L. (2020). Towards Blockchain-Enabled Security Technique for Industrial Internet of Things Based Decentralized Applications. Journal of Grid Computing, 18(4), 615–628. https://doi.org/10.1007/s10723-020-09527-x

[21] Haseli, G., Ranjbarzadeh, R., Hajiaghaei-Keshteli, M., Ghoushchi, S. J., Hasani, A., Deveci, M., & Ding, W. (2023). HECON: Weight assessment of the product loyalty criteria considering the customer decision's halo effect using the convolutional neural networks. Information Sciences, 623, 184–205. https://doi.org/10.1016/j.ins.2022.12.027

[22] Trappey, A. J. C., Trappey, C. V., Hareesh Govindarajan, U., Chuang, A. C., & Sun, J. J. (2017). A review of essential standards and patent landscapes for the Internet of Things: A key enabler for Industry 4.0. Advanced Engineering Informatics, 33, 208–229. https://doi.org/10.1016/j.aei.2016.11.007

[23] Haseli, G., Nazarian-Jashnabadi, J., Shirazi, B., Hajiaghaei-Keshteli, M., & Moslem, S. (2024). Sustainable strategies based on the social responsibility of the beverage industry companies for the circular supply chain. Engineering Applications of Artificial Intelligence, 133, 108253. https://doi.org/10.1016/j.engappai.2024.108253

[24] Hasan, M. H., Khairuddin, A. A., & Akhir, E. A. P. (2019). A Case Study to Explore IoT Readiness in Outbound Logistics. International Journal of Supply Chain Management, 8(2), Article 2. https://doi.org/10.59160/ijscm.v8i2.3013

[25] Nazarian-Jashnabadi, J., Bonab, S. R., Haseli, G., Tomaskova, H., & Hajiaghaei-Keshteli, M. (2023). A dynamic expert system to increase patient satisfaction with an integrated approach of system dynamics, ISM, and ANP methods. Expert Systems with Applications, 234, 121010. https://doi.org/10.1016/j.eswa.2023.121010

[26] Sepahi, T., Shahbazi, M., & Shafiei Roudposhti, M. (2020). Drug distribution system in Iran: A multi method study of defects and solutions. Depiction of Health, 11(4), 324–343. https://doi.org/10.34172/doh.2020.41

[27] Pappas, N., Caputo, A., Pellegrini, M. M., Marzi, G., & Michopoulou, E. (2021). The complexity of decision-making processes and IoT adoption in accommodation SMEs. Journal of Business Research, 131, 573–583. https://doi.org/10.1016/j.jbusres.2021.01.010

[28] Dokhanian, S., Sodagartojgi, A., Tehranian, K., Ahmadirad, Z., Moghaddam, P. K., & Mohsenibeigzadeh, M. (2024). Exploring the impact of supply chain integration and agility on commodity supply chain performance. World Journal of Advanced Research and Reviews, 22(1), 441-450. https://doi.org/10.30574/wjarr.2024.22.1.1119

[29] Mohammadabadi, S. M. S., Entezami, M., Moghaddam, A. K., Orangian, M., & Nejadshamsi, S. (2024). Generative Artificial Intelligence for Distributed Learning to Enhance Smart Grid Communication. International Journal of Intelligent Networks. https://doi.org/10.1016/j.ijin.2024.05.007

[30] Ahmadirad, Z. (2024). Evaluating the influence of AI on market values in finance: distinguishing between authentic growth and speculative hype. *International Journal of Advanced Research in Humanities and Law*, *1*(2), 50-57. https://doi.org/10.63053/ijrel.11

[31] Ahmadirad, Z. (2024). The Beneficial Role of Silicon Valley's Technological Innovations and Venture Capital in Strengthening Global Financial Markets. *International journal of Modern Achievement in Science, Engineering and Technology*, *1*(3), 9-17. https://doi.org/10.63053/ijset.40

[32] Razavi, H., & Habibnia, A. (2024). The Rise of AI in Middle Eastern Fintech With the Case Studies From the UAE and Turkey. In Exploring Global FinTech Advancement and Applications (pp. 259-297). IGI Global. https://doi.org/10.4018/979-8-3693-1561-3.ch010

[33] Razavi, H., Sarabadani, H., Karimisefat, A., & LEBRATY, J. F. (2019, February). Profitability prediction for ATM transactions using artificial neural networks: A data-driven analysis. In 2019 5th Conference on Knowledge Based Engineering and Innovation (KBEI) (pp. 661-665). IEEE. https://doi.org/10.1109/KBEI.2019.8735037

[34] Sheykhfard, A., Haghighi, F., Saeidi, S., SafariTaherkhani, M., Fountas, G., & Das, S. (2024). Behavioral Modeling of Drivers near Speed Control Cameras: A Dual Perspective from Micro and Macro Data. Transportation Research Record, 03611981241287787. https://doi.org/10.1177/03611981241287787
[35] Sadeghi, S., & Niu, C. (2024). Augmenting Human Decision-Making in K-12 Education: The Role of Artificial Intelligence in Assisting the Recruitment and Retention of Teachers of Color for Enhanced Diversity and Inclusivity. Leadership and Policy in Schools, 1-21. https://doi.org/10.1080/15700763.2024.2358303
[36] Patil, S. K., & Kant, R. (2014). A fuzzy AHP-TOPSIS framework for ranking the solutions of Knowledge Management adoption in Supply Chain to overcome its barriers. Expert Systems with Applications, 41(2), 679–693. https://doi.org/10.1016/j.eswa.2013.07.093
[37] Nazarian-Jashnabadi, J., Haseli, G., & Tomaskova, H. (2024). Digital transformation for the sustainable development of business intelligence goals. In Decision Support Systems for Sustainable Computing (pp. 169–186). https://doi.org/10.1016/B978-0-443-23597-9.00008-1
[38] Qi, Q., Xu, Z., & Rani, P. (2023). Big data analytics challenges to implementing the intelligent Industrial Internet of Things (IIoT) systems in sustainable manufacturing operations. Technological Forecasting and Social Change, 190, 122401. https://doi.org/10.1016/j.techfore.2023.122401
[39] Li, Y., Su, D. A., & Mardani, A. (2023). Digital twins and blockchain technology in the industrial Internet of Things (IIoT) using an extended decision support system model: Industry 4.0 barriers perspective. Technological Forecasting and Social Change, 195, 122794. https://doi.org/10.1016/j.techfore.2023.122794
[40] Hosseini Dehshiri, S. J., & Amiri, M. (2023). Evaluating the risks of the internet of things in renewable energy systems using a hybrid fuzzy decision approach. Energy, 285, 129493. https://doi.org/10.1016/j.energy.2023.129493
[41] Heidary Dahooie, J., Mohammadian, A., Qorbani, A. R., & Daim, T. (2023). A portfolio selection of internet of things (IoTs) applications for the sustainable urban transportation: A novel hybrid multi criteria decision making approach. Technology in Society, 75, 102366. https://doi.org/10.1016/j.techsoc.2023.102366
[42] Ali, S. M., Ashraf, M. A., Taqi, H. Md. M., Ahmed, S., Rob, S. M. A., Kabir, G., & Paul, S. K. (2023). Drivers for Internet of Things (IoT) adoption in supply chains: Implications for sustainability in the post-pandemic era. Computers & Industrial Engineering, 183, 109515. https://doi.org/10.1016/j.cie.2023.109515
[43] Seker, S. (2022). IoT based sustainable smart waste management system evaluation using MCDM model under interval-valued q-rung orthopair fuzzy environment. Technology in Society, 71, 102100. https://doi.org/10.1016/j.techsoc.2022.102100
[44] Yu, Z., Khan, S. A. R., Mathew, M., Umar, M., Hassan, M., & Sajid, M. J. (2022). Identifying and analyzing the barriers of Internet-of-Things in sustainable supply chain through newly proposed spherical fuzzy geometric mean. Computers & Industrial Engineering, 169, 108227. https://doi.org/10.1016/j.cie.2022.108227
[45] Asadi, S., Nilashi, M., Iranmanesh, M., Hyun, S. S., & Rezvani, A. (2022). Effect of internet of things on manufacturing performance: A hybrid multi-criteria decision-making and neuro-fuzzy approach. Technovation, 118, 102426. https://doi.org/10.1016/j.technovation.2021.102426
[46] Sumrit, D. (2024). Enhancing readiness degree for Industrial Internet of Things adoption in manufacturing enterprises: An integrated Pythagorean fuzzy approach. Heliyon, 10(20), e39007. https://doi.org/10.1016/j.heliyon.2024.e39007
[47] Nezhad, M. Z., Nazarian-Jashnabadi, J., Rezazadeh, J., Mehraeen, M., & Bagheri, R. (2023). Assessing dimensions influencing IoT implementation readiness in industries: A fuzzy DEMATEL and fuzzy AHP analysis. Journal of Soft Computing and Decision Analytics, 1(1), 102–123. https://doi.org/10.31181/jscda11202312
[48] Parra-Sánchez, D. T., Talero-Sarmiento, L. H., & Guerrero, C. D. (2021). Assessment of ICT policies for digital transformation in Colombia: Technology readiness for IoT adoption in SMEs in the trading sector. Digital Policy, Regulation and Governance, 23(4), 412–431. https://doi.org/10.1108/DPRG-09-2020-0120
[49] Nurika, O., & Jung, L. T. (2024). Assessing Malaysia's Internet of Things (IoT) Readiness Based on CREATE-IoT Key Performance Indicators. Journal of Advanced Research in Applied Sciences and Engineering Technology, 40(1), Article 1. https://doi.org/10.37934/araset.40.1.4554
[50] Yahaya, N., Zakaria, N. H., & Tahir, H. M. (2018, July 25). An Investigation on the Factors that Influence Readiness of Internet of Things Adoption in Education Sector. https://repo.uum.edu.my/id/eprint/25251
[51] Negm, E. (2022). Intention to use Internet of Things (IoT) in higher education online learning – the effect of technology readiness. Higher Education, Skills and Work-Based Learning, 13(1), 53–65. https://doi.org/10.1108/HESWBL-05-2022-0121
[52] Radenković, M., Bogdanović, Z., Despotović-Zrakić, M., Labus, A., & Lazarević, S. (2020). Assessing consumer readiness for participation in IoT-based demand response business models. Technological Forecasting and Social Change, 150, 119715. https://doi.org/10.1016/j.techfore.2019.119715

[53] Martínez, I., Zalba, B., Trillo-Lado, R., Blanco, T., Cambra, D., & Casas, R. (2021). Internet of Things (IoT) as Sustainable Development Goals (SDG) Enabling Technology towards Smart Readiness Indicators (SRI) for University Buildings. Sustainability, 13(14), Article 14. https://doi.org/10.3390/su13147647

[54] Cui, Y., Liu, W., Rani, P., & Alrasheedi, M. (2021). Internet of Things (IoT) adoption barriers for the circular economy using Pythagorean fuzzy SWARA-CoCoSo decision-making approach in the manufacturing sector. Technological Forecasting and Social Change, 171, 120951. https://doi.org/10.1016/j.techfore.2021.120951

[55] Kumar, D., Singh, R. K., Mishra, R., & Daim, T. U. (2023). Roadmap for integrating blockchain with Internet of Things (IoT) for sustainable and secured operations in logistics and supply chains: Decision making framework with case illustration. Technological Forecasting and Social Change, 196, 122837. https://doi.org/10.1016/j.techfore.2023.122837

[56] Nazarian-Jashnabadi, J., Ronaghi, M., alimohammadlu, M., & Ebrahimi, A. (2023). The framework of factors affecting the maturity of business intelligence. Business Intelligence Management Studies, 12(46), 1-39. https://doi.org/10.22054/ims.2023.74305.2346

[57] Amiri Sardari, Z., Abdoli Mohamadabadi, T., Nazarian-Jashnabadi, J., Tesoriere, G., & Campisi, T. (2024). Smart Experience and Green Health Tourism: The Moderating Role of Content Marketing. Sustainability, 16(11), 4546. https://doi.org/10.3390/su16114546

[58] Jashnabadi, J. N., Pooya, A., & Bagheri, R. (2023). Provide a model for budget policy in university-community communication programs with a system dynamics approach (case study: Ferdowsi University of Mashhad). J. Ind. Manag. Perspect, 13(1), 9–39. https://doi.org/10.48308/jimp.13.1.9

[59] Rezazadeh, J., Bagheri, R., Karimi, S., Nazarian-Jashnabadi, J., & Nezhad, M. Z. (2023). Examining the impact of product innovation and pricing capability on the international performance of exporting companies with the mediating role of competitive advantage for analysis and decision making. Journal of Operations Intelligence, 1(1), 30–43. https://doi.org/10.31181/jopi1120232

[60] Kazemi, A., Kazemi, Z., Heshmat, H., Nazarian-Jashnabadi, J., & Tomášková, H. (2024). Ranking factors affecting sustainable competitive advantage from the business intelligence perspective: Using content analysis and F-TOPSIS. Journal of Soft Computing and Decision Analytics, 2(1), 39–53. http://dx.doi.org/10.31181/jscda21202430

[61] Haseli, G., Torkayesh, A. E., Hajiaghaei-Keshteli, M., & Venghaus, S. (2023). Sustainable resilient recycling partner selection for urban waste management: Consolidating perspectives of decision-makers and experts. Applied Soft Computing, 137, 110120. https://doi.org/10.1016/j.asoc.2023.110120

[62] Sushil. (2012). Interpreting the Interpretive Structural Model. Global Journal of Flexible Systems Management, 13(2), 87–106. https://doi.org/10.1007/s40171-012-0008-3

[63] Hwang, C.-L., & Yoon, K. (1981). Multiple Attribute Decision Making (Vol. 186). Springer. https://doi.org/10.1007/978-3-642-48318-9

[64] Hooshangi, N., Mahdizadeh Gharakhanlou, N., & Ghaffari Razin, S. R. (2023). Evaluation of potential sites in Iran to localize solar farms using a GIS-based Fermatean Fuzzy TOPSIS. Journal of Cleaner Production, 384, 135481. https://doi.org/10.1016/j.jclepro.2022.135481

[65] Hajiaghaei-Keshteli, M., Cenk, Z., Erdebilli, B., Selim Özdemir, Y., & Gholian-Jouybari, F. (2023). Pythagorean Fuzzy TOPSIS Method for Green Supplier Selection in the Food Industry. Expert Systems with Applications, 224, 120036. https://doi.org/10.1016/j.eswa.2023.120036

[66] Hasani, A., Haseli, G., & Deveci, M. (2024). Analyzing operational risks of digital supply chain transformation using hybrid ISM-MICMAC method. OPSEARCH. https://doi.org/10.1007/s12597-024-00792-y

[67] Toker, K., & Görener, A. (2023). Evaluation of circular economy business models for SMEs using spherical fuzzy TOPSIS: An application from a developing countries' perspective. Environment, Development and Sustainability, 25(2), 1700–1741. https://doi.org/10.1007/s10668-022-02119-7

[68] Sirisawat, P., & Kiatcharoenpol, T. (2018). Fuzzy AHP-TOPSIS approaches to prioritizing solutions for reverse logistics barriers. Computers & Industrial Engineering, 117, 303–318. https://doi.org/10.1016/j.cie.2018.01.015