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ORIGINAL RESEARCH

Key performance indicator based dynamic decision-making framework for sustainable Industry 4.0 implementation risks evaluation: reference to the Indian manufacturing industries

Rimalini Gadekar[1] · Bijan Sarkar[2] · Ashish Gadekar[3]

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Abstract

Global corporate giants are keen to adopt Industry 4.0 (I4.0) owing to its continuous, impactful, and evident benefits. However, implementing I4.0 remains a significant challenge for many organizations, mainly due to the absence of a systematic and comprehensive framework. The risk assessment study is key to the flawless execution of any project is a proven fact. This paper aims to develop a KPIs-based sustainable integrated model to assess and evaluate risks associated with the I4.0 implementation. This research paper has developed the I4.0 risks evaluation model through fifteen expert interventions and an extensive systematic literature review. This research, based on sixteen KPIs evaluates six risks impacting the organization's decision to adopt I4.0. Initially, the Fuzzy Decision-Making Trial and Evaluation Laboratory method is used to map the causal relationship among the KPIs. Further, the additive ratio assessment with interval triangular fuzzy numbers method is used to rank the risks. The study revealed that information technology infrastructure and prediction capabilities are the most crucial prominence and receiver KPIs. Simultaneously, technological and social risks are found to be highly significant in the I4.0 implementation decision-making process. The developed model meticulously supports the manufacturer's, policymaker, and researchers' viewpoint toward I4.0 implementation in the present and post COVID-19 pandemic phases in manufacturing companies. The comprehensive yet simple model developed in this study contributes to the larger ambit of new knowledge and extant literature. The integrated model is exceptionally based on the most prominent risks and a wider range of KPIs that are further analyzed by aptly fitting two fuzzy MCDM techniques, which makes the study special as it perfectly takes care of the uncertainties and vagueness in the decision-making process.

✉ Rimalini Gadekar
raggpn@gmail.com

Bijan Sarkar
bijan.sarkar@jadavpuruniversity.in

Ashish Gadekar
avgadekar@gmail.com

1 Mechanical Engineering Department, Government Polytechnic, Gondia, Maharashtra, India

2 Production Engineering Department, Jadavpur University Kolkata, Kolkata, West Bengal, India

3 Faculty of Management, Amity Institute of Higher Education, Ebene, Mauritius

Hence, this study is pioneering and unique in context to I4.0 risks prioritization aiming to accelerate I4.0 adoption.

Keywords Industry 4.0 · Sustainability · Risk assessment · FDEMATEL · ARAS-interval-valued triangular fuzzy numbers · COVID-19

1 Introduction

The advent of Industry 4.0 (I4.0) has globally attracted attention from researchers, academicians, government, industrial, and social systems in recent years. Now, it is a known fact that I4.0 enables flexible, fast, and high-quality production by integrating different technologies that ultimately promote efficient and sustainable business management (Bai et al., 2020; Horváth & Szabó, 2019). In this context, the manufacturing sector in India is progressively advancing towards the adoption of I4.0 as companies believe by doing so, they can contribute to the nation's economies (Kamble et al., 2018; Yadav et al., 2020a). The I4.0 emerging technology's multi-faceted advantages like seamless interconnectivity and data exchange among all factory devices and machines are one of the significant advantages that clearly differentiate it from the age-old traditional approach (Bauer et al., 2015). The strong collaboration of technologies like big data analytics (BDA), Internet of Things (IoT), Industrial Internet of Things (IIoT), artificial intelligence (AI), machine learning (ML), cloud computing (CC), robots, and cobots, cyber-physical systems (CPS), Additive manufacturing, Digital twin and augmented reality/virtual reality (AR/VR) also add value to the overall digital transformation happening in manufacturing industry around the world (Arbabian & Wagner, 2020; Gadekar et al., 2020; Türkeş et al., 2019). Figure 1 elucidates the insights of I4.0 in a real-world scenario.

The journey of I4.0 adoption in the manufacturing industries is not so straight and clear, mainly because of the limited knowledge and clarity on returns on investment and projected outcomes (Chauhan et al., 2021; Li et al., 2020). At the same time, the COVID-19 pandemic further worsened it by exposing the unprepared industries to the unknown challenges of sanitization, social distance, lack of medical facilities, and inadequate resources (Adámek & Meixnerová, 2020). Suddenly, most of the industries that did not initiate digitalization in their organization came to a standstill. While this is true for most of the organizations, few considered this as an opportunity to either increase or begin digitalization in their organizations (Mckinsey, 2021; Mofijur et al., 2021). One of the aims of digitalization is to facilitate the remote handling of the companies' functionalities, which is a core aspect of the new normal arising due to the emergence of the pandemic thereby gaining a competitive advantage. Adopting the above-mentioned promising technologies in the manufacturing industries brings a plethora of opportunities as well as never-before challenges (Ben-Daya et al., 2019; Lasi et al., 2014; Nara et al., 2021). Although opportunities are evident, the barriers like lack of skills and limited understanding of technology, inadequate funding, absence of technological standards, lack of information technology (IT) infrastructure, and ineffective data security measures obstruct the progression of I4.0 (Luthra & Mangla, 2018; Mckinsey, 2021). Further, the unknown nature and dimensions of these challenges restrict decision-makers from making quick decisions, ultimately aggravating the I4.0 implementation risks impact negatively (Birkel et al., 2019). This most urgent concern motivates researchers to identify and prioritize the highest prominent I4.0 risks, which are observed missing in past studies or addressed in a very limited manner (Gadekar et al., 2020). The critical synthesis, analysis,

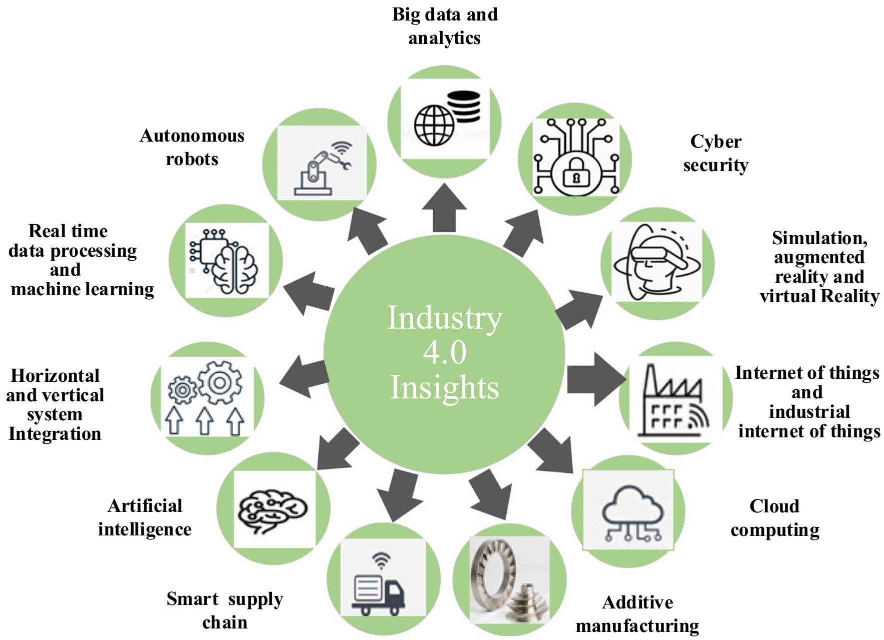

Fig. 1 Industry 4.0 insights

and application carried out in this study will fill the gap of missing extant literature and speed up the progression of sustainable I4.0 adoption.

The key performance indicators (KPIs) evaluation plays a significant role in the systematic assessment and allocation of resources and capabilities of an organization to estimate the system's performance during the transition phase (Zheng et al., 2018). It is now well-understood that the I4.0 risks will not fade away on their own, but only systematic, scientific, and strategic approaches can help control its impact (Gadekar et al., 2022). Also, a thoughtful and structured (KPIs) assessment is vital for devising an appropriate plan of action to monitor and mitigate the potentially detrimental effects of I4.0 risks which would assist in expediting I4.0 adoption (Berrah et al., 2021). Thus, the systematic identification and evaluation of KPIs and based on these identified KPIs, the assessment of the I4.0 risks, carried out in this study will aid policymakers of manufacturing industries in developing reasonable risks management strategies for the smoothening I4.0 adoption process. Therefore, this KPIs-based study is important in prioritizing crucial I4.0 risks that can drastically affect an industry's overall health, if not attended to in time (Moeuf et al., 2020; Tupa et al., 2017). In the past, very few studies, that too in a highly limited manner attempted to address this issue, which largely does not meet current needs. Hence in the present context, this is highly relevant and needed.

Multicriteria decision-making methods (MCDM) with a fuzzy set theory approach are preferred to analyze and assess complex and uncertain situations in decision-making problems. These methods are widely used because of their robustness, reliability, and appropriateness to the broad spectrum of various engineering and management applications (Zavadskas et al., 2017). The MCDM methods have evolved over a period of time to meet the complexities of the situations. It has overcome the limitations of crisp and fuzzy sets by applying the extended version of the fuzzy numbers into triangular fuzzy numbers (TFNs) and interval-valued triangular fuzzy numbers (IVTFNs) to solve challenging real-world problems. In the present context, MCDM methods are better equipped to handle the limitations of crisp and fuzzy sets to seize the vagueness and innate ambiguity of decision-maker's subjective judgments, thereby providing solutions to handle uncertain situations effectively (Saroha et al., 2021; Tseng et al., 2018). In this study, the researchers have selected the two MCDM methods, i.e., Fuzzy Decision-Making Trial and Evaluation Laboratory Method (FDEMATEL) and the extended Additive Ratio Assessment (ARAS) method using interval-valued triangular fuzzy numbers (IVTFNs). The FDEMATEL method is selected to explore the causal relationship among the identified KPIs over the conventional MCDM methods analytical hierarchy process (AHP), technique for order of preference by similarity to ideal solution (TOPSIS), elimination and choice expressing reality (ELECTRE), complex proportional assessment (COPRAS), and stepwise weight assessment ratio analysis (SWARA). These methods rank and prioritize the parameters, but they do not derive their strength, which hinders a more precise evaluation of the interaction between the parameters when instability is taken into account (Farooque et al., 2020). In addition, ARAS with IVTFNs method is chosen to handle the complexity and uncertainty in the I4.0 implementation risks assessment phenomenon because it facilitates the potential to simplify group decision-making by ensuring appropriate mapping of the complicated and conflicting factors thereby smoothening the decision-making process (Büyüközkan & Göçer, 2018).

The KPIs and most prominent I4.0 risks are judiciously selected in this study after expert intervention and systematic literature review (SLR). The fuzzy aspects of its extended version adopted in this research are another value addition that will interest professionals as it efficiently deals with ambiguity in the group decision-making process. During the transition phase, paying attention to all relevant risks, quantifying these risks based on the relevant KPIs, and assessing them in one framework becomes a major challenge for any organization. Previous research shows the FDEMATEL and ARAS with IVTFNs techniques have the potential to successfully tackle these types of issues, which is another strong reason to choose this integrated approach (Dahooie et al., 2020; Lin, 2013). This study has considered highly relevant tools and techniques to devise the integrated model. The model is assured to increase the sustainability in the manufacturing industry in the present and post-COVID-19 era as it has carefully taken into account the decision maker's needs and expectations. It is to the findings that none of the researchers in the past have used these methods to assess and analyze the I4.0 implementation risks considering the multifaceted contribution of significant KPIs (Pandey et al., 2021; Žižek et al., 2020). Further, the comprehensive identification and evaluation of various KPIs and I4.0 implementation risks are also unattended (Birkel et al., 2019; Colak et al., 2019; Hermann et al., 2016; Wang et al., 2020); this ascertained the developed model's application in real-world scenarios. Also, ensuring the right set of KPIs and I4.0 risks in consultation with experts and SLR will interest the decision-makers aiming to reinstate and strengthen the companies' confidence in I4.0 adoption. The researchers believe that this model will guide industries, entrepreneurs, governments, and consultancies in developing successful I4.0 risk management strategies in developing countries. Thus, this study has an original contribution to the extant literature and has the prospects for speeding up I4.0 adoption and supporting industries in becoming sustainable in the external competitive business environment. Hence aiming to this context, the following research objectives are framed.

RO1: Identifying potential KPIs and risks that significantly impact the implementation of I4.0 in manufacturing companies.

RO2: Establishing mutual causal dependencies relationship among KPIs using FDEMATEL.
RO3: Identifying the most critical risks affecting I4.0 implementation decision through extended ARAS method using IVTFNs.
RO4: Developing KPIs based integrated sustainable I4.0 implementation risks assessment model.
RO5: Outlining the applications and implications of the developed model.

Addressing the above research objectives, the significant contribution of this study to the extant literature is mentioned below:

1. It delves into the theoretical underpinnings of KPIs related to I4.0 adoption and the most significant I4.0 implementation risks followed by, their evaluation and assessment, using aptly selected MCDM methods makes the study unique.
2. The use of SLR, experts' engagement, and their competence in managing I4.0 projects establish the research's credibility, and the findings can be generalized.
3. The first time developed integrated model in this study has the potential to serve as a platform for further studying the findings to gain additional insights into the I4.0 implementation domain.
4. The comprehensively derived framework will assist manufacturing industry practitioners, consultants, and scholars to recommend better ways and means to achieve higher performance in the I4.0 environment through intelligent management of I4.0 KPIs and risks.
5. The distinctive addition of this study to new knowledge is that the study's findings are adequately endorsed and offer justification, based on earlier studies
6. In addition to the above, the study implications and recommendations can act as a base to smoothen the I4.0 adoption process and help manufacturing organizations effectively manage their resources and capabilities to leverage sustainability.

The paper is organized into seven sections. Section 1 is dedicated to the introduction. Section 2 critically reviewed the relevant existing literature. The research methodology is elaborated in Sect. 3. The application, relevance, and importance of these methods in a real-world scenario are illustrated in Sect. 4. Section 5 discussed and interpreted the results. Section 6 is devoted to discussion and the current study implications. Finally, the conclusion and future scope are deliberated in Sect. 7.

2 Literature review

In order to ensure the credibility and relevance of research work to the current knowledge, it is recommended to explore the existing literature comprehensively. In this study, researchers conducted the SLR of the existing literature to gain a detailed perspective and requisite statistics related to the topic undertaken for the present study (Tranfield et al., 2003; Yadav & Desai, 2016). Researchers selected the prospective documents from the refereed and indexed journals having high impact factors in maintaining the literature review quality. These documents belonged to the period from 2011 to March 2022. The literature review included highly credible documents sourced by directly referring to the databases like Elsevier, Taylor and Francis, Wiley, SCOPUS, IEEE, Web of Science, Science Direct, and EBSCO. The keywords used to search the most appropriate documents of information and knowledge are "Smart Manufacturing," "Smart Factory," 'Industry 4.0" AND "Risk management," 'Industry 4.0" AND "Risk Assessment tools," "Industry 4.0" AND "Industry 4.0 Challenges," "Industry

4.0 "AND "Sustainability," "Industry 4.0" AND "Multicriteria Decision Making Methods," "Fuzzy Decision-Making Trial and Evaluation Laboratory Method" AND "Industry 4.0", "Additive Ratio Assessment method using Interval-Valued Triangular Fuzzy Numbers," "Industry 4.0 AND "COVID-19", "Industry 4.0" AND "Maturity Model", "Industry 4.0" AND "Industry 4.0 challenges" OR "Industry 4.0 barriers". At the outset of the initial search, the researcher could reach out to 967 articles. Further, by applying the article screening process, i.e., excluding non-English articles, accepting only journal articles, omitting repeated articles, book chapters, editorial notes, etc., and adopting the forward and backward snowball technique, settled on 128 relevant articles. The purpose of using the forward and backward snowball technique is to reach only those papers directly relevant to the present study and focus precisely on the topic addressing the research objectives. The targeted articles are chosen from decision science, industrial engineering, computer science, management, sustainable production, mathematics, technological advancements, production planning and control, and operations research. Researchers have adopted the diversified approach to ensure only relevant articles are chosen for the study to assure its legitimacy. Finally, shortlisted articles are studied thoroughly to meet the current research expectations.

The primary objective of I4.0 adoption is to promote business sustainability by effectively handling the technology, productivity, and automation in every business operation (Haseeb et al., 2019). The business process becomes complex as the level of customization increases. Hence, the massive digitalization at different stages in the product life cycle seems unavoidable, which ultimately gives rise to endless uncertainties, thereby opening the doors for researchers to formulate creative and groundbreaking solutions. This has also built up an apparent research demand from societies and policymakers to synthesize solutions to the problems that never existed (Rajnai & Kocsis, 2017; Szlávik & Szép, 2022). Leonhardt and Wiedemann (2015) stressed the importance of studies addressing uncertainty related to risks and their causes before embarking on any transition. Operational risks are characterized as the eventualities that occur during the company's internal and external functions, which are closely related to I4.0 elements, like machine environment, human resources, equipment, and manufacturing technology (Lin et al., 2019; Lopes de Sousa Jabbour et al., 2018). This subsequently affects the complex, real-time self-organizing cross-company value chain networks, information security, and data integrity-related operations (Ivanov et al., 2021; Tupa et al., 2017). Birkel et al. (2019) suggested that risk structure, considering economic, social, legal/political, environmental, and I4.0 technical risks, is more significant and needs to be evaluated for responsive initiation for I4.0 adoption. According to Calabrese et al. (2020), the incompetent legal framework for I4.0 adoption and insufficient I4.0 standards have elevated the legal risks posing the dilemma among manufacturing organizations for I4.0 adoption. I4.0 technologies can monitor and control pollution-causing factors, reducing environmental risks and eliminating direct human intervention. Thus, this requires the attention of researchers and managers in manufacturing organizations to assess the implications of these risks to reap the full benefits of I4.0 (Moktadir et al., 2018), necessitating more collaborative research on environmental risks analysis and assessment (Gobbo et al., 2018).

Companies must deal with the cybersecurity risks and technical risks on priority as the combined effect of these two risks could be detrimental to the propagation of the I4.0 vision (Culot et al., 2019). The world has experienced numerous cybersecurity threats, such as The Zotob Worm, Stuxnet worm, Duqu and Flamer, BlackEnergy3 and the Ukraine Power Grid, etc., forcing the world to consider cybersecurity as one of the most destructive threats (Ivanov et al., 2021; Prinsloo et al., 2019). These cyber-attacks changed companies' everyday perceptions, forcing them to believe that cyber-attacks in the absence of cybersecurity solutions can ruin the business (Ali et al., 2021). Many researchers have discussed the I4.0 implementation risks but lacked in recapitulating the specifics of risks impacting SMEs (Habibi Rad et al., 2021; Moeuf et al., 2020). As a result, in the absence of a clear risks framework, many organizations are still at the crossroad of decision-making, while others are extra cautious (Ghobakhloo & Iranmanesh, 2021). Even though this is mainly true, exceptions exist. Slow but steady, few companies equipped with the capability to innovate are seeing this threat as an opportunity to diversify the business (Hanelt et al., 2021). Previous studies have shown that researchers either assessed the I4.0 risks in a limited manner or did not use the well-defined and most important KPIs to evaluate these risks to develop stakeholders' confidence in progressing forward on the road of the I4.0 vision (Birkel et al., 2019; Colak et al., 2019; Kodym et al., 2020; Pandey et al., 2021). This encourages the researchers to address this crucial concern of identifying the most significant I4.0 risks by considering the most important KPIs and establishing the relevance of KPIs by focusing on the causal relationship among the KPIs.

A high-tech company based in Turkey has developed a systematic competency model for workforce 4.0 based on the latest workers selection requirements in I4.0, using the FDEMATEL method (Kazancoglu & Ozkan-Ozen, 2018). Thus, this research substantiated the choice of FDEMATEL in the current context as it helps determine the causal relationship between the parameters considered for the study. The risk prioritization is done using the type-2 fuzzy AHP interval and the hesitant fuzzy TOPSIS approach for I4.0 adoption (Colak et al., 2019). AHP approach is used to test the diagnosis of the current automation of the production system in alignment with I4.0 (Saturno et al., 2017). The AHP and Analytic Network Process (ANP) tested the innovation, organization, financial and environmental dimensions as key requirements of I4.0 (Sevinç et al., 2018). Bhagawati et al. (2019) used DEMATEL to determine supply chain management's sustainability and competence. Moktadir et al. (2018) presented the framework for evaluating challenges using the best worst method (BMW) approach for the implementation of I4.0 and rated the challenges. Similarly, considering BWM and ELECTRE approaches to resolve challenges in developing a sustainable supply chain, and circular economy-based solution, Yadav et al. (2020a, 2020b)) developed a hybrid MCDM system. The research of Lin et al. (2019) used the Probit model to identify the effect of the I4.0 driving force on the performance of China's manufacturing industries. Dwivedi et al. (2022) investigated the causal relationship among the blockchain readiness challenges in product recovery systems using FDEMATEL. Braglia et al. (2022) applied DEMATEL to evaluate KPIs for I4.0 and logistic 4.0, but the authors did not cover the full spectrum of KPIs influencing I4.0 advancement. Büyüközkan and Göçer (2018) have used an integrated approach considering Interval Valued Intuitionistic Fuzzy AHP for criteria evaluation and Interval Valued Intuitionistic Fuzzy ARAS for supplier selection for Digital Supply Chain. As a result, the researchers noted that prior studies reveal a paucity of literature for evaluating I4.0 risks using specified KPIs considering precisely an integrated 'approach of FDEMATEL and ARAS with IVTFNs techniques. This unique and highly productive, as it utilizes the fuzzy aspects to build integrated model for problem-solving in industrial applications undertaken in present study to ensure the robustness and sustainable solution in an uncertain situation which, is missing in earlier studies. This proves the credibility and necessity of current study to contribute to the new knowledge which offers a solutions to researchers, decision makers and policymakers to build on their strategies for effective utilization of available capacities and resources to gain competitive advantage and sustainability.

The adverse impact of COVID-19 on global industries except pharmaceuticals can be summarized by mentioning that most the nations have registered negative industrial growth for more than two quarters in 2020 (Adámek & Meixnerová, 2020). The companies are facing tremendous challenges in handling the supply chain disruptions, workforce health and safety concerns, and the existing threats of cybersecurity, AI solutions, capacity management, and upskilling of the existing workforce (Jayathilake et al., 2021). Many researchers believe this is the right time for a paradigm shift. The unprecedented rise in digitalization and the number of internet users clearly support the claim. Robots, virtual digital platforms, digital twins, AR/VR technologies, and radio-frequency identification (RFIDs) can help to reduce the risk of virus spread, ensuring human health and safety has the potential of revamping production. (Kumar et al., 2020). Although this is the reality, it brings many risks, as argued by several studies in the literature (Bonilla et al., 2018; Chauhan et al., 2021). In this situation, the systematic analysis and synthesis of I4.0 risks and I4.0 KPIs is an urgent need of the industries. This thought is the biggest motivation for researchers to take this study on priority to devise the systematic framework for I4.0 risks evaluation based on significant KPIs. Further, we have elaborated on the existing tools and techniques observed to address similar problems in the extant literature to provide a strong base for selecting tools considered for the current study.

2.1 Past studies on research tools and techniques used for risk assessment and key performance indicators evaluation

Proper tools and techniques play an essential role in assessing and analyzing business-related decision-making problems. The literature review depicts that the MCDM techniques are the most preferred choice of decision-makers. Table 1 presents the summary of past studies highlighting research tools and techniques and their contribution to risk assessment and KPIs evaluations.

Earlier studies have focused on the evaluation of supply chain risks in the context of I4.0, blockchain deployment risks, I4.0 implementation challenges, I4.0 risks assessment, the specific impact of I4.0 KPI either in a limited or scattered manner (Chowdhury et al., 2022; Senthil et al., 2018; Ul Amin et al., 2022; Žižek et al., 2020). In addition to it, the combined approach for all prominent I4.0 risks and I4.0 KPIs evaluation in one setup is also found unattempted in past studies. Thus, these lacunas of past studies are well taken care of in the present study. Also, a critical review of the literature elaborated in Table 1 confirmed that no study had covered the wider ambit of I4.0 KPIs and I4.0 risks in one frame. The unique contribution of this study is the selection of an integrated framework of FDEMATEL to extract interrelationships among the KPIs and extended ARAS using the IVTFNs method for I4.0 implementation risks prioritization in Indian manufacturing companies, which was found unnoticed in prior studies. Owing to this, researchers have identified and highlighted the research gap in the next section.

2.2 Research gap

It is evident that the I4.0 will soon pick up the momentum in Indian manufacturing companies. Partly and surely COVID-19 has created urgency. Hence, as a matter of preparation, we must have a comprehensive yet precise framework to make the maximum of this opportunity. Studying and analyzing critical KPIs and most significant I4.0 risks, and their interrelationship will definitely make the I4.0 adoption path smoother. On the same note, researchers have identified some gaps in existing studies, which failed to deal with the most significant I4.0 risks. The research gaps are as follows:

Table 1 Tools and techniques used for the risks assessment and KPIs evaluations in past

Contributions	Study findings	Tools used for analysis	Literature support
Provided an overview of I4.0 and smart manufacturing and extracted future research prospects	High-speed internet communication network infrastructure is an essential factor for I4.0 implementation	Literature review	Thoben et al. (2017)
Risk prioritization in reverse logistics	Inventory management risk has a significant impact on reverse logistics. It is observed that customers can play a significant role in protecting the environment and addressing social concerns	AHP, FTOPSIS, and PROMETHEE	Senthil et al. (2018)
Causal relationship development among the personnel selection criteria in an I4.0 environment	The most important criteria for personnel selection concerning I4.0 requirements are found to be problem-solving, concurrent thinking, and flexibility in getting acquainted with new roles and responsibilities	fuzzy DEMATEL	Kazancoglu and Ozkan-Ozen (2018)
I4.0 implementation risks prioritization	Manufacturing process management risks are found to be the most crucial	Interval type-2 fuzzy AHP and hesitant fuzzy TOPSIS	Colak et al. (2019)
Developed an I4.0 risks framework considering a triple bottom line of sustainability	The study identified the categories of I4.0 risks as economic, social, legal and political, ecological, technological and IT-related risks	SLR and Interview	Birkel et al. (2019)
Developed the firm's export performance measurement model	Strategic goal achievement and return on investments are the crucial criteria for a firm's export performance measurement	SWARA and ARAS with IVTFNs	Dahooie et al. (2020)
Sustainability indicators assessment for renewable energy system	Environmental sustainability criteria are found to be the most important	SWARA and ARAS	Ghenai et al. (2020)

Table 1 (continued)

Contributions	Study findings	Tools used for analysis	Literature support
Framework development to mitigate SSCM challenges by adopting I4.0 and circular economy solutions	The study investigates organizational, managerial, and economic SSCM challenges which are important	BWM and ELECTRE	Yadav et al. (2020a, 2020b)
Blockchain implementation risks assessment	The study identifies security risks as the most important risks, and energy costs and data pilferage are the most prominent subfactors	SVNSs, AHP, and DEMATEL	Abdel-Monem et al. (2020)
Described the significance and role of KPIs in the deployment of I4.0	The study provides the significant KPIs for I4.0 adoption and its linkage with corporate social responsibility	Literature review	Žižek et al. (2020)
The proposed mixed-integer programming approach aimed to establish a viable model for straight shipment to customers from factories and distribution hubs while taking into account supply risks and transportation concerns	The study found, that the cost of resilience, or the investment in resources to reduce the risk, is minimal in comparison to the damages that could result from excessive unmet demand or poor service quality to the customer while handling supply chain risks	Integer programming	Prakash et al. (2020)
Circular supply chain risks solutions identification and ranking	Top management's role in formulating organizational policies and missions is crucial to mitigate circular supply chain risk management	PF-AHP, PF-VIKOR	Lahane and Kant (2021)
Big data analytics barriers evaluations	The most critical barriers in big data analytics are the limited data storage capacity, insufficient organizational strategies, uncertainty about return on investments, and inadequate IT infrastructure	Grey DEMATEL	Raut et al. (2021)

Table 1 (continued)

Contributions	Study findings	Tools used for analysis	Literature support
Identification and analysis of smart manufacturing implementation drivers	Interoperability is found as the most important driver of smart manufacturing	Grey TOPSIS and COPRAS-G	Malaga and Vinodh (2021)
Conducted bibliometric analysis to explore the role of I4.0 principles in disaster risk management	The study explored the relevance of I4.0 technologies in disaster management and their implications on resilient infrastructure, with a focus on the construction industry. The findings of this study were also used to define six target area clusters and map them according to priority using the Sendai framework for disaster risk reduction	Bibliometric analysis	Habibi Rad et al. (2021)
Developed the model which signifies the role of cloud computing, artificial intelligence, big data, and blockchain technology in I4.0 risks management	The study delves into the role of the listed I4.0 technologies in risk management, focusing on market pressure, rules and regulations, digital transformation maturity, and the technologies' resilience and usefulness in dealing with risk-related concerns	Structural equation modeling	Rodríguez-Espíndola et al. (2022)
Established KPIs to evaluateI4.0 technologies and provide recommendations to decision-makers on I4.0 deployment and performance evaluation	The main focus of the study was to provide a ready-to-use solution to the industries. Used a case study approach to justify the significance of the derived KPIs	Literature review and case study	Braglia et al. (2022)
Developed a sustainable supply chain risks management model for Pakistan logistic companies	The most prominent risk is an organizational risk, and the least essential risk is an environmental risk	Fuzzy-based VIKOR–CRITIC	Ul Amin et al. (2022)

SSCM sustainable supply chain management, *FTOPSIS* fuzzy technique for order of preference by similarity to ideal solution, *VIKOR* Vlse Kriterijumska Optimizacija I Kompromisno Resenje, *PF-AHP* pythagorean fuzzy analytic hierarchy process, *PF-VIKOR* pythagorean fuzzy VIKOR, *SVNSs* single valued neutrosophic sets, *COPRAS-G* complex proportional assessment-grey, *CRITIC* criteria importance through inter-criteria correlation method

(1) Earlier research cited in the literature review lacks a clear and comprehensive approach for I4.0 KPIs and risks assessment. These studies either have considered challenges, barriers, limited risks, and KPIs, directly or indirectly influencing the I4.0 implementation, or have disregarded the expert's interventions, making those studies primarily out of context due to truncated solutions. Also, very minimal studies have been carried out on I4.0 risks assessment, and I4.0 KPIs in one framework, motivate researchers to consider this problem to device sustainable I4.0 risks assessment model for successful implementation of I4.0 in Indian manufacturing companies.
(2) The exact consequences of I4.0 on the sustainability dimension are still unclear, and in particular, little attention has been paid to risk assessment and their interdependencies. Detailed findings on future risks have not yet been applied to a reasonable extent in managerial practices because of the visible contradiction among the practitioners, politicians, and researchers. In particular, this refers to economic problems, such as the lack of competitive advantage leading to the inability to harness the best of I4.0 (Birkel et al., 2019; Kiel et al., 2017).
(3) The Fuzzy set theory approach in selecting both the methods like FDEMATEL and extended ARAS using the IVTFNs for I4.0 KPIs evaluation and I4.0 risks prioritization has nullified the drawbacks of conventional DEMATEL and ARAS methods. FDEMATEL has been confirmed to be superior at determining the kind of link between criteria and the level of their influences on one another, allowing for a more precise and realistic solution (Seker & Zavadskas, 2017). At the same time, fuzzy sets provide the necessary information to resolve real-world problems but fail to deal with uncertain situations more efficiently. This issue has been addressed in the current study by adopting interval-valued triangular fuzzy sets, which offer an excellent ground for enhanced imagination in case of confusion and instability in the environment. Additionally, adopting extended ARAS using the IVTFNs rank the attributes while decision-making in complex problems (Dahooie et al., 2020). Thus, the deployment of integration of these two methods has taken care of the vagueness and uncertainty of the subjective judgment of the experts, proving the credibility and robustness of the findings which are lacking in earlier studies.
(4) The studies carried out on risk assessment in pre-COVID-19 may not have relevance in post-COVID-19. This study has taken due care to provide reliable solutions appealing to the Post COVID-19.

Hence researchers have taken apt care while finalizing the six risks and sixteen KPIs, leaving no scope for any limitation. The integrated model proposed in this study ensured to be highly sophisticated and applicable to support current and future requirements of I4.0 aspiring company's risk issues. This way, the study is unique and has a significant contribution to the high-quality literature. Further, I4.0 KPIs and I4.0 risks are explained in detail in Tables 2 and 3 with apt literature support.

2.3 Key performance indicators for I4.0 risks assessment and types of I4.0 implementation risks

This section elaborates on the I4.0 KPIs and I4.0 implementation risks considered in the study. Tables 2 and 3 present the reviewed literature's detailed summary to support the selection of KPIs and I4.0 implementation risks in this study.

Table 2 I4.0 Key Performance Indicators chosen for the study through literature

Code	KPIs for I4.0 implementation Risks prioritization	Description	Literature support
P1	Decentralization	The distributed delegation of authorities, facilities, and cyber-physical systems to execute decisions independently with minimal human intervention	Mittal et al. (2019), Morgan et al. (2021)
P2	Integrity	The trustworthiness of the data sources and active resources, compliant with I4.0 standards and procedures is defined as the ability to confirm the accuracy and reliability of the sourced information	Vaidya et al. (2018), Corallo et al. (2020)
P3	Availability	It describes the access to the information by the right person at the right time without compromising safety and security	Birkel et al. (2019), Corallo et al. (2020)
P4	Cost	Cost constitutes the monetary investment in infrastructure development, training, software hardware, technical support, maintenance, service, sensors, networking, and upskilling of the workforce	Mittal et al. (2018), Deloitte (2019), Morgan et al. (2021)
P5	Interoperability	The ability of a system to interconnect, integrate, coordinate, and collaborate in a self-organized mode without any turbulence	Qin et al. (2016), Ibarra et al. (2018), Mittal et al. (2019), Sun et al. (2020)
P6	Virtualization	A simulated platform of a physical system developed using the internet cloud to help a user access a physical system's characteristics in a virtual environment	Hermann et al. (2016), Siltori et al. (2021)
P7	Adaptability	It is the ability of the system to accommodate, upgrade, and respond to changes in the business environment through a data-driven decision-making process	Bartodziej (2017), Sriram and Vinodh (2020), Sony and Aithal (2020)

Table 2 (continued)

Code	KPIs for I4.0 implementation Risks prioritization	Description	Literature support
P8	Modularity	It is the approach of creating reusable building blocks/coupling or decoupling modules to facilitate production processes, which helps realign and reorganize the production lines as per requirements	Safar et al. (2018), Siltori et al. (2021), Ghobakhloo and Iranmanesh (2021)
P9	Connectivity	It reflects the high-bandwidth internet network, enhancing communication, enabling the effective exchange of data, and facilitating collaboration among all connected devices	Pedone and Mezgár (2018), Castro-martin et al. (2021)
P10	Service orientation	It is the ability of the company to customize the product based on the customer's expectations. This requires efficient communication between people and intelligent devices to capture customer inputs	Hermann et al. (2016), Kozak et al. (2018), Pedone and Mezgár (2018)
P11	IT infrastructure	It comprises the devices, networking, machines, hardware, and software that provides seamless and high-speed connectivity needed to support I4.0 requirements, i.e., self-organizing, self-controlling devices IoT, CPS, Software, hardware, etc	Lee et al. (2017), Schuh et al. (2020), Habibi Rad et al. (2021)
P12	Prediction capabilities	It is the ability of the connected devices, hardware, software, and IT infrastructure based on the predefined criteria to interpret, analyze, forecast, and decisions making in real-time	Colli et al. (2019), Habibi Rad et al. (2021)

Table 2 (continued)

Code	KPIs for I4.0 implementation Risks prioritization	Description	Literature support
P13	Flexibility	It can be defined as the degree to handle agility to accommodate last-minute changes. It is the measure of the speed to respond to the changing demand and product adaptation	VanBoskirk (2016), Mittal et al. (2018), Fragapane et al. (2020), Salunkhe and Fast-Berglund (2020)
P14	Quality	It is the measure of efficiency and effectiveness of resource utilization in manufacturing products and services. Adherence to the set standards is ensured by real-time data acquisition, processing, analytics through intensive network connectivity and infrastructure support of IoT devices BDA, CPS, AI, IoT, Cloud uses, VR, AR, etc. The cost of information is always affected by the quality of the network, integration, and collaboration across the system	Bibby and Dehe (2018), Schumacher et al. (2019), Salunkhe and Fast-Berglund (2020)
P15	Information security	It is described as maintaining the privacy and safety of the business information and data from any theft or unauthorized sharing. This information access is granted to a few authorized personnel when needed, and the data is stored and edited through standard procedures defined for verification, processing, and validation. The data collected from all the sources in the whole system should be handled securely	Geissbauer et al. (2016), Kagermann, (2015), Culot et al. (2019), Bai et al. (2020)
P16	Capacity to make real-time decisions	The intelligent factory can collect, store, analyze and process information and extract meaningful insights from the collected data to be used for making real-time decisions	Lee et al. (2017), Lu (2017), Cohen et al. (2019), Eslami et al. (2021)

Table 3 I4.0 implementation risks selected for the study through literature

Code	I4.0 implementation risks	Description	Literature support
R1	Operational risks	Operational risks are related to manufacturing process management, maintenance, tools and techniques used in specific operations, machines and manufacturing methods, human resources involved in various factory operations, and machine environments. In all the activities mentioned above, lots of data and other resources flow through the entire smart factory network, giving rise to data security, integrity, errors in data processing, and information availability issues	Tupa et al. (2017), Colak et al. (2019), Pandey et al. (2021), Rauniyar et al. (2022), Pham and Verbano (2022)
R2	Economic risks	Economic risks mainly relate to the financial issues of the company. The investment pattern and the payback period are decisive factors that control investment decisions in digitalization, technology, workforce, IT infrastructure, and the ability to handle huge data Competitors also play a critical role in exposing the company to economic risk. The decision to make or buy leading to excessive outsourcing, consultancies and exceptional interaction with experts may even force the business to face economic risks	Lee and Lee (2015), Oesterreich and Teuteberg (2016), Kiel et al. (2017), Müller and Voigt (2018), Müller et al. (2018a, 2018b), Piccarozzi et al. (2018), Habibi Rad et al. (2021), Gadekar et al. (2022)
R3	Legal/political risks	A robust and proven legal/ political framework lays a solid foundation for well-defined and structured growth. This also leads to an unequivocal and sorted approach. At the same time absence of standards means leaving the scope for deviations. In such circumstances, the organizations do not act responsibly. This is a potential threat to the systematic implementation of I4.0, meaning intellectual property, data security, and data theft are most important	Veza et al. (2015), Hossain and Muhammad (2016), Kiel et al. (2017), Müller and Voigt (2018), Müller et al. (2018a), Calabrese et al. (2020), Gadekar et al. (2022)

Table 3 (continued)

Code	I4.0 implementation risks	Description	Literature support
R4	Ecological risks	Ecological risks has direct correlations with environmental balance. Higher consumption of resources leads to an adverse impact on the environment. Increased consumerism also increases energy consumption, thereby adding toxicity and radioactive substances, and other waste materials to the environment. This waste increases pollution and perturbs the ecological balance	Wiengarten et al. (2016), Beier et al. (2017), Stock et al. (2018), Birkel et al. (2019), Habibi Rad et al. (2021), Pandey et al. (2021), Gadekar et al. (2022)
R5	Social risks	The change is mostly perceived negatively by those directly impacted. It builds massive stress among employees. Even if the change process is carried out professionally, the employees are susceptible to the unknown fear of job loss, excessive workload, loss of health and peace of mind, work-life balance, and future confusion Thus the resistance of employees to change and adapt to the new corporate culture is inevitable which can be resolved by using methods such as upskilling, counseling, and employee training, to align the employee with changing environment	Bonekamp and Sure (2015), Stock and Seliger (2016), Kazancoglu and Ozkan-Ozen (2018), Müller and Voigt (2018), Müller et al. (2018a, 2018b), Stock et al. (2018), Birkel et al. (2019), Habibi Rad et al. (2021), Pandey et al. (2021), Gadekar et al. (2022)
R6	Technological risks	The technological risks are related to the data handling, cybersecurity, cloud computing, and networking ability of a factory through the right skills and knowledge. Strategic technical integration of the technological infrastructure and resources is critical to avert technological risks. Lack of technological standards and higher dependency on external sources to handle the technology-related problem may increase the potential harm to the company	Hansen et al. (2009), Kong et al. (2015), Kuhl et al. (2016), Müller and Voigt (2018), Müller et al. (2018a, 2018b), Moeuf et al. (2020), Snieška et al. (2020), Rodríguez-Espíndola et al. (2022), Gadekar et al. (2022)

3 Research methodology

This research aims to rank the I4.0 implementation risks according to the most crucial I4.0 KPIs established from SLR and fifteen expert interventions. Researchers have received immaculate input from experts that built the confidence to derive realistic solutions. These experts have been selected onboard after assessing their competence, expertise, experience, and qualification related to the implementation of the I4.0 project in or outside the companies. Figure 2 illustrates the hierarchical decision-making framework adopted in this study to rank potential I4.0 risks, using the most important I4.0 KPIs. While doing this the significance of KPIs is also evaluated comprehensively. The detailed profile of experts, data collection, and data validation considered in this study are described in Sects. 4.1 and 4.2. Before concluding, researchers have evaluated the substantial SLR support and justified its significance to the current study, MCDM approaches like FDEMATEL were used to derive interrelationship among KPIs and extended ARAS with IVTFNs to prioritize I4.0 risks. It is confirmed from the SLR that the ARAS perfectly responds to overcome rank reversal issues (Zavadskas & Turskis, 2010) and the extension with IVTFNs takes care of unspecific and ambiguous prejudiced experts' judgment as compared to other MCDM methods (Dahooie et al., 2020). Also concluded from the SLR the FDEMATEL shows the best response to insufficient data availability, and an uncertain environment of decision making as well as to evaluate the strength of the criteria assessment as compared to conventional DEMATEL (Dwivedi et al., 2022) thus selection of apt MCDM methods for current study proves the robustness of the findings. Further, the integrated model developed in this study is elaborated in the next section.

3.1 Integrated framework using fuzzy decision-making trial and evaluation laboratory method and the additive ratio assessment method using extended interval-valued triangular fuzzy numbers

The research methodology adopted in this study consists of three phases. Phase I described an extensive process used to select KPIs, I4.0 Implementation risks, and MCDM methods. Phase II underlined the conceptualization of FDEMATEL and extended ARAS with IVTFNs methods. It also covers the KPIs interrelationship diagram and discussion on prioritization of each identified I4.0 implementation risks along with the elaboration on the importance and application of MCDM approaches to the issue being examined. Phase III is dedicated to results, which have been critically analyzed, discussed, interpreted, and validated. Figure 3 outlined the research methodology adopted in this study.

3.2 Fuzzy decision-making trial and evaluation laboratory method

FDEMATEL method is a widely used tool to establish an interrelationship among the considered attributes/criteria. This method compares and evaluates the direct and indirect causal relationship among the attributes/criteria and their degree of influence. The method also provides a simple causal diagram that segregates the set of attributes/criteria in cause-and-effect groups and a visual structural digraph. In this study, researchers have proposed the FDEMATEL method to evaluate and assess the interdependence relationship among the identified KPIs impacting I4.0 implementation risks assessment in manufacturing companies. Applications of group decision-making methods to address real-world decision-making problems in

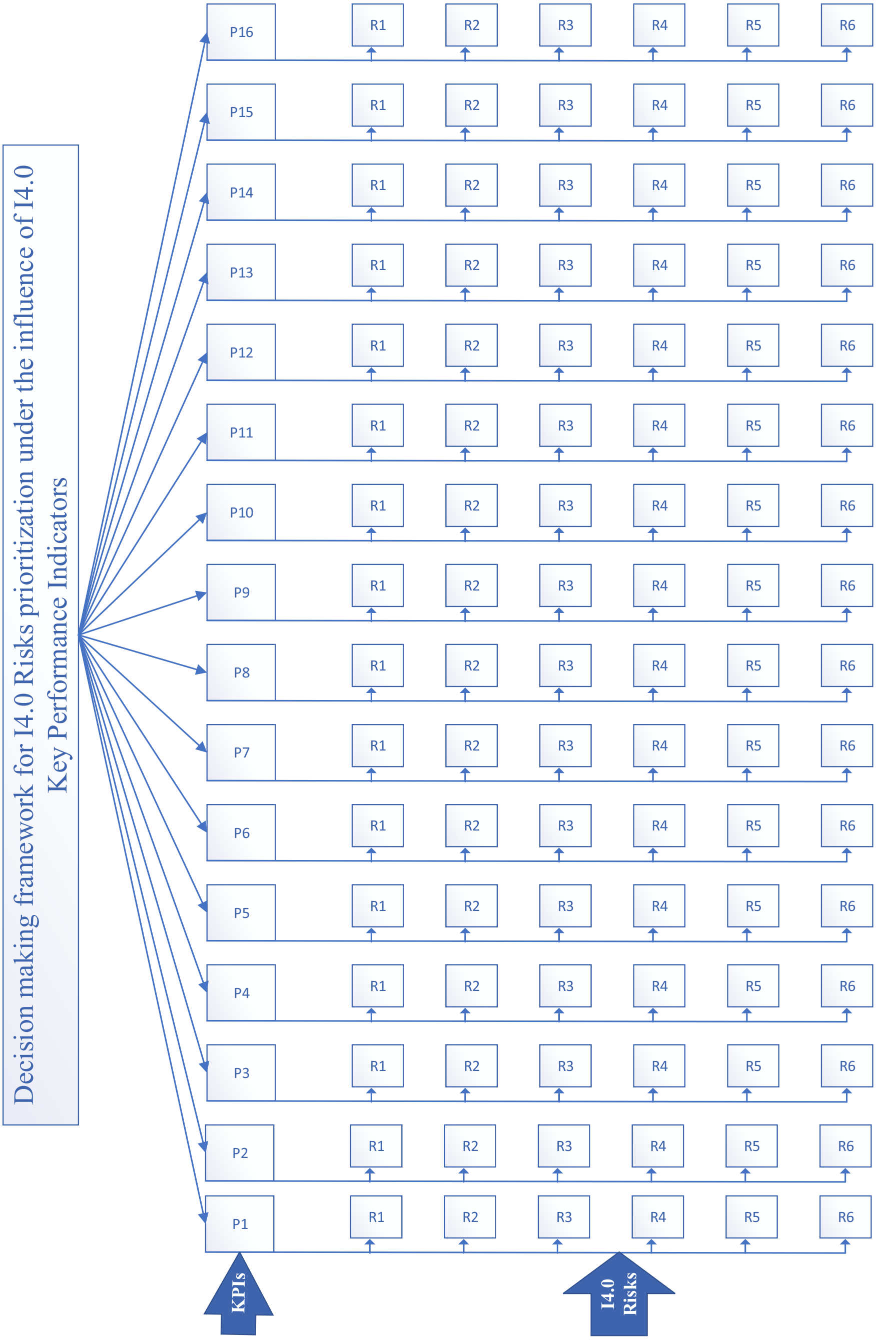

Fig. 2 Decision making hierarchical structure for Industry 4.0 Risks prioritization. I4.0 KPIs—P1: Decentralization, P2: Integrity, P3: Availability, P4: Cost, P5: Interoperability, P6: Virtualization, P7: Adaptability, P8: Modularity, P9: Connectivity, P10: Service Orientation, P11: IT Infrastructure, P12: Prediction Capabilities, P13: Flexibility, P14: Quality, P15: Information Security, P16: Capacity to make real-time decisions, I4.0 Risks—R1: Operational Risks, R2:Economic Risks, R3: Legal/Political Risks, R4: Ecological Risks, R5: Social Risks, R6: Technological Risks

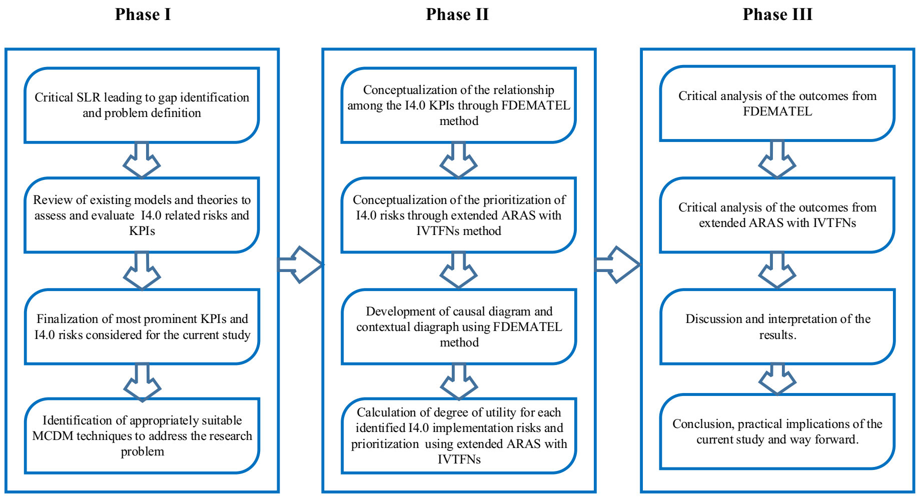

Fig. 3 An integrated decision-making research framework developed using FDEMATEL and ARAS with IVTFNs

various industrial scenarios are used widely. Experts/decision-makers tend to express themselves in linguistic expressions rather than numerical values is a well-known fact. Experts use linguistic terms to convey qualitative characteristics of specific object attributes in complex real-world problems, based on their experience and expertise. These linguistic expressions are always not clear; hence, it is difficult to interpret the hazy and ambiguous inputs, leading to data analysis challenges. In these conditions, the use of fuzzy set theory is a proven approach, as it effectively deals with these experts' uncertain subjective judgments. In this study, each expert gave a specific linguistic expression using the five-point scale shown in Table 4 to indicate the degree of relationship between the set of KPIs. This data is used as a base to formulate the triangular fuzzy numbers before administering them to the FDEMATEL to increase the method's precision. Subsequently, the initial direct relation matrix is framed and solved by applying fuzzy set theory. The prime objective of this conversion is to compensate for possible information loss due to human judgments (Chang et al., 2011; Zhou et al., 2018). This triangular fuzzy number format appears to be unsuitable for matrix

Table 4 Scale for experts linguistics expressions and equivalent triangular fuzzy numbers

Linguistic expressions	Numeric influence score	Equivalent triangular fuzzy numbers (TFNs)
No influence (NI)	0	(0, 0.1, 0.3)
Very low influence (VLI)	1	(0.1, 0.3, 0.5)
Low influence (LI)	2	(0.3, 0.5, 0.7)
High influence (HI)	3	(0.5, 0.7, 0.9)
Very high influence (VHI)	4	(0.7, 0.9, 1.0)

Source: Lin (2013)

operations; it must be defuzzified to obtain crisp values, and a new direct relation matrix is developed. Here, the defuzzification method adopted to transform fuzzy numbers into simple, crisp scores is converting the fuzzy data into crisp scores (CFCS), which has advantages over other defuzzification methods and offers improved crisp value (Opricovic & Tzeng, 2003).

The steps to be followed in the FDEMATEL method are explained below

Step 1 Construct the individual decision matrix based on each expert's linguistics opinion on the scale given in Table 4, i.e., *i*th KPI influence *j*th KPI.

Step 2 Convert the linguistic preferences obtained from the experts into triangular fuzzy numbers using Table 4. The triplet triangular fuzzy numbers, i.e. (p_1, p_2, p_3), are represented by the membership function shown in Eq. (1).

$$\mu_N(x) = \begin{cases} 0, & x < p_1 \\ \frac{x-p_1}{p_2-p_1}, & p_1 \leq x \leq p_2 \\ \frac{p_3-x}{p_3-p_2}, & p_2 \leq x \leq p_3 \\ 0, & x > p_3 \end{cases} \tag{1}$$

Step 3 Use the CSCF defuzzification process to convert fuzzy numbers into a simple, crisp score. Compute the weighted average based on the membership function's left and right scores to obtain the total score. Each expert's judgment has culminated in the initial direct influence decision matrix.

i. The normalization procedure of triangular fuzzy numbers in Eqs. (2)–(4)

$$xp1_{ij}^k = \frac{p1_{ij}^k - minp1_{ij}^k}{\Delta_{min}^{max}} \tag{2}$$

$$xp2_{ij}^k = \frac{p2_{ij}^k - minp2_{ij}^k}{\Delta_{min}^{max}} \tag{3}$$

$$xp3_{ij}^k = \frac{p3_{ij}^k - minp3_{ij}^k}{\Delta_{min}^{max}} \tag{4}$$

where $\Delta_{min}^{max} = mixp3_{ij}^k - minp1_{ij}^k$.

ii. Calculate the left crisp score *(lc)* and right crisp score *(rc)* using Eqs. (5) and (6)

$$xlc_{ij}^k = \frac{xp2_{ij}^k}{\left(1 + xp2_{ij}^k - xp1_{ij}^k\right)} \tag{5}$$

$$xrc_{ij}^k = \frac{xp3_{ij}^k}{\left(1 + xp3_{ij}^k - xp2_{ij}^k\right)} \tag{6}$$

iii. Calculate overall normalized crisp scores from the above *lc* and *rc* as shown in Eq. (7).

$$x_{ij}^k = \frac{\left[xlc_{ij}^k\left(1 - xlc_{ij}^k\right) + xrc_{ij}^k * xrc_{ij}^k\right]}{\left(1 - xlc_{ij}^k + xrc_{ij}^k\right)} \tag{7}$$

iv. Calculate crisp normalized values using the expression Eq. (8)

$$\tilde{w}_{ij}^k = minp1_{ij}^k + x_{ij}^k \Delta_{min}^{max} \tag{8}$$

v. Aggregate crisp values for k respondent's preferences are given by Eq. (9)

$$\tilde{w}_{ij}^{k} = \frac{\left(\tilde{w}_{ij}^{1} + \tilde{w}_{ij}^{2} + \cdots \tilde{w}_{ij}^{k}\right)}{k} \tag{9}$$

Step 4 The obtained aggregated matrix, i.e., initial direct relation matrix (D) shown in Eq. (10), where the numerical value of d_{ij} denotes the extent to which the ith KPI influences the jth KPI.

$$\mathrm{D} = \begin{bmatrix} 0 & d_{12} & \cdots & d_{1j} & \cdots & d_{1n} \\ d_{21} & 0 & \cdots & d_{2j} & \cdots & d_{2n} \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ d_{n1} & d_{n2} & \cdots & d_{nj} & \cdots & 0 \end{bmatrix} \tag{10}$$

Step 5 Normalize the initial direct relation matrix.

Matrix D is multiplied by s using the following Eqs. (11) and (12) to build a normalized direct relation matrix(A).

$$A = s * D \tag{11}$$

where

$$s = \frac{1}{\max\limits_{1 \le i \le n}\left(\sum_{j=1}^{n} d_{ij}\right)}, \quad i, j = 1, 2, \ldots, n \tag{12}$$

Step 6 Calculate the Total Relation matrix (T).

Using Eq. (13) total relation matrix indicated by the letter T is developed.

Where t_{ij} represents the indirect effect of the ith KPI on the jth KPI,

I indicate the Identity matrix.

$$\begin{aligned} T &= \left[t_{ij}\right]_{n \times n}, \quad i,\ j = 1, 2, \ldots, n \\ &= A(I - A)^{-1} \end{aligned} \tag{13}$$

when $s \to \infty$, $A^{s} = [0]_{n \times n}$.

Step 7 Calculate the sum of rows and columns of the T matrix.

The Eqs. (14) and (15) are used to calculate the sum of rows and columns of the T matrix denoted by vector R_i and C_j, respectively.

$$R_{i = \left[\sum\limits_{j=1}^{n} t_{ij}\right]_{n \times 1} = [t_i]_{n \times 1}}, \quad i = 1, 2, \ldots, n \tag{14}$$

$$C_{j = \left[\sum\limits_{i=1}^{n} t_{ij}\right]_{1 \times n} = [t_j]_{n \times 1}}, \quad j = 1, 2, \ldots, n \tag{15}$$

$$\text{Degree of importance } R_i + C_j \text{ and cause and effect classification } R_i - C_j \tag{16}$$

Step 8 Develop a causal diagram and digraph by setting the appropriate threshold value ($\propto$) after performing the calculations using Eqs. 14, 15, and 16.

From the *Ri, Cj, Ri − Cj,* and *Ri + Cj,* columns, the relationship is evident between the cause-and-effect KPIs. The causal diagram developed by plotting ($R_i + C_j$) values on the x-axis denotes the degree of importance of the KPIs, and ($R_i - C_j$) on the y-axis indicates the type of relationship between the KPIs. The higher the value of ($R_i + C_j$), the greater is the importance and vice versa. The visual presentation separates the KPIs into two groups:

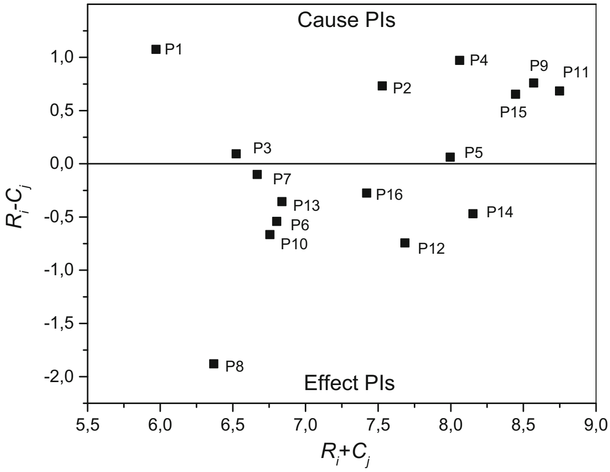

Fig. 4 Cause and effect relationship diagram among KPIs

cause and effect. As shown in Fig. 4, KPIs having a positive value in the column $R_i - C_j$, belong to the cause group or trigger group, which must be given more attention. In contrast, others with a negative value in the same column belong to the effect group. By studying Fig. 4, KPIs and their relations with others can be identified but with limited clarity. This problem is solved by systematically segregating the effect and cause group KPIs to obtain structured results. The threshold value setting is a much-simplified way to solve such complex problems. The threshold value is critical for decision making as the lower value may bring more than required information, while a higher value may omit important factors from the list. In the past, researchers have used expert inputs, the entropy method, subjective method, and means method as a base to calculate threshold values (Li & Tzeng, 2009). The researcher tried different threshold values before finally setting them at a mean + 1.5∗standard deviation (Feng & Ma, 2020). The relationship path diagram is drawn to reflect the degree of influence between KPIs (Refer to Fig. 5).

3.3 The additive ratio assessment method using extended interval-valued triangular fuzzy numbers

The additive ratio assessment (ARAS) method is a recently developed MCDM tool by Zavadskas and Turskis (2010). It is mainly applied in solving varieties of engineering and management decision-making problems due to its simple procedure and high reliability, accuracy, and precision. Its extension uses interval-valued triangular fuzzy numbers (IVTFNs), reflecting complex real-world decision-making problems dealing with the uncertainty and vagueness in subjective judgment issues (Ghenai et al., 2020). The important steps to be followed in extended ARAS with IVTFNs method are discussed below.

Step 1 Collate the individual expert linguistic opinion on KPIs weights and performance ratings related to risks.

Many researchers have used different methods to solve decision-making problems using the fuzzy numbers approach (Stanujkic, 2015). In this method, experts' linguistic opinions are recorded using a seven-point Likert scale to quantify KPIs weights and performance

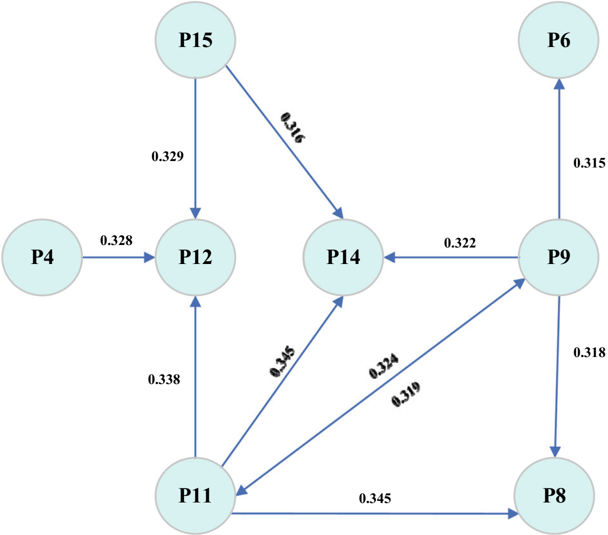

Fig. 5 Digraph showing the interrelationship between influencing significant KPIs. *Note*: P4: cost, P6: virtualization, P8: modularity, P9: connectivity, P11: IT infrastructure, P12: prediction capabilities, P14: quality, P15: information security

rating to I4.0 implementation risks and KPIs using triangular fuzzy numbers extending it to IVTFNs (Dahooie et al., 2020), as shown in Table 5.

Equations (17)–(21) are used to convert triangular fuzzy numbers to their corresponding IVTFNs to calculate the KPIs weights denoted by (w_j).

$$l = \min_k l^k \tag{17}$$

$$l' = \left(\prod_{k=1}^{K} l^k\right)^{\frac{1}{k}} \tag{18}$$

Table 5 Linguistic variables for KPIs weights and performance rating to I4.0 implementation risks and KPIs

Linguistic variables assigned to KPIs weights		Linguistic variables assigned to performance rating to risks and KPIs	
Linguistic variable	Equivalent TFNs	Linguistic variable	Equivalent TFNs
Very low (VL)	(0.0,0.0,0.1)	Very poor (VP)	(0.0,0.0,0.1)
Low (L)	(0.0,0.1,0.3)	Poor (P)	(0.0,0.1,0.3)
Medium low (ML)	(0.1,0.3,0.5)	Medium poor (MP)	(0.1,0.3,0.5)
Medium (M)	(0.3,0.5,0.7)	Fair (F)	(0.3,0.5,0.7)
Medium high (MH)	(0.5,0.7,0.9)	Medium good (MG)	(0.5,0.7,0.9)
High (H)	(0.7,0.7,1.0)	Good (G)	(0.7,0.7,1.0)
Very high (VH)	(0.9,1.0,1.0)	Very good (VG)	(0.9,1.0,1.0)

Source: Dahooie et al. (2020)

$$m = \left(\prod_{k=1}^{K} m^k \right)^{\frac{1}{k}} \tag{19}$$

$$u' = \left(\prod_{k=1}^{K} u^k \right)^{\frac{1}{k}} \tag{20}$$

$$u = \max_k \left(u^k \right) \tag{21}$$

Here $\tilde{x}^k = \left(l^k, m^k, u^k\right)$ represents the TFNs obtained from the kth decision maker's judgment, and equivalent IVTFNs denoted by $\tilde{x} = \left[\left(l, l'\right), m, \left(u', u\right)\right]$. Components l and u are the smallest and largest performance rating assigned by the experts. Involvements of more components in IVTFNs can express the opinion of the decision-maker more accurately. Hence k denotes the total number of experts who have given the inputs regarding the importance of specific KPIs in assessing the I4.0 risks. The inputs are analyzed based on the fuzzy calculation rules.

Step 2 Calculate the optimal performance rating for each KPI.

$\tilde{X}_0$ denotes the optimal performance rating representing as an interval-valued fuzzy number carries the values $\tilde{x}_{0j}$ of each jth KPI expressed in the Eq. (27) obtained from the Eqs. (22)–(26).

$$l_{0j} = \begin{cases} \max\limits_i l_{ij}; & j \in \Omega_{max} \\ \min\limits_i \ l_{ij}; & j \in \Omega_{max} \end{cases} \tag{22}$$

$$l'_{0j} = \begin{cases} \max\limits_i l'_{ij}; & j \in \Omega_{max} \\ \min\limits_i \ l'_{ij}; & j \in \Omega_{max} \end{cases} \tag{23}$$

$$m_{0j} = \begin{cases} \max\limits_i m_{ij}; & j \in \Omega_{max} \\ \min\limits_i \ m_{ij}; & j \in \Omega_{max} \end{cases} \tag{24}$$

$$u'_{0j} = \begin{cases} \max\limits_i u'_{ij}; & j \in \Omega_{max} \\ \min\limits_i u'_{ij}; & j \in \Omega_{max} \end{cases} \tag{25}$$

$$u_{0j} = \begin{cases} \max\limits_i u_{ij}; & j \in \Omega_{max} \\ \min\limits_i \ u_{ij}; & j \in \Omega_{max} \end{cases} \tag{26}$$

$$\tilde{x}_{0j} = \left[\left(l_{0j}, l'_{0j} \right), m_{0j}, \left(u'_{0j}, u_{0j} \right) \right] \tag{27}$$

Step 3 Construct a normalized decision matrix.

Only after normalization the quantitative operations can be performed on the interval-valued fuzzy numbers. The normalized decision matrix can be achieved using the Eq. (28)

$$\tilde{r}_{ij} = \begin{cases} \left[\left(\frac{a_{ij}}{c_j^+}, \frac{a'_{ij}}{c_j^+} \right), \frac{b_{ij}}{c_j^+}, \left(\frac{c'_{ij}}{c_j^+}, \frac{c_{ij}}{c_j^+} \right) \right] & if \ j \in \Omega_{max} \\ \left[\left(\frac{\frac{1}{a_{ij}}}{a_j^-}, \frac{\frac{1}{a'_{ij}}}{a_j^-} \right), \frac{\frac{1}{b_{ij}}}{a_j^-}, \left(\frac{\frac{1}{c'_{ij}}}{a_j^-}, \frac{\frac{1}{c_{ij}}}{a_j^-} \right) \right] & if \ j \in \Omega_{min} \end{cases} \tag{28}$$

where $a_j^- = \sum_{i=0}^{m} \frac{1}{a_{ij}}, \ c_j^+ = \sum_{i=0}^{m} c_{ij}, \quad (i = 0, 1 \ldots, m)$

Step 4 Construct a normalized weighted interval-valued decision matrix.

In this step, fuzzy numbers are multiplied by applying IVTFNs' multiplication operations, using the Eq. (29).

$$\tilde{v}_{ij} = \tilde{w}_j * \tilde{r}_{ij} \tag{29}$$

where $\tilde{v}_{ij}$ is denoted as the normalized weighted interval-valued fuzzy performance rating considering the ith risks of jth KPI.

Step 5 The summation matrix is derived by adding the above KPIs values corresponding to each risks using Eq. (30).

$$S_i = \sum_{j=1}^{n} \tilde{v}_{ij} \tag{30}$$

Step 6 Determination of cumulative KPIs values of interval-valued fuzzy performance evaluation.

The value of the cumulative criterion $\tilde{S}_i$ of the interval-valued fuzzy performance evaluation of the ith, risks is obtained by applying Eq. (31).

$$\left(\tilde{S}_i\right) = \frac{l + l' + m + u' + u}{5} \tag{31}$$

Step 7 Derive the degree of utility.

The defuzzified values of $\tilde{S}_o$, obtained at the most important I4.0 risks is compared with the rest $\tilde{S}_i$ Values considering one at a time. This is referred to as the degree of utility ($\tilde{Q}_i$) and calculated using Eq. (32).

$$\tilde{Q}_i = \frac{\tilde{S}_i}{\tilde{S}_o} \tag{32}$$

Step 8 The degree of utility calculated earlier is used to rank the I4.0 risks by giving the highest rank to the maximum value in the column $\tilde{Q}_i$.

The next section delves into the application of the derived MCDM approach.

4 Application of research methodology deploying fuzzy decision-making trial and evaluation laboratory method and extended additive ratio assessment method using extended interval-valued triangular fuzzy numbers for I4.0 KPIs evaluation and ranking I4.0 implementation risks based on KPIs

This section outlines the application of the developed integrated research framework. As evidenced in previous research experts' insights have always given an edge to the MCDM problem's findings. Initially, researchers contacted 31 experts, out of which 15 experts willingly agreed to contribute to the study. As mentioned in the Table 6 experts have been chosen thoughtfully, reflecting upon their capability and capacity to support the research objectives. For this analysis, fifteen experts' focused group is considered appropriate and credible, as Murry and Hammons (1995) advised. Their high-level deliberation and extensive SLR endorsed sixteen prominent KPIs and six crucial risks sufficient to build a comprehensive and robust model. The specifics of risks and KPIs are elaborated in Sect. 2.3.

Table 6 Descriptive of the focused group profile involved in the study are as follows:

Expert category	Academia/industry domain	Designation	Expertise	Qualification	Work experience
Experts from Academic Institution	Mechanical Engineering	Professor	I4.0 related risk Management, Supply chain Management, Operations management	PhD	21 years
	Information Technology	Professor	Digital technologies, Software development Management, I4.0 implementation strategies	PhD	19 years
	Computer Science	Professor	Digital technologies, Cyber security, I4.0 implementation challenges, and implementation functions	PhD	20 years
	Management	Associate Professor	Operations Management, I4.0 implementation, Supply chain, Lean and Green management	PhD	16 years
Experts From Industry	Automobile industry	Divisional Head	Production and operations management	Masters in Industrial Engineering	20 years
	Ammunition hardware manufacturing	Operations Manage	Digital technologies, Supply chain, and Circular economy	Masters in Production Engineering	18 years
	Furniture manufacturing,	Owner and CEO	Digital technologies, Production, and Operations management	PhD in Production Engineering	25 years
	Plastic industry,	CEO	Supply chain, I4.0, Lean management	Masters in Plastic technology	21 years
	Energy sector	Senior manager	Sales and marketing, Operations management, I4.0	Masters in Electrical Engineering	17 years

Table 6 (continued)

Expert category	Academia/industry domain	Designation	Expertise	Qualification	Work experience
	Textile manufacturing	Senior manager	Digital technologies, Circular economy	PhD in Textile Manufacturing	19 years
	IT and software industry	General Manager	Cyber security, I4.0, Circular economy, Software solutions	Masters in Computer Science	16 years
Experts from I4.0 solutions providing Consultancy	I4.0 operations and service providing consultancy	Owner	Digital technologies, Circular economy, Supply chain	Masters in Computer Science	24 Years
	I4.0 operations and service providing consultancy	Owner	Software solutions, Process digitalization, Supply chain, I4.0	Masters in Computer Science	21 Years
Data scientists	I4.0 operations and services	Functional Head	Software solutions for I4.0 implementation	Masters in Computer Science and PG Diploma in Business analytics	20 Years
	I4.0 operations and services	General Manager	Designing and developing the solutions for remote handling company functions	Masters in Mechanical Engineering and Diploma in Big data analytics	22 Years

4.1 Experts profile who contributed to this research, data collection, and data validation

Experts having a wide range of skills, experience, knowledge, and visibility to their credit through I4.0 projects are selected for the study. The researcher ensured that all of them belong to the leading manufacturing companies and academic institutes in India's public and private sectors that represent the manufacturing ecosystem at its best. These companies are among the few in the industry who aspired to incorporate I4.0 technologies in their business functions to stay competitive in local and global markets. Their initiatives included tasks, i.e., installing sensors, IIoT devices, data centers, and upskilling the current workforce, resulting in tracking, decision-making, risk management, and real-time machine health monitoring. The most influential aspect of these activities is upgrading, training, and enabling employees to learn innovative ways of doing things through emerging technologies. These are blockchain, 3D printing, robotics and cobots, CC, VR and AR, ML, AI, IIoT, and CPS so that the companies could meet the market demand at a much faster rate than ever. Approximately 50% of the experts who added high value to the research, directly belong to the industry. The other experts' involved from the different fields; four professors from leading institutions/universities in India, contributed to the academic perspective of the problem under consideration, two consultants from the I4.0 domain from India brought new insights based on their experiences in handling I4.0 implementation-related projects in the industries, two experts in data analytics are added to the group to highlight the importance of data handling and decision-making while implementing I4.0. Table 6 focuses on the specifics of the expert profile.

4.2 Data collection and validation

While manufacturing industries aggressively embraced the I4.0 vision through ongoing innovation, testing, and development, some unresolved challenges related to risk management are still hindering the expected growth. Hence I4.0 implementation risks assessment and evaluation attracted the urgent attention of policymakers, academicians, and technocrats. The researchers sought to obtain data from experts based on their knowledge, experience, and competence. The true picture of I4.0 implementation in Indian manufacturing organizations is ensured by selecting the experts from a multitude of fraternities, who are trying to address the prevailing uncertainty about I4.0 adoption in industries. The identified alternatives (I4.0 implementation risks) and criteria (KPIs) in the study are the outcomes of detailed and structured literature reviews and insightful focus group interviews and discussions. In this study, first, the experts are provided with a detailed description of each KPI to bring the understanding parity among all the experts. Followed by this exercise, all of them are provided with a blank matrix reflecting the impact relations between the KPIs, i.e., ith KPI's impact on the jth KPI, for submitting the KPIs interrelationship data. This definitely helped the experts understand the problem easily and genuinely fill up the matrix based on their expertise in I4.0. Each expert has been asked to fill up the matrix as per the linguistic scale given for denoting the relationship, as shown in Table 4 for conducting FDEMATEL. The researcher approached experts again to collect the data for conducting extended ARAS using IVTFNs. This time the experts are provided with the empty matrix defining the relationship between ith I4.0 risks and jth KPIs. The experts are asked to assign the weights to the KPIs and performance ratings to risks and KPIs using the linguistic scale as provided in Table 5.

The data is collected from the experts through face-to-face meetings, phone calls, emails, and Google Form at their convenience.

The data analysis and the mathematical calculations are performed in Microsoft Excel code by preparing templates for FDEMATEL and ARAS using IVTFNs method procedural calculations. A MATLAB code is used in the calculation of the FDEMATEL method.

The inputs collected and subsequent results obtained are discussed with 10 fellow researchers and experts from industry and academia having professional experience of more than 20 years and expertise in I4.0 projects, as well as actively doing research in the I4.0 domain, operations management, supply chain. These experts and fellow researchers did not participate in the interviews and data collection process mentioned earlier. They have been involved in testing and validating the developed framework. This data validation process was followed to avoid the biases and the misinterpretation of data collected and ensure the reliability and coherence of the obtained results from an external perception point of view (Yin, 2009).

4.3 Application of FDEMATEL

The original data matrix in linguistic form from expert 1 is shown in Table 7. The data is converted into triangular fuzzy numbers using Table 4 before embarking on calculations. Similarly, the data matrix is collected from all the experts and culminated to form the final initial direct relation matrix, using Eqs. (1)–(9). The resultant matrix is formulated as shown in Eq. (10) and Table 8.

Further normalized initial direct relation matrix is obtained using the Eqs. (11) and (12), and the Total relation matrix (T) is developed using Eq. (13) as shown in Tables 9 and 10. A MATLAB code is used to achieve a (T) matrix. *Ri* and *Cj* values are calculated using Eqs. (14) and (15). The degree of importance (R_i + C_j) and cause and effect classification (R_i- C_j) are calculated by using Eq. (16). As shown in Table 11, the *Ri* + *Cj* and *Ri*-*Cj* column values are used to draw the causal diagram for criteria, shown in Fig. 4, reflecting the sixteen KPIs division into groups of cause and effect. The cause group consists of decentralization (P1), integrity (P2), availability (P3), cost (P4), interoperability (P5), connectivity (P9), IT infrastructure (P11), information security (P15), and the effect group consists of virtualization (P6), adaptability (P7), modularity (P8), service orientation (P10), prediction capabilities (P12), flexibility (P13), quality (P14), capacity to make a real-time decision (P16). As mentioned in Sect. 3.2, step 8 is used to set the threshold value ($\propto$) to 0.314. The (T) matrix values greater than the threshold value identified by the marking '*' in the cell are considered to draw a digraph shown in Fig. 5. The digraph portrays the most critical contextual relationship within the KPIs.

4.4 Application of extended ARAS method using IVTFNs

The extended ARAS method using IVTFNs deployed for prioritizing the six I4.0 risks based on the sixteen KPIs mentioned earlier in Sect. 2.3. The researchers contacted again the selected fifteen experts to receive inputs for the application of the extended ARAS method using IVTFNs. Experts are requested to assign weights to each KPI in linguistic form as per the scale shown in Table 5. Thus Table 12 shows the KPIs weights in linguistic expression and corresponding TFNs assigned by expert 1.

Table 13, given below is achieved using Eqs. (17)–(21), which explain the interval-valued triangular fuzzy weights assigned to KPIs by all fifteen experts.

Table 7 Original linguistic preferences received from expert 1 represent the initial direct influence matrix

KPIs	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14	P15	P16
P1	0	NI	VLI	HI	HI	NI	VHI	HI	HI	I	I	HI	VHI	HI	HI	NI
P2	HI	0	NI	HI	I	I	HI	I	HI	HI	HI	I	VHI	HI	I	VHI
P3	NI	VLI	0	VLI	HI	I	I	HI	VHI	VHI	HI	HI	VLI	VHI	NI	VLI
P4	HI	HI	I	0	HI	I	HI	HI	HI	HI	HI	VHI	HI	I	HI	HI
P5	VLI	NI	HI	HI	0	VHI	HI	I	HI	HI	I	VHI	VHI	HI	I	I
P6	NI	NI	HI	I	HI	0	VLI	NI	I	I	HI	I	HI	HI	I	HI
P7	I	I	I	HI	I	VLI	0	I	I	I	HI	I	VLI	HI	I	I
P8	NI	NI	NI	NI	NI	VLI	VLI	0	HI	I	HI	HI	I	HI	I	VLI
P9	HI	I	HI	HI	HI	VHI	HI	HI	0	HI	VHI	I	HI	HI	HI	HI
P10	NI	VLI	I	I	HI	VLI	I	I	I	0	HI	HI	I	I	I	I
P11	HI	I	I	HI	I	HI	VHI	VHI	VHI	I	0	VHI	HI	VHI	HI	HI
P12	VLI	HI	HI	I	VLI	NI	I	HI	HI	HI	VHI	0	VLI	HI	I	I
P13	NI	NI	VLI	I	I	HI	I	I	I	HI	I	I	0	HI	VHI	HI
P14	HI	I	I	VLI	HI	HI	I	VHI	HI	HI	I	VHI	I	0	I	I
P15	I	HI	HI	HI	HI	HI	HI	I	HI	I	HI	VHI	HI	HI	0	HI
P16	NI	VLI	VLI	VLI	HI	HI	I	I	I	HI	HI	HI	HI	VHI	HI	0

Table 8 Initial direct relation matrix (Obtained from the aggregated crisp value after defuzzification of k respondents) (D)

KPIs	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14	P15	P16
P1	0.875	0.000	0.185	0.576	0.576	0.012	0.681	0.576	0.500	0.300	0.300	0.498	0.681	0.500	0.576	0.000
P2	0.575	1.000	0.000	0.576	0.378	0.378	0.502	0.378	0.500	0.500	0.500	0.300	0.681	0.500	0.378	0.765
P3	0.000	0.311	0.875	0.186	0.576	0.378	0.305	0.576	0.673	0.674	0.498	0.500	0.106	0.673	0.000	0.186
P4	0.576	0.690	0.378	0.875	0.576	0.378	0.505	0.576	0.500	0.500	0.500	0.673	0.505	0.300	0.576	0.576
P5	0.185	0.125	0.576	0.576	0.875	0.765	0.505	0.378	0.498	0.498	0.300	0.673	0.681	0.500	0.378	0.378
P6	0.000	0.125	0.576	0.378	0.576	0.875	0.107	0.000	0.300	0.300	0.500	0.300	0.505	0.500	0.378	0.576
P7	0.378	0.500	0.378	0.576	0.378	0.185	0.752	0.378	0.300	0.300	0.500	0.300	0.107	0.496	0.378	0.378
P8	0.000	0.125	0.000	0.000	0.000	0.186	0.106	0.875	0.500	0.300	0.498	0.500	0.305	0.500	0.378	0.185
P9	0.576	0.500	0.576	0.576	0.576	0.765	0.505	0.576	0.720	0.498	0.673	0.300	0.503	0.498	0.576	0.576
P10	0.000	0.310	0.378	0.378	0.576	0.186	0.305	0.379	0.300	0.725	0.500	0.500	0.305	0.300	0.378	0.378
P11	0.576	0.500	0.378	0.576	0.378	0.576	0.681	0.765	0.673	0.300	0.722	0.673	0.505	0.673	0.576	0.576
P12	0.186	0.690	0.576	0.378	0.186	0.000	0.305	0.576	0.500	0.500	0.673	0.722	0.106	0.500	0.378	0.378
P13	0.000	0.125	0.185	0.378	0.378	0.576	0.305	0.378	0.300	0.496	0.300	0.300	0.752	0.500	0.765	0.576
P14	0.576	0.500	0.378	0.186	0.576	0.576	0.306	0.765	0.500	0.500	0.300	0.673	0.305	0.720	0.378	0.378
P15	0.378	0.690	0.576	0.576	0.576	0.576	0.505	0.378	0.500	0.300	0.500	0.673	0.503	0.500	0.875	0.575
P16	0.000	0.310	0.185	0.186	0.576	0.576	0.305	0.378	0.300	0.500	0.500	0.500	0.502	0.673	0.576	0.875

Table 9 Normalized initial direct relation matrix (A) obtained

KPIs	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14	P15	P16
P1	0.096	0.000	0.020	0.063	0.063	0.001	0.075	0.063	0.055	0.033	0.033	0.055	0.075	0.055	0.063	0.000
P2	0.063	0.110	0.000	0.063	0.041	0.041	0.055	0.041	0.055	0.055	0.055	0.033	0.075	0.055	0.041	0.084
P3	0.000	0.034	0.096	0.020	0.063	0.041	0.033	0.063	0.074	0.074	0.055	0.055	0.012	0.074	0.000	0.020
P4	0.063	0.076	0.041	0.096	0.063	0.041	0.055	0.063	0.055	0.055	0.055	0.074	0.055	0.033	0.063	0.063
P5	0.020	0.014	0.063	0.063	0.096	0.084	0.055	0.041	0.055	0.055	0.033	0.074	0.075	0.055	0.041	0.041
P6	0.000	0.014	0.063	0.041	0.063	0.096	0.012	0.000	0.033	0.033	0.055	0.033	0.055	0.055	0.041	0.063
P7	0.041	0.055	0.041	0.063	0.041	0.020	0.082	0.041	0.033	0.033	0.055	0.033	0.012	0.054	0.041	0.041
P8	0.000	0.014	0.000	0.000	0.000	0.020	0.012	0.096	0.055	0.033	0.055	0.055	0.033	0.055	0.041	0.020
P9	0.063	0.055	0.063	0.063	0.063	0.084	0.055	0.063	0.079	0.055	0.074	0.033	0.055	0.055	0.063	0.063
P10	0.000	0.034	0.041	0.041	0.063	0.020	0.033	0.041	0.033	0.079	0.055	0.055	0.033	0.033	0.041	0.041
P11	0.063	0.055	0.041	0.063	0.041	0.063	0.075	0.084	0.074	0.033	0.079	0.074	0.055	0.074	0.063	0.063
P12	0.020	0.076	0.063	0.041	0.020	0.000	0.033	0.063	0.055	0.055	0.074	0.079	0.012	0.055	0.041	0.041
P13	0.000	0.014	0.020	0.041	0.041	0.063	0.033	0.041	0.033	0.054	0.033	0.033	0.082	0.055	0.084	0.063
P14	0.063	0.055	0.041	0.020	0.063	0.063	0.033	0.084	0.055	0.055	0.033	0.074	0.033	0.079	0.041	0.041
P15	0.041	0.076	0.063	0.063	0.063	0.063	0.055	0.041	0.055	0.033	0.055	0.074	0.055	0.055	0.096	0.063
P16	0.000	0.034	0.020	0.020	0.063	0.063	0.033	0.041	0.033	0.055	0.055	0.055	0.055	0.074	0.063	0.096

Table 10 Total relation matrix (T) obtained

KPIs	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14	P15	P16	*Ri*
P1	0.216	0.156	0.170	0.232	0.248	0.168	0.237	0.260	0.238	0.204	0.219	0.254	0.243	0.255	0.249	0.173	3.524
P2	0.201	0.299	0.168	0.260	0.259	0.243	0.243	0.266	0.267	0.258	0.275	0.262	0.278	0.291	0.260	0.301	4.130
P3	0.103	0.183	0.242	0.171	0.237	0.204	0.179	0.248	0.249	0.241	0.234	0.241	0.164	0.265	0.163	0.186	3.308
P4	0.212	0.283	0.232	0.312	0.300	0.259	0.260	0.311	0.289	0.277	0.297	0.328*	0.273	0.290	0.299	0.295	4.517
P5	0.145	0.192	0.241	0.252	0.311	0.285	0.233	0.259	0.263	0.255	0.248	0.300	0.266	0.285	0.248	0.247	4.030
P6	0.095	0.152	0.203	0.187	0.233	0.258	0.149	0.167	0.194	0.189	0.222	0.209	0.206	0.236	0.202	0.227	3.131
P7	0.153	0.207	0.180	0.220	0.214	0.178	0.234	0.223	0.204	0.194	0.231	0.217	0.167	0.243	0.210	0.209	3.284
P8	0.071	0.116	0.093	0.100	0.112	0.129	0.109	0.224	0.173	0.142	0.177	0.181	0.138	0.184	0.159	0.135	2.244
P9	0.215	0.263	0.263	0.283	0.311	0.315*	0.265	0.318*	0.321*	0.2848	0.324*	0.293	0.280	0.322*	0.305	0.302	4.665
P10	0.095	0.173	0.173	0.184	0.224	0.169	0.169	0.209	0.191	0.232	0.219	0.227	0.177	0.207	0.198	0.198	3.045
P11	0.219	0.269	0.241	0.285	0.287	0.293	0.287	0.345*	0.319*	0.263	0.333*	0.338*	0.280	0.345*	0.309	0.304	4.716
P12	0.135	0.240	0.210	0.203	0.199	0.165	0.190	0.259	0.238	0.227	0.263	0.275	0.173	0.255	0.219	0.219	3.470
P13	0.099	0.159	0.160	0.192	0.213	0.227	0.175	0.216	0.198	0.214	0.206	0.215	0.238	0.240	0.255	0.233	3.241
P14	0.187	0.226	0.205	0.197	0.264	0.249	0.203	0.296	0.254	0.244	0.238	0.289	0.216	0.299	0.238	0.235	3.842
P15	0.190	0.285	0.259	0.279	0.304	0.287	0.260	0.289	0.291	0.257	0.299	0.329*	0.273	0.316*	0.333*	0.298	4.550
P16	0.110	0.195	0.173	0.185	0.252	0.243	0.190	0.235	0.216	0.231	0.246	0.256	0.226	0.280	0.250	0.284	3.573
Cj	2.448	3.398	3.215	3.544	3.967	3.672	3.384	4.125	3.906	3.710	4.033	4.215	3.597	4.312	3.897	3.848	59.271

Table 11 Prominence causal values are derived for each KPI

KPIs	KPI's names	*Ri*	*Cj*	*Ri* − *Cj*	*Ri* + *Cj*	Criteria group
P1	Decentralization	3.524	2.448	1.076	5.971	Cause
P2	Integrity	4.130	3.398	0.732	7.529	Cause
P3	Availability	3.308	3.215	0.094	6.523	Cause
P4	Cost	4.517	3.544	0.972	8.061	Cause
P5	Interoperability	4.030	3.967	0.063	7.996	Cause
P6	Virtualization	3.131	3.672	− 0.541	6.803	Effect
P7	Adaptability	3.284	3.384	− 0.100	6.668	Effect
P8	Modularity	2.244	4.125	− 1.880	6.369	Effect
P9	Connectivity	4.665	3.906	0.759	8.571	Cause
P10	Service orientation	3.045	3.710	− 0.666	6.755	Effect
P11	IT. infrastructure	4.716	4.033	0.683	8.749	Cause
P12	Prediction capabilities	3.470	4.215	− 0.744	7.685	Effect
P13	Flexibility	3.241	3.597	− 0.356	6.838	Effect
P14	Quality	3.842	4.312	− 0.470	8.153	Effect
P15	Information security	4.550	3.897	0.653	8.446	Cause
P16	Capacity to make real time decision	3.573	3.848	− 0.275	7.421	Effect

After assigning the weights to the KPIs, all experts are again asked to assign performance ratings to I4.0 risks and KPIs using the linguistic scale in Table 5. Hence Table 14 shows the decision matrix by expert 1 in linguistic form.

Table 15 below shows the corresponding fuzzy triangular numbers matrix with the conversion of linguistic expression in IVTFNs reflecting assigned performance ratings to I4.0 risks and KPIs given by expert 1.

Table 16 below shows the interval-valued fuzzy performance rating for fifteen experts assigned to I4.0 risks and KPIs by converting triangular fuzzy numbers into interval-valued fuzzy numbers using Eqs. (22)–(26).

Further Table 17 represents Optimal interval-valued triangular fuzzy performance ratings (X_0) for all experts achieved using Eq. (27) obtained from Eqs. (22)–(26).

Further fuzzy interval-valued numbers are then normalized using Eq. (28), and a normalized weighted interval-valued decision matrix is derived using Eq. (29), as shown in Table 18.

Finally, the degree of utility is calculated using Eqs. (30)–(32). Based on the degree of utility, the final ranking of I4.0 risks is calculated and shown in Table 19.

It is observed from Table 19 that Technological risks (R6) is ranked first as it is showing the highest degree of utility, and social risks (R5) is ranked second. The findings and discussions are further detailed in the next section. Figure 6 elucidates the findings schematically using the data from Table 19 reflecting clear visualization of the findings of the study.

Table 12 The weights assigned by expert 1 to KPIs are presented in linguistic expressions and their corresponding triangular fuzzy numbers

KPIs	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14	P15	P16
Linguistic expression	VL	ML	ML	H	H	ML	ML	VL	H	ML	VH	H	ML	H	H	H
TFNs	0, 0, 0.1	0.1, 0.3, 0.5	0.1, 0.3, 0.5	0.7, 0.7, 1	0.7, 0.7, 1	0.1, 0.3, 0.5	0.1, 0.3, 0.5	0, 0, 0.1	0.7, 0.7, 1	0.1, 0.3, 0.5	0.9, 1, 1	0.7, 0.7, 1	0.1, 0.3, 0.5	0.7, 0.7, 1	0.7, 0.7, 1	0.7, 0.7, 1

Table 13 Interval-valued triangular fuzzy weights assigned to KPIs by all fifteen experts

KPIs	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14	P15	P16
IVTFNs weights	(0, 0), 0, (0.20, 0.5)	(0.1, 0.22), 0.46, (0.67, 0.9)	(0, 0), 0, (0.23, 0.5)	(0.5, 0.64), 0.73, (0.97, 1)	(0, 0), 0.58, (0.85, 1)	(0, 0), 0, (0.26, 1)	(0, 0), 0, (0.25, 0.5)	(0, 0), 0, (0.22, 0.5)	(0.5, 0.69), 0.75, (0.98, 1)	(0, 0), 0, (0.25, 0.9)	(0.5, 0.72), 0.81, (0.97, 1)	(0, 0), 0.52, (0.8, 1)	(0, 0), 0, (0.29, 1)	(0.5, 0.69), 0.75, (0.98, 1)	(0.5, 0.73), 0.79, (0.99, 1)	(0, 0), 0, (0.71, 1)

Table 14 The decision matrix of assignment of performance rating to I4.0 risks and KPIs is given by expert 1 (In linguistic expressions)

Risks/KPIs	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14	P15	P16
R1	VP	F	VP	MG	G	VP	F	MG	G	MG	G	VG	F	G	VG	F
R2	MG	MG	P	F	MP	MP	MP	P	MG	F	G	MP	F	F	VG	F
R3	VP	F	VP	MP	P	VP	P	VP	F	MP	F	VP	MP	F	VG	F
R4	VP	P	VP	F	VP	P	VP	P	MP	F	G	MP	G	G	F	F
R5	F	MG	F	VG	G	G	G	G	VG	MG	VG	G	VG	VG	VG	VG
R6	MG	MG	G	VG	VG	VG	VG	G	VG	G	VG	G	VG	VG	VG	VG

Table 15 Decision matrix by expert 1 (Triangular fuzzy numbers derived from the linguistic expressions)

Risks/KPIs	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14	P15	P16
R1	0, 0, 0.1	0.3, 0.5, 0.7	0, 0, 0.1	0.5, 0.7, 0.9	0.7, 0.7, 1	0, 0, 0.1	0.3, 0.5, 0.7	0.5, 0.7, 0.9	0.7, 0.7, 1	0.5, 0.7, 0.9	0.7, 0.7, 1	0.9, 1, 1	0.3, 0.5, 0.7	0.7, 0.7, 1	0.9, 1, 1	0.3, 0.5, 0.7
R2	0.5, 0.7, 0.9	0.5, 0.7, 0.9	0, 0.1, 0.3	0.3, 0.5, 0.7	0.1, 0.3, 0.5	0.1, 0.3, 0.5	0.1, 0.3, 0.5	0, 0.1, 0.3	0.5, 0.7, 0.9	0.3, 0.5, 0.7	0.7, 0.7, 1	0.1, 0.3, 0.5	0.3, 0.5, 0.7	0.3, 0.5, 0.7	0.9, 1, 1	0.3, 0.5, 0.7
R3	0, 0, 0.1	0.3, 0.5, 0.7	0, 0, 0.1	0.1, 0.3, 0.5	0, 0.1, 0.3	0, 0, 0.1	0, 0.1, 0.3	0, 0, 0.1	0.3, 0.5, 0.7	0.1, 0.3, 0.5	0.3, 0.5, 0.7	0, 0, 0.1	0.1, 0.3, 0.5	0.3, 0.5, 0.7	0.9, 1, 1	0.3, 0.5, 0.7
R4	0, 0, 0.1	0, 0.1, 0.3	0, 0, 0.1	0.3, 0.5, 0.7	0, 0, 0.1	0, 0.1, 0.3	0, 0, 0.1	0, 0.1, 0.3	0.1, 0.3, 0.5	0.3, 0.5, 0.7	0.7, 0.7, 1	0.1, 0.3, 0.5	0.7, 0.7, 1	0.7, 0.7, 1	0.3, 0.5, 0.7	0.3, 0.5, 0.7
R5	0.3, 0.5, 0.7	0.5, 0.7, 0.9	0.3, 0.5, 0.7	0.9, 1, 1	0.7, 0.7, 1	0.7, 0.7, 1	0.7, 0.7, 1	0.7, 0.7, 1	0.9, 1, 1	0.5, 0.7, 0.9	0.9, 1, 1	0.7, 0.7, 1	0.9, 1, 1	0.9, 1, 1	0.9, 1, 1	0.9, 1, 1
R6	0.5, 0.7, 0.9	0.5, 0.7, 0.9	0.7, 0.7, 1	0.9, 1, 1	0.9, 1, 1	0.9, 1, 1	0.9, 1, 1	0.7, 0.7, 1	0.9, 1, 1	0.7, 0.7, 1	0.9, 1, 1	0.7, 0.7, 1	0.9, 1, 1	0.9, 1, 1	0.9, 1, 1	0.9, 1, 1

Table 16 Interval-valued fuzzy performance ratings are shown for risks and KPIs for fifteen experts

Risks/KPIs	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14	P15	P16
R1	(0, 0), (0), (0.1, 0.1)	(0.1, 0.28), (0.49), (0.69, 0.9)	(0, 0), (0), (0.1, 0.1)	(0.5, 0.5), (0.7), (0.9, 0.9)	(0.7, 0.7), (0.7), (1, 1)	(0, 0), (0), (0.1, 0.1)	(0.3, 0.3), (0.5), (0.7, 0.7)	(0.5, 0.5), (0.7), (0.9, 0.9)	(0.7, 0.7), (0.7), (1, 1)	(0.5, 0.5), (0.7), (0.9, 0.9)	(0.7, 0.7), (0.7), (1, 1)	(0.9, 0.9), (1), (1, 1)	(0.1, 0.29), (0.49), (0.7, 0.9)	(0.01, 0.69), (0.73), (0.99, 1)	(0.9, 0.9), (1), (1, 1)	(0.1, 0.29), (0.49), (0.7, 0.9)
R2	(0.3, 0.48), (0.64), (0.87, 1)	(0.5, 0.5), (0.7), (0.9, 0.9)	(0, 0), (0) , (0.29, 0.5)	(0.1, 0.29), (0.49), (0.7, 0.9)	(0, 0), (0.29), (0.49, 0.7)	(0, 0), (0.29), (0.49, 0.7)	(0.1, 0.1), (0.3), (0.5, 0.5)	(0, 0), (0), (0.29, 0.5)	(0.5, 0.5), (0.7), (0.9, 0.9)	(0.1, 0.29), (0.49), (0.7, 0.9)	(0.7, 0.7), (0.7), (1, 1)	(0, 0), (0.27), 0.48, 0.7)	(0.1, 0.29), (0.49), (0.7, 0.9)	(0, 0.3), (0.5), (0.7, 0.7)	(0.9, 0.9), (1), (1, 1)	(0.1, 0.29), (0.49), (0.7, 0.9)
R3	(0, 0), (0), (0.1, 0.1)	(0.3, 0.3), (0.5), (0.7, 0.7)	(0, 0), (0), (0.1, 0.1)	(0, 0), (0), (0.44, 0.7)	(0, 0), (0), 0.28, 0.5)	(0, 0), (0), (0.1, 0.1)	(0, 0), (0), (0.25, 0.5)	(0, 0), (0), (0.1, 0.1)	(0.1, 0.29), (0.49), (0.7, 0.9)	(0, 0), (0.29), (0.49, 0.7)	(0.1, 0.27), (0.48), (0.69, 0.9)	(0, 0), (0), (0.1, 0.1)	(0.1, 0.1), (0.3), (0.5, 0.5)	(0, 0.29), (0.49), (0.7, 0.9)	(0.9, 0.9), (1), (1, 1)	(0.1, 0.28), (0.49), (0.69, 0.9)
R4	(0, 0), (0), (0.1, 0.1)	(0, 0), (0), (0.27, 0.5)	(0, 0), (0), (0.1, 0.1)	(0.1, 0.28), (0.49), (0.69, 0.9)	(0, 0), (0), (0.1, 0.1)	(0, 0), (0), (0.28, 0.5)	(0, 0), (0), (0.1, 0.1)	(0, 0), (0.1), (0.3, 0.3)	(0.1, 0.1), (0.3), (0.5, 0.5)	(0.1, 0.29), (0.49), (0.7, 0.9)	(0.5, 0.7), (0.72), (0.99, 1)	(0, 0), (0.28), (0.49, 0.7)	(0.5, 0.69), (0.75), (0.98, 1)	(0.01, 0.7), (0.72), (0.99, 1)	(0.1, 0.28), (0.49), (0.69, 0.9)	(0.1, 0.27), (0.49), (0.69, 1)
R5	(0.1, 0.27), (0.48), (0.69, 1)	(0.3, 0.49), (0.68), (0.89, 1)	(0.1, 0.27), (0.48), (0.69, 0.9)	(0.9, 0.9), (1), (1, 1)	(0.5, 0.7), (0.72), (0.99, 1)	(0.5, 0.69), (0.73), (0.99, 1)	(0.5, 0.69), (0.75), (0.98, 1)	(0.5, 0.69), (0.73), (0.99, 1)	(0.9, 0.9), (1), (1, 1)	(0.5, 0.5), (0.7), (0.9, 0.9)	(0.9, 0.9), (1), (1, 1)	(0.5, 0.7), (0.72), (0.99, 1)	(0.9, 0.9), (1), (1, 1)	(0.28, 0.9), (1), (1, 1)	(0.9, 0.9), (1), (1, 1)	(0.9, 0.9), (1), (1, 1)
R6	(0.3, 0.49), (0.68), (0.89, 1)	(0.5, 0.5), (0.7), (0.9, 0.9)	(0.5, 0.69), (0.73), (0.99, 1)	(0.9, 0.9), (1), (1, 1)	(0.9, 0.9), (1), (1, 1)	(0.9, 0.9), (1), (1, 1)	(0.9, 0.9), (1), (1, 1)	(0.7, 0.7), (0.7), (1, 1)	(0.9, 0.9), (1), (1, 1)	(0.5, 0.69), (0.75), (0.98, 1)	(0.9, 0.9), (1), (1, 1)	(0.5, 0.7), (0.72), (0.99, 1)	(0.9, 0.9), (1), (1, 1)	(0.28, 0.9), (1), (1, 1)	(0.9, 0.9), (1), (1, 1)	(0.9, 0.9), (1), (1, 1)

Table 17 The optimal interval-valued triangular fuzzy performance ratings (X_0) are shown for all experts

KPIs	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14	P15	P16
Optimal	(0.3, 0.49), (0.68), (0.89, 1)	(0.5, 0.5), (0.7), (0.9, 1)	(0.5, 0.69), (0.73), (0.99, 1)	(0.9, 0.9), (1), (1, 1)	(0.9, 0.9), (1), (1, 1)	(0.9, 0.9), (1), (1, 1)	(0.9, 0.9), (1), (1, 1)	(0.7, 0.7), (0.73), (1, 1)	(0.9, 0.9), (1), (1, 1)	(0.5, 0.69), (0.75), (0.98, 1)	(0.9, 0.9), (1), (1, 1)	(0.9, 0.9), (1), (1, 1)	(0.9, 0.9), (1), (1, 1)	(0, 0.29), (0.49), (0.7, 0.7)	(0.1, 0.9), (1), (1, 1)	(0.9, 0.9), (1), (1, 1)

Table 18 A normalized weighted interval-valued triangular fuzzy performance rating matrix

KPIs	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14	P15	P16
Optimal	(0, 0), (0), (0.04, 0.12)	(0.01, 0.02), (0.05), (0.1, 0.15)	(0, 0), (0), (0.06, 0.14)	(0.07, 0.09), (0.11), (0.15, 0.16)	(0, 0), (0.11), (0.16, 0.19)	(0, 0), (0), (0.06, 0.23)	(0, 0), (0), (0.05, 0.1)	(0, 0), (0), (0.05, 0.1)	(0.07, 0.1), (0.12), (0.16, 0.16)	(0, 0), (0), (0.04, 0.14)	(0.07, 0.09), (0.12), (0.14, 0.14)	(0, 0), (0.09), (0.14, 0.18)	(0, 0), (0), (0.05, 0.16)	(0, 0.03), (0.06), (0.11, 0.11)	(0.01, 0.09), (0.11), (0.14, 0.14)	(0, 0), (0), (0.11, 0.15)
R1	(0, 0), (0), (0, 0.01)	(0, 0.01), (0.04), (0.08, 0.14)	(0, 0), (0), (0.01, 0.01)	(0.04, 0.05), (0.08), (0.14, 0.14)	(0, 0), (0.08), (0.16, 0.19)	(0, 0), (0), (0.01, 0.02)	(0, 0), (0), (0.04, 0.07)	(0, 0), (0), (0.04, 0.09)	(0.06, 0.08), (0.08), (0.16, 0.16)	(0, 0), (0), (0.04, 0.13)	(0.05, 0.07), (0.08), (0.14, 0.14)	(0, 0), (0.09), (0.14, 0.18)	(0, 0), (0), (0.03, 0.14)	(0, 0.08), (0.09), (0.15, 0.16)	(0.07, 0.09), (0.11), (0.14, 0.14)	(0, 0), (0), (0.07, 0.13)
R2	(0, 0), (0), (0.04, 0.12)	(0.01, 0.02), (0.05), (0.1, 0.14)	(0, 0), (0), (0.02, 0.07)	(0.01, 0.03), (0.06), (0.11, 0.14)	(0, 0), (0.03), (0.08, 0.13)	(0, 0), (0), (0.03, 0.16)	(0, 0), (0), (0.03, 0.05)	(0, 0), (0), (0.01, 0.05)	(0.04, 0.05), (0.08), (0.14, 0.14)	(0, 0), (0), (0.03, 0.13)	(0.05, 0.07), (0.08), (0.14, 0.14)	(0, 0), (0.03), (0.07, 0.13)	(0, 0), (0), (0.03, 0.14)	(0, 0.03), (0.06), (0.11, 0.11)	(0.07, 0.09), (0.11), (0.14, 0.14)	(0, 0), (0), (0.07, 0.13)
R3	(0, 0), (0), (0, 0.01)	(0.01, 0.01), (0.04), (0.08, 0.11)	(0, 0), (0), (0.01, 0.01)	(0, 0), (0), (0.07, 0.11)	(0, 0), (0), (0.04, 0.09)	(0, 0), (0), (0.01, 0.02)	(0, 0), (0), (0.01, 0.05)	(0, 0), (0), (0, 0.01)	(0.01, 0.03), (0.06), (0.11, 0.14)	(0, 0), (0), (0.02, 0.1)	(0.01, 0.03), (0.06), (0.1, 0.13)	(0, 0), (0), (0.01, 0.02)	(0, 0), (0), (0.02, 0.08)	(0, 0.03), (0.06), (0.11, 0.14)	(0.07, 0.09), (0.11), (0.14, 0.14)	(0, 0), (0), (0.07, 0.13)
R4	(0, 0), (0), (0, 0.01)	(0, 0), (0), (0.03, 0.08)	(0, 0), (0), (0.01, 0.01)	(0.01, 0.03), (0.06), (0.1, 0.14)	(0, 0), (0), (0.02, 0.02)	(0, 0), (0), (0.02, 0.11)	(0, 0), (0), (0.01, 0.01)	(0, 0), (0), (0.01, 0.03)	(0.01, 0.01), (0.04), (0.08, 0.08)	(0, 0), (0), (0.03, 0.13)	(0.04, 0.07), (0.08), (0.14, 0.14)	(0, 0), (0.03), (0.07, 0.13)	(0, 0), (0), (0.04, 0.16)	(0, 0.08), (0.09), (0.15, 0.16)	(0.01, 0.03), (0.06), (0.1, 0.13)	(0, 0), (0), (0.07, 0.15)

Table 18 (continued)

KPIs	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14	P15	P16
R5	(0, 0), (0), (0.03, 0.12)	(0.01, 0.02), (0.05), (0.1, 0.15)	(0, 0), (0), (0.04, 0.12)	(0.07, 0.09), (0.11), (0.15, 0.16)	(0, 0), (0.08), (0.16, 0.19)	(0, 0), (0), (0.06, 0.23)	(0, 0), (0), (0.05, 0.1)	(0, 0), (0), (0.05, 0.1)	(0.07, 0.1), (0.12), (0.16, 0.16)	(0, 0), (0), (0.04, 0.13)	(0.07, 0.09), (0.12), (0.14, 0.14)	(0, 0), (0.07), (0.14, 0.18)	(0, 0), (0), (0.05, 0.16)	(0.02, 0.1), (0.12), (0.16, 0.16)	(0.07, 0.09), (0.11), (0.14, 0.14)	(0, 0), (0), (0.11, 0.15)
R6	(0, 0), (0), (0.04, 0.12)	(0.01, 0.02), (0.05), (0.1, 0.14)	(0, 0), (0), (0.06, 0.14)	(0.07, 0.09), (0.11), (0.15, 0.16)	(0, 0), (0.11), (0.16, 0.19)	(0, 0), (0), (0.06, 0.23)	(0, 0), (0), (0.05, 0.1)	(0, 0), (0), (0.05, 0.1)	(0.07, 0.1), (0.12), (0.16, 0.16)	(0, 0), (0), (0.04, 0.14)	(0.07, 0.09), (0.12), (0.14, 0.14)	(0, 0), (0.07), (0.14, 0.18)	(0, 0), (0), (0.05, 0.16)	(0.02, 0.1), (0.12), (0.16, 0.16)	(0.07, 0.09), (0.11), (0.14, 0.14)	(0, 0), (0), (0.11, 0.15)

Table 19 I4.0 Risks ranking on the basis of interval-valued triangular fuzzy performance evaluation

	S_i	$\widetilde{S_i}$	$\tilde{Q}_i$	Rank
Optimal	(0.29, 0.53), (0.9), (1.71, 2.54)	1.19	1	
R1	(0.27, 0.46), (0.74), (1.5, 2.03)	1	0.84	3
R2	(0.21, 0.36), (0.59), (1.29, 2.08)	0.91	0.76	4
R3	(0.09, 0.23), (0.39), (0.92, 1.46)	0.62	0.52	6
R4	(0.07, 0.23), (0.38), (0.96, 1.57)	0.64	0.54	5
R5	(0.37, 0.59), (0.9), (1.72, 2.56)	1.23	1.03	2
R6	(0.37, 0.59), (0.93), (1.76, 2.57)	1.25	1.04	1

Fig. 6 I4.0 Risks Prioritization Based on KPIs. Note: I4.0 Risks—R1: Operational Risks, R2: Economic Risks, R3: Legal/Political Risks, R4: Ecological Risks, R5: Social Risks, R6: Technological Risks

5 Results and analysis

This study is intended to analyze the most significant I4.0 implementation risks among all considered and rank them according to the significant I4.0 KPIs. Researchers have also explored the interrelationship among these KPIs to bring more clarity to the findings. Undoubtedly the findings will pave the way to the adoption of I4.0 practices leading to sustainable competitive advantage in Indian manufacturing companies. The critical analysis of the KPIs considered for the I4.0 implementation risks assessment using FDEMATEL is concluded in Table 11. Values in the column $R_i - C_j$ classify the KPIs in the cause and effects groups as shown in Fig. 4. The KPIs listed in the cause section are the ones responsible for the changes, and those in the effect section are the outcomes. The importance hierarchy of KPIs based on the values in the column ($R_i + C_j$) is reflected through the sequence as IT Infrastructure (P11) > Connectivity (P9) > Information security (P15) > Quality (P14) > Cost (P4) > Interoperability (P5) > Prediction capabilities (P12) > Integrity (P2) > Capacity to make real-time decision (P16) > Flexibility (P13) > Virtualization (P6) > Service orientation (P10) > Adaptability (P7) > Availability (P3) > Modularity (P8) > Decentralization (P1). It is evident from the results that the strength of the relationship among KPIs varies from lowest to highest, reflecting its importance in decision-making. It is highly unlikely that all the KPIs will hold equal importance in decision-making in any given situation. This leads to the belief that there must be a few vital relationships that need urgent attention. It is also not logical and feasible to consider all the KPIs with equal priority and urgency when the relationship values vary. Thus the KPIs are first segregated into cause and effect groups using a combination of fuzzy logic set theory and DEMATEL techniques. The threshold value is set to 0.314 to avoid insignificant relationships without missing any highly significant relationships.

The most significant cause KPIs impacting I4.0 risks assessment, as shown in Table 11 column $Ri - Cj$ has maximum positive values ranging from 1.076 to 0.653, which means the KPIs, Decentralization (P1), Integrity (P2), Cost (P4), Connectivity (P9), IT Infrastructure (P11), and Information security (P15) should be given the highest consideration as they cause the impact. The finding is further endorsed by column Ri where the KPIs have high positive values. Similarly, the highest negative values in column $Ri - Cj$ range from − 1.880 to − 0.47, where the KPIs Virtualization (P6), Modularity (P8), Service orientation (P10), Prediction capabilities (P12), and Quality (P14) are found to be largely influenced by others. This means they are significantly impacted. These KPIs are easily affected by others; hence they also need to be cautiously handled. This is confirmed by Cj column values also.

According to the hierarchy taken from the $Ri + Cj$ column, the top rank KPI is P11: IT infrastructure. The same is shown in Fig. 5 for better understanding, highlighting the significant relationships with other KPIs. The strategic importance of these KPIs can be understood by taking a look at the list of other KPIs; it is impacting, i.e., modularity (P8), connectivity (P9), prediction capabilities (P12), and quality (P14). From the group of causes, connectivity (P9) has a dual relationship with IT infrastructure (P11), meaning they are influencing each other. The other significant cause KPIs are cost (P4) and information security (P15), and the effect KPI is virtualization (P6), which also needs monitoring and control. Similarly, quality (P14) and prediction capabilities (P12) are identified as important I4.0 KPIs.

Further, the ranking obtained from the application of extended ARAS with INTFNs is illustrated in Table 19. The finding is very much signifying the current conditions in the manufacturing sector. The top rank is held by Technological risks (R6) as it shows the highest value of the degree of utility ($\tilde{Q}_i$) i.e. 1.04, followed by Social risks (R5) showing the second-highest value of the degree of utility ($\tilde{Q}_i$) i.e. 1.03. Thus, the key observation in Table 19 is that the Social risks secured the position at second rank, leaving no doubt about their significance in the risks framework. Being on the 2nd position in the list, the social risks aspects of I4.0 also need urgent attention. Figure 6 reflects the various positions of the other four risks i.e. R1: Operational Risks R2: Economic Risks, R4: Ecological Risks, and R3: Legal/Political Risks as per the value of the degree of utility ($\tilde{Q}_i$). Schematic visualization of six I4.0 risks clearly shows the significance and priority professionals should give to them while embarking on the transition towards I4.0 implementation. Further, the outcomes of the study are exclusively shared with the experts, we received commendable remarks from them which ascertains the utility of the devised model and can be made available for further investigations. Also, the developed model is validated by other experts and fellow researchers mentioned earlier in this study who did not participate in data collection for this study. The unbias and external perspectives of these experts along with suggestions and inputs received from them have increased the plausibility of this study.

6 Discussion and study implications

This research is primarily aiming to determine the critical role of I4.0 KPIs and the prioritization of I4.0 risks for simplifying the I4.0 implementation in Indian manufacturing industries. The study used FDEMATEL to establish that IT infrastructure is the most important KPI among the 16 chosen. This finding attracts urgent attention from researchers and policymakers in developing countries like India because of the prevailing low state of IT infrastructure (Gadekar et al., 2020; Luthra et al., 2020). Except for a few very large companies, no other companies have dared to install dedicated and customized infrastructure for company use, as it needs heavy capital investment. Although a viable IT infrastructure is a fundamental requirement for I4.0 propagation, most of the companies are watchful and reserved because of their limited capacity or capability. Additionally, IT infrastructure also needs continuous technological up-gradation maintenance and updated skills which demands more capital investment. Considering this fact, it is advised to carry out an IT infrastructural readiness analysis, and projected outcomes assessment before installing the IT infrastructure (Birkel et al., 2019; Colak et al., 2019; Ghobakhloo & Iranmanesh, 2021). In the present context, this study urgently invites government interventions to handle IT infrastructure issues with strong political will. An effective and efficient solution to address the small companies' concerns smartly, is the need for an hour. The government may also take up this concern by providing subsidies on financial facilities, tax benefits, and streamlining universal I4.0 standards that can gear up the IT infrastructural growth. In these conditions, companies are advised to look at the IT infrastructure as the highest important KPI; to achieve this objective the role of the top management of the manufacturing organizations is crucial, otherwise, it can break the momentum of the aspiring companies. Thus, the companies can also collaborate in a timebound manner, by sharing resources to install common IT infrastructure.

One of the interesting findings of this study as shown in Fig. 5 is the dual relationship between the KPIs of IT infrastructure and connectivity. This signifies robust IT infrastructure and seamless network connectivity is one of the must-have resources for smooth adoption of I4.0 practices. Effective communication among machines, equipment, clouds, and servers is another requirement to monitor the shop floor manufacturing operation. Ivanov et al. (2021) also endorsed that seamless communication between Machine-Machine and Man–Machine is key to the overall performance of the I4.0 compliant company. Thus, collaborative amalgamation of IT infrastructure and digital connectivity (Cimini et al., 2021) among the whole business ecosystem is a must for efficient human resource handling, capacity, and capabilities deployment. This could be possible only by incorporating a dedicated interoperable planning and execution system for various business functions and manufacturing assets. Once the IT infrastructure and connectivity issues are resolved efficiently, maintenance capabilities can be ensured by deploying IoT, IIoT devices, and CC to big data analytics. A well-maintained and up-to-date system leads to high productivity and agility in the overall system. Also, this will help in adopting modularity in the production system through reconfiguration and flexibility and ultimately will result in the improving quality of manufacturing processes. These findings are agreeable with the study (Morgan et al., 2021).

The noteworthy result of this study is that cost, information security, and virtualization are three important KPIs. Contemplating to this the study affirms the finding by Mittal et al. (2019), Gadekar et al. (2020), and Ghobakhloo and Iranmanesh (2021) that information security, as described through the standards and procedures of data acquisition, processing, cloud computing, and analytics, is one of the most critical KPIs. Attention to this will be helpful to mitigate the risks related to issues on the way to the successful adoption of the I4.0 vision. Similarly, the cost-effective, flexible, and high-performing infrastructure that will serve seamless internet connectivity, to support real-time data to decision-makers is one of the must-have facilities in I4.0 adoption. This study broadly supports the claims by Mittal et al. (2019) and Shivajee et al. (2019) that cost, and data security are the keys to the successful implementation of I4.0. Hence, data generation, recording, storage, and making it available to real-time decision-makers (man or machine) without compromising information security is another challenge that needs attention (Hughes et al., 2022; Khan & Turowski, 2016a; Kusiak, 2018). The tremendous data and information is generated by volume, veracity, velocity, variety, and value at every stage of I4.0 implementation, as a result of man–machine integration, a network of IoT devices, as well as horizontal, vertical, and end-to-end integration of the physical and virtual system, which is very much susceptible to the threat throughout the manufacturing operations (Frank et al., 2019; Kiel et al., 2017; Veza et al., 2015) needs to be handled carefully. This could be accomplished by introducing a service-oriented cloud platform for data handling, storage, retrieval, and analytics, as well as integrating production systems effectively, which will ensure information execution with end-to-end encryption, information security, and timely availability to decision-makers. Further to that the study also confirms that virtualization and modularity are other significant concerns. Thus, making available the standardized platform, protocol, and communication network to facilitate quick interaction between companies and suppliers can optimize the inventory management and streamline the supplies. This finding is also supported by Gökalp et al. (2017) and Malaga and Vinodh (2021) as a means to boost confidence among stakeholders while embarking on I4.0 adoption.

Additionally, the study also reflects that quality and prediction capabilities are prime concerns while focusing on the economic perspective of I4.0, endorsed by the findings of the studies (Hossain & Muhammad, 2016; Kiel et al., 2017). The majority of manufacturing application risks come from information security, data integrity loss, and cyber-attacks (Corallo et al., 2020; Tupa et al., 2017). Thus, secure network, data privacy, trust in information sharing among the system's peripherals, interoperability, and integrity contribute to the efficient predicting capability (Malaga & Vinodh, 2021). It means there is a need for every company to install robust IT infrastructure like data centers, cloud computing, and big data storage and analytics facilities to ensure precise and assured predictions are made in real-time. Hence, deploying intelligent IT infrastructure aids in real-time monitoring, which stimulates transparency and control over manufacturing activities on the shop floor by assessing the overall equipment effectiveness (OEE) of the system, resulting in overall quality performance on the shop floor. This improves the manufacturing system's responsiveness and prediction capabilities, allowing it to extract the desired insights from received data for future decision-making initiatives. Thus, we affirm that the identified cause KPIs, influencing the effect KPIs in this study, provide the key insights that justify their existence in the risk management framework of the I4.0 implementation. Hence a clear focus on raising IT infrastructure is a must, which will ensure the high standards of prediction capability, information security, quality, data analytics, secure network, connecting devices, and human skills through the optimum utilization of resources, helps in successful transition towards I4.0 adoption leading to achive sustainability which is the ultimate goal of any manufacturing organization.

The remarkable outcome of this research gained from the application of the MCDM method extended ARAS with INTFNs applied to KPIs and I4.0 risks for its prioritization demonstrates the urgent necessity to address the Technological risks which can be observed in Table 19 and Fig. 6 in the context to the I4.0 advancements in Indian manufacturing industries. As the business models will adopt emerging technologies and smart business practices, the organizational structure and leadership are bound to change from a traditional approach to a highly dynamic digital approach. The mature, flexible, robust, and supportive IT imbibed technological infrastructure will open the flood gates of opportunities for I4.0 project teams. Here data scientists, programmers, and core technology experts will innovate new ways of doing business that will be far more flexible, reliable, fast, cost-effective, and impart high quality. Similarly, strong technical support needs to be deployed to tackle cyber-attack issues, data security, and interoperability among connected devices, i.e., sensors, machines, storage devices, and real-time decision-making capabilities through digitization of the entire value chain. Existing technological infrastructure modification, renovation, and up-gradation towards I4.0 compliant business model require a lot of refurbishments. Even if the new technological infrastructure investment is made viable, the disposal of existing machinery and other resources remains a big concern. Another challenge is the integration, collaboration, and interconnectedness of the man and machines throughout the business functions, which is a must condition to rip the great potential of I4.0. But it comes with lots of complexity, uncertainty, and massive costs (Bonilla et al., 2018; Machado et al., 2019). In the absence of cybersecurity solutions, internet-based technologies and online platforms have raised high apprehensions related to data security and transparency restricting manufacturers from welcoming I4.0 open-heartedly despite having equipped with other necessary resources (Gadekar et al., 2020; Parhi et al., 2021). Sooner or later, the companies will have to inculcate the new normal of I4.0. Those who will adopt it willingly or forcefully will survive, and those who will not increase the chances of being thrown out of the race.

Another significant outcome derived from this study is the social risks that require the immediate attention of policymakers researchers, and managers of manufacturing organizations followed by managing technological risks. This means people's resistance to change to a new paradigm of organizational transformation could be disastrous to the I4.0 implementation (Kiel et al., 2017; Raj et al., 2020) if not handled effectively and in a time-bound manner. Nevertheless, manpower management and a people-centric approach are still deciding factors, as revealed by the study. Organizations must have balanced, and progressive human resource strategies focused on employees' work-life balance, self-development, respectful empowerment, and a productive environment, which will inspire them to give their best. Hence to establish belongingness and ownership towards the job and organization, people at the forefront and behind the technical solutions must be looked after well to empower them through addressing their cognitive and affective concerns considering their work roles and responsibilities.

The automation of the processes and operations is guided by many factors like cost–benefit analysis, creativity, skilled workforce availability, work conditions, and customer demand. As a result, the repetitive and least creative tasks in nature may be considered for early automation. Even the managerial functions of planning and decision-making in manufacturing activities are expected to be replaced by automated devices and software applications. This does not mean the companies will run without light. The human role will remain vital in the system; only the duties dimensions may change, steered by all kinds of IT skillset to effectively handle the stand-alone, autonomous, and integrated systems (Kaasinen et al., 2020; Khan & Turowski, 2016b; Müller et al., 2018b). This thought also has a negative side, which may instill fear of becoming obsolete, losing a job, or becoming incompatible, as an effect of I4.0 implementation. Such a situation needs to be attended to with care and passion. A well-thought and transparent change management plan that sympathetically approaches the employee problems by neither frightening and stressing them about work loss and compatibility with new job demands nor compromising organizational interests could be a potential game-changer. If aligned with the people's aspirations, the new wave of digital transformation can change the employee's mindsets to successfully tackle digital transformation challenges (Bhagawati et al., 2019; Leonhardt & Wiedemann, 2015; Raj et al., 2020). The future workforce must be counseled, mentored, and guided to develop new skills and necessary competencies required to handle data analytics, machine learning, artificial intelligence, information, and cybersecurity issues, IoT devices, etc. Continuous upskilling, training, and educating the employee through an appropriate support system may help to realize change management goals with minimal effort (Masood & Sonntag, 2020). Another societal perspective of data protection, privacy rights, surveillance, and security issues of IoT and RFID devices, cloud services, data uses, and data-sharing agreements with the employee and enterprises, i.e., reliable users, contributes towards mitigating the social risks. Thus, to minimize these adversities, industries will have to build on their capacity and capability to train and develop their employees to keep them updated and compatible with the new work demand and handle the new technology efficiently and effectively to get all benefits out of it. A consultative approach in critical decision-making has better chances of success. Transparency and a trustful work culture regarding personal and professional information management policies through end-to-end encrypted solutions are vital in winning the system's confidence and faith (Kumar & Singh, 2021). This study has the unique contribution to the extant litrature and pioneer in evaluating the large set of I4.0 KPIs which tried to cover maximum possible ambit to prospective KPIs which is found lacking or partially addressed in prior studies. Further extending it to evaluating the sustainable I4.0 implementation risks is another significant contribution of the current study which remained unattended in past studies. The findings of the studies are well supported with evidence and validated with the past studies has confirmed the credibility of the developed model in current study. Further we eloborate on the implications recommandations of this study.

6.1 Theoretical implications

According to the SLR conducted and expert opinions used in this study, Indian manufacturing organizations have yet to catch up with the momentum. Apprehensions about the lack of clarity on I4.0 risks management KPIs and unclear estimation of anticipated benefits are still holding companies from I4.0 adoption. The existing literature also lacks the context for the fast-tracked development happening in the I4.0 era. Even the process of selecting appropriate MCDM methods among the many available is not explicitly highlighted in prior studies in this context. This study has overcome these drawbacks by describing the process of selecting MCDM methods and validation tools fit for the developed risks assessment framework in the current study. On this note, a few major theoretical implications of this study are outlined below.

The six most critical risks are critically assessed on sixteen KPIs, which cover all prospective risks assessment dimensions. The study has also explored the cause-and-effect relationship among the KPIs. Thereby, the integrated model developed has the potential to guide and support the decision-makers involved in I4.0 implementation. As a result, we encourage researchers to consider this study as a reference point for building on their research problems, who are working on similar projects, to uncover other layers of I4.0 risks management to take up the outcome of this study to the new paradigm. The visualization of the interrelationship among the KPIs presented in Fig. 5 helps the quick and easy assimilation of the internal dynamics of KPIs which will be helpful to devise a strategic plan of action for addressing the most prominent KPIs as per their significance while embarking on I4.0 implementation, for this purpose the Fig. 5, which is the innovative investigation of this study can act as a ready reckoner for the researchers and extant literature. As it is evident from the study that technical and social risks are the most critical, reflected in Fig. 6 the academicians and researchers can align the strategies, policies, and roadmap appropriately by investing in human resources to make them competent to handle I4.0 technology more efficiently. This way, the research can impact India's Digital India initiative and form the base of a new research model and framework in the future to advise scholars on better approaches to attain higher performance in the I4.0 environment by managing I4.0 KPIs and risks intelligently. The outcomes of the study endorse the findings of prior studies and justify with legitimate arguments, is the pioneering contribution of this study to the new knowledge thus proving the robustness of the developed model.

6.2 Practical implications

This research has provided practitioners, managers, and policymakers with some outstanding practical recommendations. The systematic and critical analysis of the I4.0 risks and KPIs have evolved many insightful findings from this study, which will add value to decision-making. The division of the KPIs into two groups, namely cause and effect, brings extra clarity while devising the I4.0 implementation strategies and policies. The study has also demonstrated the critical relationship among the KPIs, which may be of special interest to the managers, policymakers, consultants, and other stakeholders to drive every effort into success. As mentioned earlier, segregating the KPIs into cause-and-effect groups and the contextual interrelationship in Figs. 4 and 5 are the key outcomes of this research, which will serve as a predecessor and guide decision-makers in speeding up the implementation of I4.0 by concentrating on the most influencing and affecting KPIs. This will also provide the base to plan and formulate the strategies and framework to mitigate the risks related to I4.0 implementation. Findings suggest practitioners should focus more on the identified causes of decentralization, integrity, availability, cost, interoperability, connectivity, IT infrastructure, information security, with the most critical prominence KPIs being IT Infrastructure, connectivity, information security, cost, and receiver KPIs prediction capabilities, quality, modularity, and virtualization. Proper planning and management of the cause-and-effect KPIs will help to avert the I4.0 risks. The investigations obtained from this study also suggest that the practitioners should enhance their capabilities and capacities by boosting the awareness and technological know-how related to I4.0 standards and risks by raising the intelligent IT infrastructure and other necessary resources of cloud platform with inhouse and external interconnected network facility.

The managers should be careful while selecting third-party vendors for hosting and operationalizing company data. More attention given to IT infrastructure and information security will develop trust in the information sources. This way, transparency through big data analytics, blockchain technology adoption, and receiving and sharing of real-time data throughout the value chain will enhance the practitioner's confidence to adopt I4.0. A strong, robust, and the secured technological platform is a must to tackle these KPIs effectively. Wireless IoT devices operating in the public network are more exposed to an information security threat. Therefore, data sharing and data transfer should be end-to-end encrypted. In this case, cloud technology will restrict unauthorized and unauthentic access and ensure data security and seamless availability as and when required (Singh & Bhanot, 2020). Many companies outsource different manufacturing and production operations due to capital investment constraints by sharing information via the cloud (Prinsloo et al., 2019). This draws urgent attention from policymakers to build safe and secure cloud-based IT infrastructure. This study's findings will provide an opportunity and platform for stakeholders to monitor, quantify, control, and analyze the risks while adopting I4.0 policies. Thus, we believe the developed integrated model is scalable to micro, small, medium, and large-scale companies. It also takes care of the social sustainability, IT infrastructure management, information security, and quality of the I4.0 setup. The stress-free but cautious, vigilant, and innovative mindset of the policymakers is essential for the high precision and accuracy in decision-making in developing countries like India. The cost aspect of all of this is also equally important as it reflects the overall assessment of the resource's effective utilization.

Emerging technologies like AI, AR/VR, IoT, horizontal and vertical integration, self-driven and self-optimizing decision-making systems, additive manufacturing, autonomous robot, big data analytics, cloud computing, and cybersecurity has redefined the traditional business model into a new global business landscape. Sound understanding and knowledge of these technologies will help practitioners and managers appropriately create space for these technologies in the plans and strategies. To survive in highly dynamic, volatile, and complex market conditions where product and service customization is rising, the standardization in the product, process, man–machine, customer, CPS, and production layout is a prime technological concern in I4.0 adoption. An employee is one of the crucial resources of every company. Inculcating a collaborative, cooperative environment by changing the mindset towards the new work culture, skill sets, and attitude can help managers achieve success in I4.0 endeavors. The benefits of I4.0 implementation can be derived through the tailor-made training and development programs for employees to nurture specific skill sets and competencies such as IT infrastructure management, software, hardware handling, big data analytics, human–machine interaction, cloud computing, collaborative robots management, AI, use of AR/VR technology in training, networking and connectivity protocol handling expertise, could also be the approaches to make the human resource more productive and engaged in company management (Bologa et al., 2017; Karadayi-Usta, 2019; Kazancoglu & Ozkan-Ozen, 2018; Raut et al., 2021). Policymakers should take due care in recognizing human performance and organizational culture to attend to the social risks of I4.0 implementation (de Sousa Jabbour et al., 2018; Ghobakhloo, 2020). They should also specify the sustainable objectives for selecting appropriate I4.0 technology to create smart products and processes (Schmidt et al., 2015; Yadav et al., 2020b). This research recommends that managers, stakeholders, and policymakers create a comprehensive and solid foundation of sustainable long-term policies, which will assure the success and viability of I4.0 in the long run by minimizing technical and social risks.

The Government of India has initiated efforts for smart advancements in manufacturing activities to instill a fast forward transition through the SAMARTH UDYOG BHARAT platform, to develop awareness through a consultative approach to accomplish objectives of I4.0 technology adoption in many industries by the year 2025 (Mukhuty et al., 2022). Thus, we believe based on the outcomes of this study, manufacturers will be motivated to adopt I4.0 technology enablers; as a result, the study may serve as a quick reference for consultants, service providers, and managers in strategizing and policy reforms to accelerate I4.0 adoption. Researchers have expanded on the significance of this study in dealing with post-COVID-19 challenges in the next section.

6.3 Study contribution towards post-COVID-19 advances in the manufacturing industry

Risk management has become one of the most crucial tasks of business operations than ever due to the sudden hit by the COVID-19. This has disturbed the carefully calibrated operations over the years. The disturbance is so catastrophic that few companies had to close down as they could not sustain the huge losses incurred due to the extreme imbalance in supply and demand. Furthermore, the restrictions like social distancing, use of masks, lockdowns, and limited mobility also have put some businesses at high risk. In contrast, others considered it an opportunity to innovate. The researcher found the fast-paced digital technology adoption within manufacturing processes will inspire companies to upskill, train, and prepare the company's human resources to become technology savvy. It is time to collaboratively rethink, reinvent, reskill, and revamp the development of the human being to meet the new and unknown challenges (Harikannan et al., 2020; Mckinsey, 2021). This is the test of the resilience of the manufacturing companies. The companies should create crisis management plans by re-configuring, and re-orienting the supply chain, communication channels, and production processes. The resources should be spent to build on its capacity and capability-building facilities, helping maintain the competitive edge during and after the COVID-19 pandemic. Technology know-how and digital competencies to access physical equipment, i.e., machines and devices, remotely through deploying sophisticated sensors, and cameras supported by IoT applications is a must. Also, integrating it with AI and satellite technology to capture and track real-time data has become a necessity for every business (Lepore et al., 2021; Sarkis et al., 2020). It enables the operator to communicate with the machines remotely with minimal physical attention, rectifying and monitoring the machine's health, performance, efficiency, etc. The introduction of automated manufacturing processes is driven by advanced digital transformation through CPS, 3D printing, IIoT, RFID, AI, sensors, blockchain, and BDA, making the supply chain and production system transparent and traceable (Lepore et al., 2021; Raj Kumar Reddy et al., 2021). The companies who already have implemented these technologies fully or partially are reported at ease while dealing with situations like lockdown, confinement, social distancing, use of masks, and sanitizers, enforced due to COVID- 19. The best solution to work remotely could be through the extensive use of cobots and humanoid robots, with minimal human intervention, which will be the new normal in future operations.

Thus researchers argue that the most prominent risks i.e. technological risks and social risks along with I4.0 KPIs as found in this study should be given due importance to propagate the I4.0 implementation drive. The Emergence of COVID-19 and its implications prompted the acceleration of the I4.0 vision thus attracting the attention of researchers, practitioners, and policymakers to devise a plan of action. The current situation is very volatile due to pandemics and other economic uncertainties. Sustained efforts to mitigate the technological risks and social risks as described in this study, will prepare the ground for companies to gain the confidence to survive in the post-COVID-19 era. Hence considering prevailing eventuality our research will guide practitioners, technocrats, managers, and policymakers to prepare the individual roadmap for implementing I4.0 taking into account the above risks as a primary concern during and after the COVID 19 pandemic. The research findings of this study are discussed with the experts, and they confirm the results obtained. Thus, society's progressive mindset and welcoming attitude toward the adoption of new technology are proving vital to fighting the adversities due to COVID-19.

7 Conclusions and future directions

The comprehensive SLR and I4.0 expert intervention used in this study confirm that the Indian manufacturing industry is keen to ramp up I4.0 adoption; rather, the sudden outbreak of COVID-19 and its implications has created its urgency. Although this is true, the scarcity of a systematic framework to deal with the projected I4.0 risks and I4.0 KPIs has impeded its progress in Indian manufacturing industries. This has inspired the researcher to address this critical issue in the current research. In this study, the final list of KPIs and perceived risks for the I4.0 implementation are identified through SLR and further validated by the fifteen experts from various domain areas holding expertise in I4.0 implementation in manufacturing industries and academic institutions. The FDEMATEL method is used to establish causal dependency and interrelationship among the crucial KPIs. The KPI, IT infrastructure is found to be a top influencer, while KPI prediction capabilities are found to be the highest impacted by all other KPIs. The overall findings and results from FDEMATEL integrated with extended ARAS with IVTFNs have culminated into a comprehensive model. The application of extended ARAS with IVTFNs revealed that technological risks and social risks among all the six identified I4.0 implementation risks considered in the study need urgent attention. The findings of the study confirmed the developed integrated model's robustness, eventually justifying its readiness for real-world applications.

I4.0 has a huge potential to positively turn around the complete industrial value chain by making it more customer oriented. The entire organization's digitization in a single attempt to become I4.0 compliant is impossible for the industry because of complex constraints like quality, technology, and workforce management. Even though it seems lucrative and attractive in the first instance, many challenges and risks are hidden inside the shell. These KPIs and risks, if not assessed in advance, may ruin the overall mission of implementing I4.0. As found in the literature review, very limited researchers in the past studied risks to evaluate the impact on I4.0 implementation. Still, no one has investigated the causal relationship between KPIs and risks priority for I4.0 adoption empirically. Even the choice of selected MCDM methods is not substantiated before using them in the research context of I4.0. This study is the first of its kind which has developed the robust integrated I4.0 risks assessment model considering the larger ambit of I4.0 KPIs and prospective I4.0 risks which is found missing in earlier studies. Thus, the findings of this study are very promising and will guide policymakers, researchers, and industrial personnel to make better decisions while adopting I4.0 practices in their respective manufacturing industries. This will facilitate the manufacturing to harness sustainable organizational performance leading to achieving sustainability.

Since I4.0 comparatively is at the infant level in research and implementation, there is no unified and generalized roadmap/guideline covering all the dimensions of I4.0. This study is a holistic effort to focus on identifying risks and impacting KPIs. Still, this research has some limitations that are worth considering for future research. This study identified sixteen KPIs based on which six risks for the I4.0 adoption have been evaluated. These KPIs and risks are extracted from the literature and validated by experts having expertise in I4.0 practices from India. If the study carried out in other developed countries may give more significant insights into KPIs and types of risks affecting the implementation of I4.0 in specific states/countries.

The integrated FDEMATEL and extended ARAS with IVTFNs methodology used are subjective to the judgments of the academicians, industrial practitioners, and consultants, which are used to establish interrelationships among the selected KPIs and to prioritize the most prominent risks impacting I4.0 adoption. Even though the researcher has taken due care to avoid biases, the selected expert's personal preferences are unavoidable in the outcomes. Further, we recommend validating this study's outcome by a survey-based method, adopting an empirical research design approach to confirm the findings. The application of other MCDM techniques and structural equation modeling tools may provide more precise insights in this context.

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