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Research Article

Industry 4.0 Digital Technologies as Enablers of Sustainable Supply Chain Operations Performance

Piyusha Nayyar, Pratibha Garg, Neha Gupta
Amity School of Business, Amity University Uttar Pradesh, Noida, India
Email corresponding author: pgarg1@amity.edu

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ABSTRACT

The objective of this paper is to find the best industry 4.0 digital technologies as enablers amongst the available alternatives based on sustainable supply chain operations performance. Numerous sustainability advantages are provided by these technologies, from the possibility of reducing energy consumption and waste generation to increased prospects for recycling and industrial symbiosis. Using twenty sustainable supply chain performance criteria, we identified ten industry 4.0 digital technologies and used the Multi-criteria Decision Making (TODIM) technique to rank the best of them in a hierarchical fashion. In order to assist newly emerging firms in identifying the best industry 4.0 practices, this study analyzes the dominance of industry 4.0 digital technologies based on the significance and dominance of sustainable supply chain operations performance measures. The results show that the most important Industry 4.0 digital technologies for a sustainable supply chain are IoT, Big Data Analytics, and Blockchain; hence, enterprises should prioritize these technologies more to reap their benefits.

Keywords: Multi criteria decision making, TODIM, supply chain sustainability, performance measures, Industry 4.0 digital technologies.

INTRODUCTION

Amidst technological innovations in many industries, there has been a notable emphasis on enhancing supply chain management (SCM) to drive efficiency (Balfaqih et al., 2016). This shift towards supply chain optimization aligns with broader efforts to integrate sustainability into business practices, encompassing the entire journey of products from raw material sourcing to customer delivery. Stakeholders are increasingly prioritizing sustainable strategies to uphold ecological equilibrium, catalysing a transition from traditional supply chains to more sustainable ones (Seuring et al., 2022; Wang et al., 2020). Consequently, supply chains are pivoting towards sustainable goals through collaborative ventures, enhanced connectivity, strategic partnerships, innovative solutions, real-time monitoring, and stringent control measures. This pursuit of sustainability has been underscored by its recognition as a pivotal social goal for long-term development by organizations like the United Nations (UNO) (UN, 2015). The overarching objective is to elevate industrial practices to a world-class standard of sustainable manufacturing (Dubey et al., 2016). The measurement of a company's supply chain's alignment with its goals for environmental, social, and economic sustainability is known as sustainable supply chain performance, or SSCP. Sustainable supply chain enhances a business's long-term financial health by cutting expenses and increasing productivity, in addition to helping the environment and society. Embracing sustainability within supply chains empowers businesses to prioritize customer needs, foster innovation, and optimize resource utilization, capabilities, and productivity while upholding key environmental considerations (Junaid et al.,2022). Achieving a well-rounded sustainable supply chain performance necessitates staying informed about current technological trends, remaining attentive to digital transformation endeavors, and simultaneously emphasizing operational excellence (Mangla et al., 2020). Companies must concentrate on implementing new digital technologies in their core operations to drive customer integration, sales and business development, the creation of new products and services, and the achievement of better customer experience, operational excellence, and improved relationships with trading partners in an era characterized by the rapid digitalization of societies and industries (Ghobakhloo and Fathi, 2019). These days, businesses have to move their emphasis from just cutting costs and improving operations to using innovative technologies to leverage their supply chains as sources of real value. This entails meeting evolving customer expectations, facilitating new processes, and fostering greater integration, transparency, and agility within their organizations. Embracing a digital supply chain model offers a responsive, customer-centric approach that enhances productivity and enables the delivery of differentiated services to meet the needs of today's discerning consumers. Supply chains have been further empowered by the introduction of Industry 4.0 digital technologies, which have improved information accessibility, made it possible to collect data in real-time, optimized supply chain management practices, reduced production and transaction costs, streamlined product delivery schedules, and increased the general efficacy and efficiency of supply chain operations (Nayal et al.,2022; Bigliardi et al., 2022). Businesses could achieve operational efficiency, reduce the bullwhip effect, and improve internal processes by implementing industry 4.0 technologies (Queiroz et al., 2021). The digitalization process has been accelerated by the emergence of Industry 4.0 technologies, which include Internet of Things, advanced robotics, drones, business intelligence, blockchain, autonomous vehicles, artificial intelligence, 3D printing, augmented reality , machine learning, cloud computing, big data analytics [Frederico et al., 2020; Aryal et al., 2018]. By utilizing these technologies, Industry 4.0's digitization of supply chains promises to digitize information and the movement of goods, bringing the fragmented supply chain landscape together and simplifying it so that individual consumers may be served while fostering stronger relationships in the real world. urthermore, existing research has examined how digital technologies associated with industry 4.0 affect the effectiveness of sustainable supply chains (Dalenogare et al., 2018; Frank et al., 2019; Ghobakhloo and Fathi, 2019; Hofmann et al., 2019), yet it fails to provide a comprehensive list of criteria for selecting the most effective industry 4.0 digital technology practices aimed at enhancing the performance of sustainable supply chain processes. Additionally, it does not propose a detailed methodology that enables decision makers to integrate these criteria and choose the most suitable industry 4.0 technologies for sustainable supply chains in an objective manner. This study has made an effort to close this gap by presenting a TODIM technique to select the optimal I4.0 technology according to the twenty performance criteria for sustainable supply chain. As a result, the following research questions apply to this paper: RQ1: Which Industry 4.0 techniques are better suited for a sustainable supply chain? RQ2: What are the different performance metrics for sustainable supply chain processes? RQ3 what criteria allow us to rank and select the top Industry 4.0 technology for sustainable supply chain? This paper's remaining sections are arranged as follows. Section 2 provides the literature review on industry 4.0 technologies and then gives a brief description of the enablers. Section 3 provides an illustration of the analysis process that was used. This section outlines the different stages of the TODIM approach for identifying the leading industry 4.0 digital technology enablers of sustainable supply chain performance. Section 4 provides a discussion of the research and its implications. Conclusions are given in Section 5, while limitations and potential avenues for further research are shown in Section 6.

LITERATURE REVIEW

2.1 Supply chain management

Due to rising competition, rising costs, and the speed at which technology is developing globally, the supply chain (SC) is becoming a more fragile and complicated structure (Kumar & Kumar Singh, 2021). From the procurement of raw materials to the delivery of completed goods to final consumers worldwide, supply chains facilitate the end-to-end production of goods and/or services. They also present numerous chances for increased sustainability at every stage, from more strategic purchasing to the implementation of more environmentally friendly modes of transportation (McGrath et al., 2021). Additionally, supply chains are altering how businesses communicate, work together, and exchange information (Hopkins 2021). Therefore, every move toward increased digitalization in supply chains offers significant transformational potential. Embracing new technologies frequently propels digitalization (Waller and Fawcett 2013), affecting various functions throughout supply chains, such as procurement, manufacturing, logistics, warehousing, inventory management, retailing, as well as supplier and customer interactions (Hofmann and Rüsch 2017). In the current environment, the use of digital technologies, where supply chains contend with one another, is increasingly vital to maintain competitiveness (Akbari and Do 2021). As a result, supply chain management (SCM) has transitioned into a phase where utilizing emerging Industry 4.0 digital technologies is essential for facilitating data-driven decision-making, transforming business processes, and endorsing innovative changes in manufacturing, transportation, and warehousing (Abbasi et al. 2016). Organizations have begun to acknowledge the substantial effects of cutting-edge digital technologies, which act as catalysts for sustainable initiatives and enhance supply chain performance (Fuchs 2008). With the ongoing growth of globalization, there is also a rising global consciousness regarding its effects on the environment, society, and economy (Fiorini and Jabbour 2017). Sustainability is characterized as the equilibrium between environmental, social, and economic aspects (Seuring et al. 2008). Therefore, the incorporation of sustainable practices needs to be thoughtfully considered, necessitating that supply chain managers are adequately prepared for this task.

Sustainable supply chain management (SSCM) refers to the administration of supply chain activities, resources, information, and finances to optimize social welfare (Karmaker et al., 2021) and enhance supply chain profitability while minimizing ecological impacts (Wang-Mlynek & Foerstl, 2020). It constitutes a pivotal element in establishing competitive advantage within global markets by focusing on optimizing resource consumption. Operating under ethical principles, it guides stakeholders in sustaining value and reciprocal relationships within the chain (Kumara et al, 2021). With the use of infrastructure design and technological advancements, Industry 4.0 seeks to improve supply chains' sustainable performance by enabling process interconnectivity and integration (Acioli et al., 2021; Karmaker et al., 2021; Bayramova et al., 2021; Kurpjuweit et al., 2021, Singh et al., 2020).

2.2 Industry 4.0 technologies

Industry 4.0 is predicted to create significant disruption to the future global trade and supply chains (Piccarozzi et al. 2018). The term "industry 4.0" has been widely used to refer to the fourth industrial revolution, which is represented by the convergence of digital technologies that are changing supply chains, business models, and production processes in a variety of industries (Liao et al., 2017b; Ghobakhloo, 2018). According to Horvath and Szabo (2019), there are four key factors driving this revolution: meeting unforeseen client demands is the main driver, followed by reducing the product life cycle, preserving product flexibility, and observing what rivals are doing. Utilizing information and communication technology extensively to facilitate the integration of the real and virtual network worlds and create a system of people, information, and resources is the fundamental idea behind Industry 4.0 (Barata, 2021; Lemstra and de Mesquita, 2023). Although the rise of several important digital technologies is one of the primary forces behind I4.0, there is presently no agreed-upon description of the precise collection of digital technologies that make up I4.0 (Hopkins 2021). Ten exemplary Industry 4.0 technologies—big data analytics, artificial intelligence, the Internet of Things, cloud computing, blockchain, augmented reality, 3D printing, advanced robotics, drones, and autonomous vehicles—have been identified in this paper (Table 1) based on a comprehensive literature review Vehicles (Azuma 1997; Steuer 1992; Bai et al., 2020; Ghobakhloo, 2019).

Big data analytics. The vast and complex set of data is termed as “big data”, which is kept on increasing at a rate of doubling its volume every 1.2 years (Chen and Zhang, 2014). From the point of origin to the point of consumption, supply chains produce enormous volumes of data (Wang et al. 2016). A vital success mechanism for SCM is offered by BDA (Hazen et al. 2018). To increase operational efficiency, better target marketing, forecast accuracy, agility, customer focus, and explore new opportunities, BDA uses advanced analytics techniques, such as statistical and predictive analysis, data mining, etc., on a large number of datasets to uncover hidden patterns and correlations and draw valuable insights and useful information (Gandomi and Haider, 2015). Brinch (2018) used value creation, value discovery, and value capture to demonstrate the use of big data in the SCM. Big data analytics applications in SCM were identified by Nguyen et al. (2018). Sustainable projects are greatly impacted by each of these elements (Akbari and Do 2021).

Artificial Intelligence focuses on the ability of robots to exhibit some intellect like to that of humans (Kaplan, 2016). The goal of AI development is to create user interfaces that are both intuitive and adaptable to changing conditions (Agrawal et al., 2017). Real-time fraud and risk management (Lotakov 2016), improved inventory placement (Frommberger et al. 2012), energy efficiency (Jahanshahi et al. 2020), and a decrease in human engagement in the workplace are all made possible by advancements in artificial intelligence. According to McKinsey (2017), AI is expected to replace over 30% of current tasks in a number of US occupations.

Internet of things is a global network of interconnected devices. These devices are connected, monitored, and controlled by wireless, wired, or hybrid networks (Lee and Lee, 2015). The Internet of Things (IoT) reconnects people, things, and information by gathering data from actual objects, turning that data into usable information, and then providing that information to users so they can decide whether to change the real objects. Application of IoT advantages supply chain featuring real-time tracking, tracing, predictive maintenance, precise forecasting, sales data, tailored marketing, enhanced attainment of sustainability practices, waste control and overproduction, more opportunities for waste product reuse and recycling, packaging, and industrial symbiosis (De Vass et al., 2021; Koot et al., 2021).

Cloud computing Cloud computing often known as “cloud,” is the trending resource system today as it can store a significant amount of data and functions without the user’s direct intervention. According to Ardito et al. (2019) and Novais et al. (2019), it is a way to run programs and save data over the Internet rather than use a local or personal server. Resource pooling, quick flexibility, on-demand service, extensive network access, and measured service are some of its salient characteristics (Che et al., 2011; Kavis, 2014). The modern supply chain has grown into multi-tier supply networks, which require a lot of data to be exchanged electronically between the partners. However, cloud computing unifies the systems by centralizing these documents and streamlines the supply chain in terms of performance and operation, which lowers the cost of entering the market and makes it easier for small businesses to enter it (Novais et al., 2019; Ozu et al., 2020). Because of this change, supply networks built in the cloud are more elastic, scalable, and sustainable than those utilizing resources in conventional data centers (Shashi & Shashi, 2023).

Blockchain. Blockchain is a distributed ledger system that is defined as a virtual electronic ledger and a decentralized, open-source, distributed database for storing transactional data (Francisco and Swanson 2018; Sivula et al. 2021). Transparency and traceability in the supply chain could be improved by this technology (van Hoek, 2019 Rogerson and Parry 2020). This system's sustainability impact may include transforming supply chain operations for provenance and product traceability (Popper and Lohr 2017; Baker and Steiner 2015). By lowering carbon footprints, blockchain can also help achieve the goal of creating sustainable supply chain networks (Kouhizadeh et al. 2021). Because distributed ledger technology eliminates human mistake and misunderstanding throughout the distribution process, it can lower the rate of returns.

Augmented reality Augmented reality (AR) offers an interactive experience where computer-generated information is overlaid on physical objects in the real world. According to Barfield (2015), AR extends the tangible world by layering computer-generated data and information onto real-life situations. This technology enhances collaboration among stakeholders and promotes environmentally friendly behaviors regardless of their physical locations (Hopkins and Hawking 2018). AR is transforming supply chain industries, shifting from a slow, traditional paper-based model to one that heavily utilizes technology. It can accelerate the order picking process, reduce production time, minimize machine downtime, lower internal costs, and decrease error rates, thereby boosting overall productivity (Palmarini et al., 2018).

3D printing. 3D printing, sometimes referred to as additive or layered manufacturing, is a method for fabricating three-dimensional solid objects by converting a 3D digital model into the final product, layer by layer, without the use of cutting tools or molds (Ozceylan et al., 2017). This technology offers numerous advantages, such as the dematerialization of physical goods (Vendrell-Herrero et al. 2017), which leads to reduced transportation and storage costs, improvements in last-mile delivery (McKinnon 2016), shorter product life cycles (Rehnberg and Ponte 2018), shared costs from manufacturers to end-customers (Rayna and Striukova 2014), energy savings, and decreased CO_2 emissions (Gebler et al. 2014). Furthermore, 3D printing has the potential to disrupt the spare parts market (Rehnberg and Ponte 2018). It has enhanced the flexibility and responsiveness of supply chains; in the future, customers may place orders first, after which a nearby automated 3D printing facility will manufacture the product, potentially using drones for delivery (Chan et al., 2018; Ryan et al., 2017).

Advanced robotics. Autonomous robots are devices that perform various tasks with minimal to no human involvement (Eckert et al. 2016). These robots are capable of learning from their surroundings and making independent decisions. They have been implemented in manufacturing, final assembly, warehousing, and other supply chain functions involving high-risk tasks (Bechtsis et al., 2017). Advanced robotics enhances efficiency in material handling, picking and packing, welding and inspection, reduces the need for intensive and repetitive labor, lowers costs, saves energy, and creates a safer and more sustainable work environment (Ganesan et al. 2017). Increased automation more broadly leads to a reduced need for human presence, resulting in lower emissions and energy savings due to less commuting (Moglia et al. 2021).

Drones. Drones, also known as unmanned aerial vehicles, can be remotely controlled or operate autonomously using onboard sensors, GPS, and software-controlled flight plans (Nentwich and Horváth 2018; Schröder et al. 2018). They can navigate warehouses without needing lasers or markers. Drones enable quick movement of small items, replacing traditional forklift and conveyor systems used to transport goods in distribution centers (Marintseva et al., 2019). Initially developed for military applications, drones have emerged as a viable solution for supply chain challenges such as urban package delivery, inventory management, surveillance, inspection, traffic control, and pollution reduction (Kille et al., 2019; Xu et al., 2018).

Autonomous Vehicles. Integrating technologies throughout the global supply chain represents an evolutionary step towards digital supply chain networks (Bechtsis et al. 2018), with one significant advancement being the use of long-haul autonomous trucks (Abbott et al. 2018). The adoption of these vehicles is expected to lower overall shipping expenses, reduce accidents, decrease fuel consumption, cut greenhouse gas (GHG) emissions, and lower labor costs.

Table 1: Industry 4.0 technologies

Technology	Description	Reference
Big data analytics (BDA)	vast and complex data set that was unlikely to be analyzed using traditional business tools	Chen and Zhang, 2014
Artifcial Intelligence (AI)	ability of machines to mimic human intellect	Kaplan, 2016
Internet of things (IoT)	a worldwide network of interconnected things using sensing technologies in an articulated intelligence network	Lee and Lee, 2015
Cloud computing (CC)	ways to use the Internet to store data and run programs rather than a local or personal server	Ardito et al. (2019), Novais et al. (2019)
Blockchain (BC)	decentralized system in which all transactions are permanently recorded and stored	Francisco and Swanson 2018
Augmented reality (AR)	extension of the physical world by using computer-generated layers of data and information in actual situations.	Barfield (2015)
3D printing (3DP)	used to create three dimensional solid objects with layer- by- layer construction without the need of moulds or cutting tools starting with a 3D digital software model	Ozceylan et al., 2017
Advanced Robotics (ARO)	devices with programming that carry out various tasks with little to no assistance from humans	(Eckert et al. 2016)
Drones (DR)	Unmanned aerial vehicles equipped with sensors, GPS and software-controlled flight plans that enable them to operate remotely or autonomously	(Nentwich and Horváth 2018; Schröder et al. 2018)
Autonomous Vehicles (AV)	Vehicles with intelligence that can react to any unforeseen circumstance in their surroundings	(Hagen et al. 2007)

2.3 Sustainability

Sustainability is a multifaceted concept that includes business's social, environmental, and economic facets. The main objective of any business is to turn a profit in order to maintain long-term economic viability through cost and revenue management during the procurement, manufacturing, and distribution of goods and services. In the present-day business environment, there is a heightened focus on environmental sustainability due to global pressures, climate change, and pollution (Boons et al. 2013). This emphasis is on reducing the use of natural resources, lessening waste, and pollution (air, water, and land), and increasing the use of renewable energy in production and distribution. Social sustainability includes aspects like the workplace culture, morale and satisfaction of employees, equity, and community social integration.

2.4 Industry 4.0 enabling sustainable supply chain

Industry 4.0 technologies are meant to play a major role in directing businesses in the direction of long-term sustainability (de Sousa Jabbour et al. 2018). Junge and Straube (2020) studied impact of digital technologies on sustainable supply chain performance and found that it help drives efficient demand and supply planning, engage in sustainable sourcing, promote transparency, reduce environmental footprints, energy consumption, overproduction and waste of resources. I4.0 technologies such as artificial intelligence and machine learning can predict the likely demand for products, ensuring that only enough raw materials are used in the production process and reducing wastage (Lee 2021; Zimon, Tyan, and Sroufe 2019). Kamble et al. (2018) investigated the impact of I40 adoption in organizations for offering customised goods, reducing lead times, enhancing product quality, improving the working environment, and boosting employee morale. Braccini and Margherita (2019) examined the impact of I40 adoption in a manufacturing firm and revealed improvements in product quality and productivity, energy monitoring and consumption reduction, work environment safety and job satisfaction for workers. Birkel and Muller (2021) provided a literature review focused on the potential of I40 to positively impact the triple bottom line of sustainability in supply chain planning, sourcing, logistics, and recycling.

According to Stock and Seliger (2016), I4T has a major economic impact by fostering value creation, production flexibility, and product customization, all of which raise customer happiness. I40's automation and digitalization capabilities help manufacturers cut costs, enhance quality, and shorten lead times (Oesterreich & Teuteberg 2016). I4T reduces raw material stocks and enables efficient capacity usage (Wang et al. 2016). Digital technologies enable flexible supply chain planning and efficient decision making to achieve high quality with low cost and risk in sustainable purchasing (Gottge et al. 2020). Product life cycle, industry economic performance, and demand planning and inventory management synchronization can all be enhanced by I40 (Dev et al. 2016). Higher operational efficiency, ad-hoc dynamic planning, collaborative planning, collaborative product design, marketing efficacy, financial flow, and deeper customer integration are some advantages that a digital supply chain may provide (Dolgui et al. 2019).

I40 is environment friendly since its implementation will result in reduction of raw materials and resources like materials, energy, water, and products (Stock and Seliger 2016). I4T also supports lower energy consumption (Herrmann et al. 2014), lower greenhouse gas emissions (Peukert et al. 2015), lower scrap and waste due to better logistics and transportation planning, and the use of cutting-edge tracking and monitoring systems (Müller et al 2017).

In terms of the social sustainability dimension, I4T offers a wide range of opportunities for employees to learn new skills, which boost motivation and morale (Herrmann et al. 2014). I4.0 offers employees with a secure working environment, flexibility, reduce stress and hazardous tasks (kamble et al. 2018). AI and data analytics can help in improving learning and development (Stone et al. 2018).

Based on the literature, the authors have identified the best industry 4.0 digital technologies by using 20 criteria for evaluating the performance of sustainable supply chains that take into account the economic, environmental, and social aspects of business while taking into account the triple bottom approach to sustainability.

RESEARCH METHODOLOGY

3.1 The TODIM Technique

The early 1990s saw the development of TODIM, a discrete multi-criteria decision-making technique based on Prospect Theory. In Portuguese, it is referred to as Interactive and Multicriteria Decision Making (Kahneman & Tversky, 1988). In multi-criteria decision-making, the common assumption is that the best solution maximizes a global measure value. For instance, in the Multi-Attribute Utility Theory (MAUT), the solution is identified by the highest global value of a multi-attribute utility function (Keeney & Raiffa, 1993). However, the TODIM method distinguishes itself by applying the principles of Prospect Theory to determine the global value. TODIM focuses on how people make decisions under risk, incorporating both descriptive and empirical evidence. It relies on a multi-attribute value function, which combines various mathematical descriptions to represent gain and loss functions. These functions are then aggregated across all criteria to derive the final decision. The TODIM method's value function resembles the gain/loss function of Prospect Theory in shape, though not all multi-criteria problems involve risk. Certain types of gain and loss functions are evaluated in TODIM computations using a single parameter. Once these forms are empirically validated, they help develop the additive difference function—a global multi-attribute function that measures the dominance of each alternative over others (Tversky, 1969). This makes TODIM akin to outranking methods like PROMETHEE (Brans & Mareschal, 1990), as the final global value of each alternative is relative to its dominance over others. Although the validation process may seem complex, leading some decision analysts to opt for other gain or loss functions, it is straightforward. The mathematical forms used in the nineties have practical applications and have been empirically validated in various contexts (Gomes & Lina, 1992a, b; Trotta et al., 1999). The TODIM additive difference function, like a multi-attribute value function, must be validated by verifying the condition of mutual preferential independence, which orders the global values of the alternatives (Clemen & Reilly, 2013; Keeney & Raiffa, 1993). The differences between the values of any two alternatives in relation to a referential criterion for each criterion are the definition of this function in TODIM. Consequently, trade-offs are avoided due to non-compensatory methods (Bouyssou, 1986). Roy and Bouyssou (1993) described TODIM as "a method based on both the French School and the American School. It combines aspects of the Multi-attribute Utility Theory, the AHP method, and the ELECTRE methods." Barba-Romero & Pomerol (2000) observed that TODIM "is based on a notion extremely similar to a net flow, in the PROMETHEE sense," as the multi-attribute function's expressions of gains and losses resemble those of the PROMETHEE methods, which employ net outranking flow. Imagine a situation where m qualitative and quantitative criteria must be used to rank n alternatives, with one criterion serving as the reference criterion. Regarding the goal of the criterion, experts estimate the values for each criterion c and each alternative i. Normalization is necessary because these estimated values for each alternative in respect to the criteria must be numerical. Similarly, criteria values must be converted from a verbal scale to a cardinal scale. The alternatives' performances in relation to the criteria such as calculating engine power in horsepower or noise levels in decibels are used to determine the criteria values. As a result, the TODIM approach normalizes both quantitative and qualitative criteria by translating verbal scale criteria into cardinal scales. For every pair of alternatives, the relative measure of one alternative's dominance over another is calculated by adding the relative gain or loss function values for each criterion. This total will indicate profits, losses, or zeros based on how each option performs in relation to each criterion. A numerical matrix is produced after the alternatives are calculated in respect to each criterion. After that, this matrix is normalized to produce a matrix with values ranging from zero to one by dividing each alternative's matrix value by the total number of alternatives for each criterion. As shown in Table 2, this normalized matrix, which shows how well the alternatives score in relation to the criteria, is written as $P = P_{nm}$, where n is the number of alternatives and m is the number of criteria.

Table 2: Normalized Alternative's Matrix against criteria

Alternative/Criteria	C_1	C_2	$\cdots$	C_m
A_1	P_{11}	P_{12}	$\cdots$	P_{1m}
A_2	P_{21}	P_{22}	$\cdots$	P_{2m}
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$
A_n	P_{n1}	P_{n2}	$\cdots$	P_{nm}

The final dominance matrix and partial dominance matrices must be found after the normalized alternative scores have been assessed. Decision makers have to choose a reference criterion r for further calculations based on the relative weights given to each criterion. Out of all the criteria, the reference criterion is selected as the one with the highest importance value. Each criterion is given a numerical value by decision makers (ranging from 1 to 5 for example), which needs to be normalized. The weight w_{rc} is defined as the weight of criterion c divided by the weight of the reference criterion r. This makes it possible to express every variation in performance measurements in terms of the dimension of the reference criterion. The measure of each alternative A_i dominance over all other alternatives with elements from Prospect Theory, A_j, is represented by the following expression:

$$\pi(A_i, A_j) = \sum_{c=1}^{m} \delta_c(A_i, A_j) \qquad \forall\ (i, j) \tag{1}$$

when

$$\delta_c(A_i, A_j) = \begin{cases} \sqrt{\dfrac{w_{rc}(P_{ic} - P_{jc})}{\sum_{c=1}^{m} w_{rc}}}, & if\ (P_{ic} - P_{jc}) > 0 \quad (2) \\ 0, & if\ (P_{ic} - P_{jc}) = 0 \quad (3) \\ -\dfrac{1}{\theta}\sqrt{\dfrac{w_{rc}(P_{ic} - P_{jc})}{\sum_{c=1}^{m} w_{rc}}}, & if\ (P_{ic} - P_{jc}) < 0 \quad (4) \end{cases}$$

The measurement of alternative A_i dominance over alternative A_j is represented by $\pi(A_i, A_j)$ in this case. The variable m is the number of criteria, and c is any criterion where c = 1, ..., m. The weight of criterion c divided by the weight of the reference criterion r is known as the term w_{rc}. The performances of alternatives A_i and A_j in respect to criterion c are denoted as P_{ic} and P_{jc} respectively. The attenuation factor for losses is the variable θ. The shapes of the prospect theoretical value function in the negative quadrant vary depending on the value of θ.

The expression $\delta_c(A_i, A_j)$ denotes the contribution of criterion c to the function $\pi(A_i, A_j)$ when comparing alternative A_i with alternative A_j. If $\pi(A_i, A_j)$ is positive, it represents a gain function of $\pi(A_i, A_j)$, and thus Eq. (2) is used. If $(P_{ic} - P_{jc})$ is zero, the value will be zero, as assigned by Eq. (3). If $(P_{ic} - P_{jc})$ is negative, it represents a loss function, and Eq. (4) is used. Therefore, the expression $\delta_c(A_i, A_j)$ aligns the problem data with the value function of Prospect Theory, accounting for risk aversion and risk propensity. This function has an "S" shape, as shown in Fig. 1. The concave curve above the horizontal axis represents gains and reflects risk aversion, while the convex curve below the horizontal axis represents losses and reflects risk propensity.

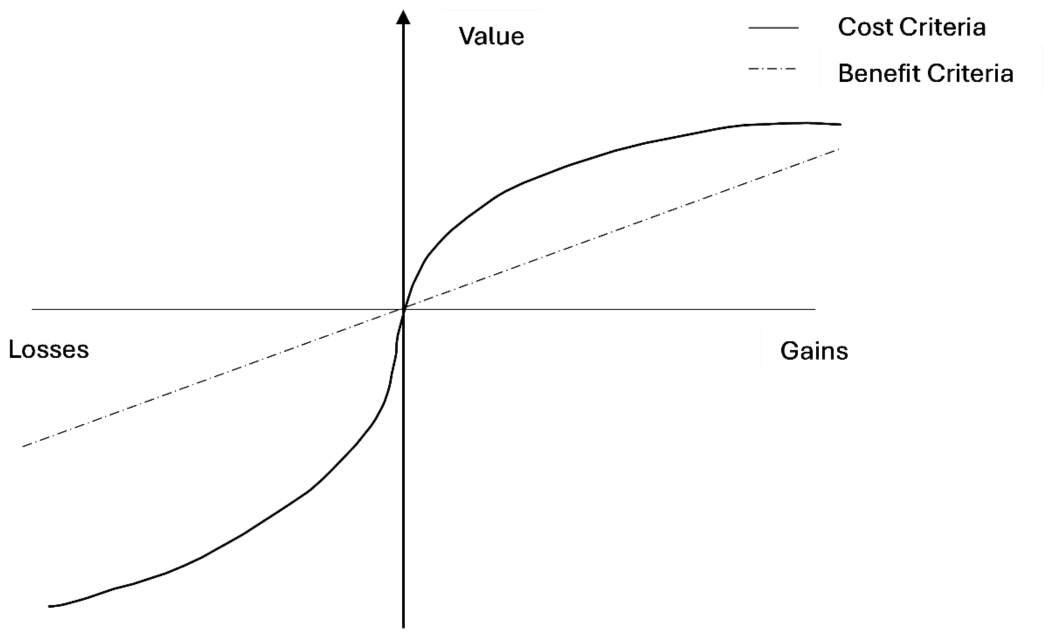

Figure 1: Value function of the TODIM method (Gomes & Lina, 1992a)

After calculating the various partial dominance matrices for each criterion, the final dominance matrix for the general element $\pi(A_i, A_j)$ is determined by summing the elements of the different matrices. Expression (5) is then used to determine the overall value of alternative i by normalizing the corresponding dominance measurements. The respective values are then ranked to assign a rank to each alternative.

$$\varphi_i = \frac{\sum_{j=1}^{n} \pi(A_i, A_j) - min \sum_{j=1}^{n} \pi(A_i, A_j)}{max \sum_{j=1}^{n} \pi(A_i, A_j) - min \sum_{j=1}^{n} \pi(A_i, A_j)} \tag{5}$$

As a result, the global values that come from the calculation with Eq. (5) enable the full rank ordering of every alternative.

3.2 The Proposed Methodology

The industry 4.0 digital technologies are analysed using the TODIM technique to see how well they support sustainable supply chain operations performance. To stay competitive, the industries are concerned about managing, particularly issues related to volume and access. While there are numerous industry 4.0 digital technologies available, their implementation often requires substantial investment. The industries, which are gradually expanding, cannot afford such large investments. Consequently, these companies face a dilemma in selecting cost-effective industry 4.0 digital technologies that align with their specific requirements.

To address this, we identified several industry 4.0 digital technologies that could help in driving the sustainable supply chain operations performance according to the company's needs, highlighting ten specific technologies as alternatives. Additionally, we identified twenty criteria essential for improving overall supply chain performance.

The TODIM method was chosen for this evaluation despite the availability of many other multi-criteria decision-making methods for the following key reasons:

1. The TODIM method effectively combines both qualitative and quantitative data, offering decision-makers a comprehensive approach for selecting the most suitable options for their companies.

2. Unlike other multi-criteria decision-making (MCDM) approaches, TODIM uniquely addresses risk by utilizing gain and loss functions based on prospect theory.

Tables 3 and 4 provide representations of the criteria and alternatives, respectively. The following notations represent the industry 4.0 digital technologies and criteria needed for the analysis:

Table 3: Representation of Criteria

Parameter	Criteria	Code
Economic	1. Reduced supply chain costs.	C_1
	2. Reduced manufacturing lead time and order delivery cycle time.	C_2
	3. Improved value to the customers (reduced price, improved quality, product functionalities, customer service level) and profitability.	C_3
	4. Improved supply chain resilience.	C_4
	5. Reduction of raw material inventories and effective capacity utilisation.	C_5
	6. Flexible supply chain planning and effective decision making.	C_6
	7. Integration with all supply chain players (suppliers, customers and within organizations) and shares information through information network.	C_7
	8. Improved synchronization of demand planning and inventory management.	C_8
Environmental	9. Reduction in scrap.	C_9
	10. Reduction in resources.	C_{10}
	11. Reduction in energy consumption.	C_{11}
	12. Improved transportation and logistics planning.	C_{12}
	13. Transparency	C_{13}
	14. Advanced tracking and tracing systems to improve recycling of materials.	C_{14}
	15. real time monitoring of entire supply chain	C_{15}
	16. improved the reuse and, parts and components. (SSCM14)	C_{16}
Social	17. Reduction of stress and hazardous tasks	C_{17}
	18. Safe and secure working environment	C_{18}

	19. Boosting morale and motivation	C_{19}
	20. Improved Learning and development	C_{20}

Table 4 Representation of Alternatives

Industry 4.0 digital technologies	**Code**
BDA	A_1
AR/VR	A_2
Blockchain	A_3
Robotics	A_4
IOT	A_5
AV	A_6
AI	A_7
Cloud computing	A_8
Drones	A_9
3D	A_{10}

These notations help in the systematic analysis and application of the TODIM method to assess and rank the alternatives according to the specified criteria.

3.3 Data Collection and Analysis

A well-structured questionnaire was used to collect the data. Five specialists who are well-versed in all the digital technologies covered in this study were chosen. Many practitioners in India lack a thorough understanding of industry 4.0 digital technologies because the technology is still in its early phases of acceptance and deployment. The authors interviewed with the experts and chose five for the final responses in order to remove any potential prejudice resulting from this ignorance. Table 5 provides a complete profile of the responders.

Table 5: Respondent Profile

Expert	**Industry**	**Experience**	**Profile**	**Level of Technology Implementation**
Expert 1	Manufacturing	15 years	Chief Technology Officer at a leading manufacturing company. Specializes in IoT and predictive maintenance.	Advanced: Full implementation of IoT and predictive analytics.
Expert 2	Automotive	20 years	Head of Digital Transformation at a major automotive firm. Focuses on robotics and AI integration.	Advanced: Automated assembly lines, AI-driven quality control.
Expert 3	Healthcare	12 years	Director of Innovation at a healthcare technology company. Expert in AI and big data analytics for patient care.	Intermediate: Implementation of AI for diagnostics and data analytics.
Expert 4	Logistics & Supply Chain	18 years	Senior Vice President of Technology at a global logistics company. Expert in blockchain and IoT for supply chain transparency.	Advanced: Blockchain for supply chain transparency, IoT for real-time tracking.
Expert 5	Energy	10 years	Lead Engineer at a renewable energy company. Specializes in smart grid technology and AI-based energy management.	Intermediate: Smart grids, AI-based demand response systems.

Here the integration of digital technologies represents the level of technology implementation with criteria aimed at improving supply chain operations performance. The degree of supply chain integration of industry 4.0 digital technologies is shown in Table 5's "Level of Technology Implementation" column. This integration level is reflected by the integration rank, which runs from Rank 1 to Rank 5. It is based on pairwise comparison on a scale from 1 to 5, where 1 denotes "very unimportant" and 5 denotes "very important." Similarly, this scale is used to rank alternatives, with '1' indicating 'very poor' and '5' indicating 'very good.' Expert rankings are gathered and adjusted in order to establish the reference criterion and define the weights for each criterion. The weights of the criterion that resulted are shown in Table 6.

Table 6: Weights of the criteria

Criterion	**Weight**	W_{rc} **Values**	**Representation**
Criterion 1	0.0523	0.5660	W_{71}
Criterion 2	0.0718	0.7771	W_{72}
Criterion 3	0.0365	0.3950	W_{73}
Criterion 4	0.0642	0.6948	W_{74}
Criterion 5	0.0847	0.9167	W_{75}
Criterion 6	0.0519	0.5617	W_{76}
Criterion 7	0.0924	1.0000	W_{77}
Criterion 8	0.0321	0.3474	W_{78}
Criterion 9	0.0745	0.8063	W_{79}
Criterion 10	0.0556	0.6017	W_{710}
Criterion 11	0.0628	0.6797	W_{711}
Criterion 12	0.0417	0.4513	W_{712}
Criterion 13	0.0709	0.7673	W_{713}
Criterion 14	0.0583	0.6310	W_{714}
Criterion 15	0.0612	0.6623	W_{715}
Criterion 16	0.0473	0.5119	W_{716}
Criterion 17	0.0385	0.4167	W_{717}
Criterion 18	0.0731	0.7911	W_{718}
Criterion 19	0.0637	0.6894	W_{719}
Criterion 20	0.0610	0.6602	W_{720}

The criterion with the greatest weight is designated as the reference criterion, and the values of w_{rc} for each criterion are computed using this reference criterion as a base. Following the determination of these weights (refer to Table 7), we must use the expert ranks to compute the normalized matrix of alternatives with regard to the criteria (refer to Table 8).

Table 7: Matrix of alternatives' scores against criteria by experts

Criteria \ Alternatives	**A1**	**A2**	**A3**	**A4**	**A5**	**A6**	**A7**	**A8**	**A9**	**A10**
C1	4	3	5	2	3	4	5	1	3	2
C2	3	4	2	5	1	3	4	2	5	1
C3	5	3	4	2	4	5	2	3	1	4
C4	2	5	3	4	2	1	4	5	3	2

Criteria \ Alternatives	**A1**	**A2**	**A3**	**A4**	**A5**	**A6**	**A7**	**A8**	**A9**	**A10**
C5	3	2	4	5	3	4	1	2	5	3
C6	4	3	5	1	3	2	4	5	2	4
C7	1	4	2	5	3	4	3	2	5	1
C8	5	3	4	2	4	5	2	3	1	4
C9	2	5	3	4	2	1	4	5	3	2
C10	3	2	4	5	3	4	1	2	5	3
C11	4	3	5	1	3	2	4	5	2	4
C12	1	4	2	5	3	4	3	2	5	1
C13	5	3	4	2	4	5	2	3	1	4
C14	2	5	3	4	2	1	4	5	3	2
C15	3	2	4	5	3	4	1	2	5	3
C16	4	3	5	1	3	2	4	5	2	4
C17	1	4	2	5	3	4	3	2	5	1
C18	5	3	4	2	4	5	2	3	1	4
C19	2	5	3	4	2	1	4	5	3	2
C20	3	2	4	5	3	4	1	2	5	3

Table 8: Matrix of normalized alternatives' scores against criteria

Criteria \ Alternatives	**A1**	**A2**	**A3**	**A4**	**A5**	**A6**	**A7**	**A8**	**A9**	**A10**
C1	0.80	0.60	1.00	0.40	0.60	0.80	1.00	0.20	0.60	0.40
C2	0.60	0.80	0.40	1.00	0.20	0.60	0.80	0.40	1.00	0.20
C3	1.00	0.60	0.80	0.40	0.80	1.00	0.40	0.60	0.20	0.80
C4	0.40	1.00	0.60	0.80	0.40	0.20	0.80	1.00	0.60	0.40
C5	0.60	0.40	0.80	1.00	0.60	0.80	0.20	0.40	1.00	0.60
C6	0.80	0.60	1.00	0.20	0.60	0.40	0.80	1.00	0.40	0.80
C7	0.20	0.80	0.40	1.00	0.60	0.80	0.60	0.40	1.00	0.20
C8	1.00	0.60	0.80	0.40	0.80	1.00	0.40	0.60	0.20	0.80
C9	0.40	1.00	0.60	0.80	0.40	0.20	0.80	1.00	0.60	0.40
C10	0.60	0.40	0.80	1.00	0.60	0.80	0.20	0.40	1.00	0.60
C11	0.80	0.60	1.00	0.20	0.60	0.40	0.80	1.00	0.40	0.80
C12	0.20	0.80	0.40	1.00	0.60	0.80	0.60	0.40	1.00	0.20
C13	1.00	0.60	0.80	0.40	0.80	1.00	0.40	0.60	0.20	0.80
C14	0.40	1.00	0.60	0.80	0.40	0.20	0.80	1.00	0.60	0.40
C15	0.60	0.40	0.80	1.00	0.60	0.80	0.20	0.40	1.00	0.60
C16	0.80	0.60	1.00	0.20	0.60	0.40	0.80	1.00	0.40	0.80
C17	0.20	0.80	0.40	1.00	0.60	0.80	0.60	0.40	1.00	0.20
C18	1.00	0.60	0.80	0.40	0.80	1.00	0.40	0.60	0.20	0.80

Criteria \ Alternatives	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10
C19	0.40	1.00	0.60	0.80	0.40	0.20	0.80	1.00	0.60	0.40
C20	0.60	0.40	0.80	1.00	0.60	0.80	0.20	0.40	1.00	0.60

Equations 2, 3, and 4 are then used to calculate the normalized matrix and ascertain the partial dominance of each alternative. The partial dominance values for the remaining alternatives are similarly computed. Equation 1 is used to get the final dominance values from these partial dominance values, allowing us to eliminate the criteria by adding the partial dominance matrices for each criteria. We must compute the global values (see Table 10) following the determination of the final dominance values for each alternative (see Table 9). After that, these global values are ordered and normalized based on their values.

Table 9: Final dominance values of all the alternatives

	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10
A1	0	1.2	0.8	1.1	0.9	1.3	0.7	1.0	0.6	1.4
A2	-1.2	0	1.4	1.7	1.1	0.9	1.2	1.3	0.8	1.5
A3	-0.8	-1.4	0	1.0	1.2	1.5	1.1	1.4	0.9	1.6
A4	-1.1	-1.7	-1.0	0	1.3	1.2	1.4	1.5	1.1	1.7
A5	-0.9	-1.1	-1.2	-1.3	0	1.0	1.3	1.6	1.2	1.8
A6	-1.3	-0.9	-1.5	-1.2	-1.0	0	1.5	1.7	1.3	1.9
A7	-0.7	-1.2	-1.1	-1.4	-1.3	-1.5	0	1.8	1.4	2.0
A8	-1.0	-1.3	-1.4	-1.5	-1.6	-1.7	-1.8	0	1.5	2.1
A9	-0.6	-0.8	-0.9	-1.1	-1.2	-1.3	-1.4	-1.5	0	2.2
A10	-1.4	-1.5	-1.6	-1.7	-1.8	-1.9	-2.0	-2.1	-2.2	0

Each cell of Table 9 represents the dominance value of alternative A_i over alternative A_j. Positive values indicate that A_i over alternative A_j, while negative values indicate that A_j over alternative A_i. The diagonal elements are zero because an alternative cannot dominate itself.

Table 10: Final values and ranking of all the alternatives

Alternative	Sum of Dominance Values	Rank
A1	8.7	2
A2	-6.6	8
A3	6.5	3
A4	2.4	5
A5	9	1
A6	-6.7	9
A7	4.4	4
A8	0.5	6
A9	-2	7
A10	-16.2	10

Based on the ranks of each alternative, the alternative A5, which is IOT, has achieved the first rank. This indicates that IOT is the best technology, satisfying the optimal conditions and criteria for firms to enhance the complete implementation of the supply chain. Followed by BDA (A1), Blockchain (A3), and Cloud computing (A7) while the least important is 3D (A10) and AV (A6).

DISCUSSION AND IMPLICATIONS

The integration of digital technology for industry 4.0 into sustainable supply chains requires significant financial, temporal, and organizational restructuring investments. Thus, before launching such initiatives, businesses need to determine the key elements that propel industry 4.0 in the supply chain and evaluate which industry 4.0 practices are better than the others. Each practice's final global values are computed, normalized, and then ranked order is established. The findings make it abundantly evident that the three most important Industry 4.0 practices for sustainable supply chains are "IoT," "big data analytics," and "blockchain technology." As a result, businesses must place a greater focus on these technologies to fully benefit from them. The results align with the findings of the study by Rajput and Singh (2019), which showed that IoT and Big Data are the primary factors enabling the implementation of Industry 4.0 across various sectors. The capacity of IoT to facilitate enhanced supply chain transparency and information sharing has been shown to improve sustainable performance (de Vass et al. 2021). IoT devices, including sensors, RFID, and GPS, assist in reducing disruptions and failures by allowing for real-time asset monitoring, tracking, and alerts (Ben-Daya et al., 2017). As noted by Hong et al. (2019), adopting IoT technologies also allows companies to compete on a global scale and meet international standards. Big Data Analytics (BDA) is understood to impact sustainable performance because it can oversee the internal processes that contribute to sustainable capability (Singh and El-Kassar 2019). Big data can synchronize demand planning and inventory management. Predictive analytics transforms blind forecasting into a more informed process by integrating additional customer data and market insights, thereby improving forecast accuracy (Hofmann and Rutschmann, 2018). According to Mani et al. (2017), BDA can also be leveraged to forecast and alleviate various supply chain risks, such as workforce safety, monitoring fuel consumption, workforce health, security, vehicle maintenance, speeding, and traffic violations. Pereira et al. (2017) noted that concerns about data security and the risk of losing confidential information are significant challenges when adopting new digital technologies in businesses. "Blockchain" could serve as a viable solution to address these challenges (Demirkan et al., 2020). Blockchain technology enhances sustainable supply chain performance by eliminating intermediaries, speeding up transactions, lowering costs, and increasing data security. It can help reduce inventory waste by lessening the bullwhip effect and improving product safety and traceability (Esmaeilian et al. 2020; Tian 2016). The conclusions of this research further support the findings from Rejeb et al. (2020), which asserted that the combination of IoT, big data analytics, and blockchain technology will deliver greater value to businesses and aid in enhancing processes such as traceability and product identification.

Other significant enablers of Industry 4.0 digital technologies for a sustainable supply chain include "AI," "Robotics," and "cloud computing." AI and robotics technologies facilitate digital advancement, intelligent supply chains, cognitive planning, and smart manufacturing, leading to improved operational efficiency. AI is a suitable choice for dynamic fulfillment by automatically triggering replenishment orders (Przegalinska et al., 2019). Advanced autonomous robots can function independently alongside humans and can adjust to any changes in their environment (Bogue, 2016). Like BDA, AI employs predictive analytics to model future scenarios, which can be utilized to enhance waste management (Ramchandran et al. 2017), improve energy efficiency (Dauvergne 2020), manage risk (Baryannis et al. 2019), and aid society in reducing energy, water, and land consumption (Nishant et al. 2020). AI can assist managers in recognizing new trends in employee data for tailored training and development opportunities (Lengnick-Hall et al. 2018), while AI-driven location awareness systems can identify human or machine actions that may present safety risks (Ghobakhloo 2020; Kamble et al. 2018). The application of robotics has also been associated with decreased energy consumption and greenhouse gas emissions (Lee et al. 2015a, b), as well as more efficient utilization of raw materials (Cousineau and Miura 1998), the capacity for extensive environmental monitoring (Dunbabin and Marques 2012), and enhancements in safety that lead to fewer injuries and fatalities (Castro-Lacouture 2009). cloud computing reduces redundancy and makes supply chain networks more cost-effective; it promotes scalability, efficiency, and integration (Frank et al., 2019).

According to this study, the performance of sustainable supply chains is less affected by AR, AV, drones, and 3D technology. According to popular belief, drones can improve the sustainability of business-to-customer (B2C) deliveries while lowering pollution and traffic congestion (Rao et al. 2016). They can also help humanitarian supply chains with transportation issues (Azmat and Kummer 2020) and encourage cleaner agricultural production and CE strategies (Mahroof et al. 2021). Wearable technology with augmented reality capabilities can guide workers through their jobs. These gadgets track employees' movements and task durations continually, which could help with scheduling and assignment optimization (Palmarini et al., 2018). Customers can facilitate large customisation of items by using 3D printing to enable on-demand and on-site manufacture (Chan et al., 2018). Because of better routing, eco-driving, and the shorter travel times between cars, AVs are predicted to use less fuel and produce fewer greenhouse gas emissions than existing automobiles (Khakurel et al. 2018).

CONCLUSION

The study concludes that enterprises should give high priority to the development of IoT platforms, big data analytics and blockchain since these technologies have the ability to enhance supply chain performance in a sustainable way by improving operational resilience, forecasting accuracy, and transparency. This paper presents businesses with a clear implementation roadmap for a range of industry 4.0 digital technologies, acting as enablers in a hierarchical fashion to maximize new opportunity benefits and boost sustainable supply chain performance. Although there is a lot of opposition when changes are first implemented, if they are done gradually, stakeholders will get more confident and new technology will be further adopted within the company. This study broadens our understanding of supply chain sustainability by offering fresh viewpoints on a variety of technologies. The use of Industry 4.0 technologies is entering an exciting phase and holds considerable promise for promoting digitalization and its associated sustainability advantages.

LIMITATION AND SCOPE FOR FUTURE RESEARCH

The study highlights several critical areas that warrant further investigation. For instance, researchers could address the same problem using fuzzy or grey TODIM techniques to manage the uncertainty inherent in expert decisions. Additionally, the effectiveness of multi-criteria decision-making models is heavily reliant on the information provided by respondents from the case organizations. Thus, selecting the appropriate pool of experts is crucial. Relying on a single expert can introduce bias, so it is beneficial to involve experts from various functional areas who possess relevant knowledge and expertise. Otherwise, the process may suffer from the "garbage in, garbage out" problem. Ensuring that the feedback represents a consensus is also important, and this can be achieved using group decision-making methods such as the geometric mean (Ramkumar & Jenamani, 2012; Ramkumar et al., 2016). To further enhance the model, additional field surveys could be conducted. Moreover, refining the model based on widely accepted theoretical perspectives, rather than just existing literature, would be valuable. It is also vital to evaluate the influence of each criterion on the final decision.

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