



Effective use of artificial intelligence in healthcare supply chain resilience using fuzzy decision-making model

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Abstract

AI technologies are absolutely changing the rules of the game all around the world. However, the diffusion rate of AI is widely ranging across countries. This study aims to fulfill a research gap regarding multidimensional comprehensive studies which could provide academic information to the policy makers, technology promoters, adopters of technology and the workforce. Friction against the use of new technologies has been existing since the beginning of industrial revolution. This study examines the possible factors behind the friction in AI adoption process. The subject of the course in this study is the supply chain resilience which is a keystone in healthcare sector especially after the recent pandemics. Studies promise the efficiency improvements and cost reductions in healthcare when AI technologies are implemented in supply chain management of the industry. This paper proposes a fuzzy Aczel–Alsina-based decision-making model to analyze the factors that enhance the diffusion of AI technologies in healthcare supply chain management. The model is tested for the case of Turkish healthcare industry. Fuzzy decision-making model is used to solve the complexities in unveiling success factors in the implementation and diffusion phases. Results show that among many other factors tested, technology intensity, trialability and government support and policies are the most important AI success factors. The results are discussed to reveal potential policy recommendations.

Keywords Healthcare · Supply chain · Resilience · Artificial intelligence · Aczel–Alsina norms · Fuzzy multi-criteria decision-making model

1 Introduction

In his famous quote Elbert Hubbard states “One machine can do the work of fifty ordinary men. No machine can do the work of an extraordinary man”. AI is capable of lot. From business, private sector and management to government, public sector and science and technology, AI increasing its orbit with ground-breaking improvements in machine learning and autonomous decision-making. However, it is the human ability to decide how to use,

where to use and to what extent to use the AI. Different industries are in need of AI for different reasonings under different conditions. Manufacturing (Chatterjee et al. 2021; Waltersmann et al. 2021), banking, insurance, automation, energy (Ahmad et al. 2021), education, digital commerce, tourism and healthcare are only some of these industries in where AI has been changing the rule of the game. Challenges are also emerging in the adaptation process causing organizations to stagger in using new strategies. In this sense, multidisciplinary approaches are required to ease transformation period (Dwivedi et al. 2021). Still, we are in need of these extraordinary men who are capable of understanding and realizing the actual potentials of AI for the sake of humankind.

Artificial intelligence (AI) is in the focus of economists and managers as well as mathematicians and engineers. As the technology advances, the adoption of AI in businesses accelerating (Wamba-Taguimdje et al. 2020). Studies show that AI technologies are highly useful in creating business

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value (Enholm et al. 2022). A study by Ransbotham et al. shows that even in 2017, 85% of organizations consider AI as a strategic tool to achieve competitive advantage (Ransbotham et al. 2017). Although there are challenges for some organizations to use AI technologies, possible extended benefits attract managers to find solutions in adaptation process of AI (Fountain et al. 2019).

Especially, in solving supply chain issues AI practices are of special interest. Supply chain is a complex network involving all of the stages in the transformation of the raw materials into delivered products to the customers. The connections among economic units, activities, organizations such as suppliers, manufacturers, logistic units, sellers and customers create the complexity. Lately, globalization added new positive and negative dimensions to the issue such as extending opportunities for lower costs (Roh et al. 2014) or increasing business uncertainty (Kim and Chai 2016). In that respect, AI solutions are highly promising in supply chain management. Dora et al. (2022) reveal the challenges in practicing the AI technologies for supply chain issues (Dora et al. 2022). Supply chain management requires fast and sound decision-making given a big, multidimensional data that AI technologies can be successful on (Barryannis et al. 2019). Data from Statista show that as of 2022, global widescale AI adoption rate in supply chain and manufacturing businesses reaches 34% and 32% uses AI limited. For 11% of the respondents AI is critical. In 2025, almost 95% of the business is expected to adopt AI technologies in supply chain (Thormundsson 2022). Numbers imply that there is a strong necessity to analyze the pre-conditions and consequences of AI practices in supply chain management in different industries.

Efficient supply chain creates a process in which the product is offered to the customer with lower prices and higher quality conditions. Firms increase their competitive advantage through effectively developed supply chain (Li et al. 2006). Other business functions, product development, marketing, operations, distribution, finance and customer service affect and are affected by efficient supply chain. Therefore, supply chain management plays a crucial role in firm performance (Ou et al. 2010). In the wake of recent crises and political instabilities in global scale such as 2008 financial crisis, Brexit, USA-China trade war, Russia-Ukraine war, conflicts in Middle East and North Africa, COVID-19 pandemics, earthquakes, fuel crisis, and increasing security concerns with terrorism supply chain in many industries have been taking big hits globally and locally. The resilience of supply chain is more important than ever now. Building resilient supply chains is in the focus of international institutions such as World Economic Forum (Bahatiah et al. 2013), World Bank (Brenton et al. 2022), International Monetary Fund (Jiang et al. 2021) in the last decade. Digitalization and the use of new

technologies is the first requirement listed in the to-do lists. Use of new technologies could improve resilience of supply chain through widening flexibility, developing abundance, creating cooperation and strengthening agility (Tukamuhabwa et al. 2015). AI techniques are specifically promising to increase the resilience of supply chain. Belhadi et al. (2022) analyzed 479 manufacturing companies and determined the most effective AI solution which add to supply chain resilience. Fuzzy logic programming, machine learning big data and agent-based systems are identified as most effective methods (Belhadi et al. 2022).

Among other industries, healthcare industry is object to increasing number of new problems put by pandemic, wars or political instabilities such as sustainability issues or inequities (Isik and Altürk 2022). The use of AI in medicine or medical specialties benefits patients as well as doctors (Kumar et al. 2023a, b). Mimicking human functions, AI shift the healthcare especially by providing accurate analysis of big healthcare data (Jiang et al. 2017). Sustainability of the supply chain is another dimension that can be improved through AI technologies (Naz et al. 2022). AI application was quite effective during COVID-19 pandemic in detecting virus spreading estimates, patient diagnosis and vaccine development (Yi et al. 2022). Indeed, the paradigm shift in health industry caused rise of new approach health 4.0 with the wide practice of Industry 4.0 technologies in health sector through designing precision medicine, clinical optimization via AI tools, machine health awareness analytics (Siodia and Jindal 2021). Karatas et al. (2022) survey the literature on how big data changed the healthcare services via Internet of Things implementations, smart sensors and wearables (Karatas et al. 2022).

Higher costs in healthcare industry are real trouble for all of the shareholders. Especially in the recent years, due to reflection of inflation in the sector through higher factor prices (Fleron et al. 2022) and urgent requirement for research and development activities (Oliver et al. 2019), costs are accelerating. Therefore, the role of supply chain management is getting more and more important. The quality of healthcare, success of treatment and so the patient satisfaction are directly related to the availability of medical supplies and physicians. That is why supply chain management is a keystone for efficiently working healthcare industry (Mathur et al. 2018). While improving the supply chain management in healthcare industry is the interest of organizations, use of recent technologies and AI is getting more and more common (Eskandari-Khanghahi et al. 2018; Mosallanezhad et al. 2023; Haghjoo et al. 2020; Goodarzian et al. 2021; Damoah et al. 2021; Bag et al. 2023; Benzidia, et al. 2021; Kamran et al. 2023).

AI technologies are used to perform tasks that require human intelligence. However, the full potential of AI is not

in use. In 2017, adoption rate of AI was only 23% according to a survey of 3000 companies in global scale (Ransbotham et al. 2017). Factors and conditions of successful implementation of AI technologies are newly started to be analyzed in academia (Kinkel et al. 2022). Technology diffusion in the society determines the extent of successful use of new technologies. The barriers to technology adoption in general results from wide range of technical, economic and social issues. Parente and Prescott (1994) shows that barriers to technology adoption differ across countries and industries. Societal differences can play a crucial role in effect. Moreover, even small differences can cause large income inequalities among countries and further barriers to new technology adoptions (Parente and Prescott 1994). In his seminal work which dates back to 1962, Rogers (2010) emphasizes the importance of social process. Diffusion of innovations requires social acceptance as well as technical infrastructure (Rogers 2010). When it comes to diffusion of AI, technical barriers are also accompanied with social considerations such as unemployment risk, lack of know-how and environmental concerns (Isik et al. 2023; Cubric 2020).

The literature is short of comprehensive studies that put on a multidimensional approach on diffusion of AI in healthcare industry (Almaiah et al. 2022; Gardas 2022). Kumar et al. (2023a) uses a multidimensional analysis to identify the success factors of practicing AI techniques in healthcare management and use a case of India. Although the healthcare is in enormous need of implementing AI techniques, diffusion rate of AI is critical. The number of studies that search for AI diffusion in different countries and in different industries should increase for realizing potentials of AI in a near future.

This study proposes to contribute to fulfilling the research gap by providing a structure to explore necessary conditions for successful implementation of AI in an industry. To this aim, the supply chain of healthcare in Türkiye is considered in this study. In constructing the case study, the paper aims to choose an environment that is suitable for the introduction of the new technologies but there could be some factors that can prevent easy adoption process. A developing country of high-middle income level has such a macroeconomic environment, and at the same time, the friction in the adoption process can be tested for different factors. Therefore, the healthcare sector of Türkiye is analyzed as the use of AI technologies are promoted both in public and private sector. Therefore, the study also contributes to supply chain management literature by analyzing the healthcare industry and discussing some policy implications for managers, regulatory authorities and other shareholders of the industry.

In this study, the fuzzy Aczel–Alsina-based Logarithmic Methodology of Additive Weights (LMAW) (Deveci et al.)

is used to determine the weights of the indicators. The LMAW method has recently been successfully applied to various multi-criteria decision-making (MCDM) problems. Tešić et al. (2023) improved a fuzzy LMAW-based gray MARCOS model for selection of a dump truck. Božanić et al. (2022) developed a triangular fuzzy number-based LMAW to solve the problem of the location selection for a landing operations point in combat operations of the army. Asadi et al. (2023) examined the adoption of blockchain technology in small and medium-sized enterprises using fuzzy LMAW. Pamučar et al. (2022) studied a decision analysis model including fuzzy LMAW model for smart mobility system development under circular economy. Additionally, fuzzy MCDM-based models have been applied to decision-making problems (Alavi et al. 2022; Abbas et al. 2022; Adak and Kumar 2023; Cubukcu and Cantekin 2022; Tešić et al. 2023). The used model for determining the weights of criteria has nonlinear fuzzy Aczel–Alsina functions that provide the processing of complex and uncertain information. Finally, the model enables objective reasoning while regarding the interrelationships between decision attributes.

The rest of the paper is organized as follows: Sect. 2 presents the literature review. The problem definition is given in Sect. 3. Section 4 presents the Aczel–Alsina norms decision-making model. The experimental results are provided in Sect. 5. Section 6 presents the results and discussion, and Sect. 7 summarizes the conclusion.

2 Literature review

2.1 Technology diffusion models

Diffusion of technology is the process by which new technology is used and spread through different channels (Rogers 2010). The extent that the diffusion of a new technology, an innovation or a new product will be successful after it is introduced depends on many factors that are country- and industry-specific. Since Gabriel Tarde introduced the diffusion of innovation theory and sketched the first S-curve of technology diffusion in 1903 (Barry and Thrift 2007), vast number of studies focused on the factors that influence the success rate of diffusion or time of success. In 1962, Rogers extended the adopters model by Ryan and Gross (1943) (Rogers 2010).

As Kaminski (2011) summarizes according to Rogers's diffusion of technology theory, consumers of a technology can be categorized in five groups according to their adaptation behavior: Technology enthusiasts, visionaries, pragmatists, conservatives and skeptics. The peer networks are crucial for spread of the new technology. Also, the time stages from the point when the technology is first

introduced to the point when it is fully realized should be carefully followed. Characteristics of the new technology as observability, relative advantage, compatibility, trialability and complexity are important during the adoption process. Communication channels and the social system are critical for the diffusion of the new technology (Kaminski 2011).

Geroski (2000) provides a compact analysis of technology diffusion models. Derived from typical S-curve models, epidemic model focuses on the effects of social elements on information spillover (Lundbald 2003). Model explains the major barrier in adoption process as the lack of information. Alternatively, probit model explains the diffusion process in effect of individual choices of decision-makers. Firms or consumers of a new technology in general choose to adopt a new technology depending on the expected returns. Therefore, probit models suggest that firm size, investment size, opportunity costs and switching costs, supply process of the new technology and technological expectations in the ecosystem are the limits in diffusion process. Population models, on the other hand, focus on the population of firms that have already realized the new technology. The aggregate use of the technology creates an unfolding impact on society (Geroski 2000).

AI technologies are one of the most promising new technologies. Empirical data and cases on country and firm level show that the diffusion of technology theory and the models derived from it are useful in analyzing the adoption rate of AI. Kinkel et al. (2022) provides a comprehensive analysis of a cross-national survey of 655 companies from manufacturing industry. They show that the organizational factors such as firm size, digitalization, research and activity concentration are significantly influential on the successful implementation of AI technologies. Information structure is also effective (Kinkel et al. 2022). Type of industry, data quality, insecure data, lack of customized solutions, compatibility issues and high costs are also addressed as barriers in implementing AI technologies (Lee et al. 2018; Bughin et al. 2017; Geissbauer et al. 2017).

2.2 AI technologies in healthcare sector and supply chain management

Ali et al. (2023) provided a comprehensive guide regarding the recent uses of AI technologies in healthcare sector (Ali et al. 2023). AI technologies make healthcare data more available and provide more rapid, accurate analysis. Although AI's potential substitution for human physicians is a kind of threat for the labor force in the industry, it doesn't look like a near future scenario. AI provides support in clinical decisions through recent medical information from publications or clinical practices. It reduces health risks by analyzing massive patient data. Electronic

health record systems become more efficient with the help of AI technologies. Machine learning, natural language processing, rule-based expert systems, physical robots and robotic process automation are the most common AI methods used in healthcare (Davenport and Kalakota 2019; Jiang et al. 2017).

Another practice field of AI in healthcare is in administrative issues and in supply chain management. Arji et al. (2023) identify AI, block chain and big data analytics as the most important technologies used in healthcare supply chain management (Arji et al. 2023). Healthcare supply chain is a very complex network which is highly significant in success of treatments and patient satisfaction. Resource management requires organization of supplies, delivery of medical products to physicians or patients is the major focus of the supply chain, and failure of the system costs the industry a huge waste (Donner 2014). Cooperation among supply chain partners provides cost effective process in the industry (Nachtmann and Pohl 2009). Yet, the survey by Nachtmann and Pohl (2009) show that 60% of the respondents reveal that missing trust prevents the collaboration in the industry. Kwon et al. (2016) propose that successful deployment of supply chain management in healthcare requires adoption of innovative tools to implement standardized supply chain principles. Therefore, an economic surplus can be created which can be used to overcome problems in supply chain community. The talent shortage can be reduced through surplus created by innovations (Kwon et al. 2016). Cannavale et al. (2022) show that AI is helpful in providing the information such as up-to-date prices, stock levels and delivery options. This kind of information is required to prevent coordination failures in supply chain community (Cannavale et al. 2022).

Innovations are proven to be helpful in solving issues in supply chain management in healthcare (Kwon et al. 2016; Cannavale et al. 2022). However, the diffusion of innovation is not straightforward. In the health report prepared by Cain and Mittman, success of innovations' implementation is explained to be strongly tied to ten dimensions: Relative advantage of the innovation, trialability of the innovation before a full commitment, observability of returns in the community, communication channels, similar characteristics of the users in the group, reinvention pace of innovation, the spillover in the social network, existence of opinion leaders in the community, compatibility of the innovation with the existing technologies, technical infrastructure (Cain and Mittman 2002). These ten dimensions are in parallel with the Roger's diffusion theory and S-curve model. Also, the shareholders' adoption willingness is highly important as it is implied in these dimensions. Shareholders of the healthcare supply chain related to technology adoption can be defined as: The policy makers and regulators, the supply chain community,

the payer such as national insurance institution or other insurers who decides payments on treatments, the provider institution such as hospital, the patient, the vendor company that run the research and development activities.

The effect of new technologies on the society is positive in general. Yet, its effect on workforce can be sometimes seen as a threat. The same applies to healthcare supply chain community. For example, the use of AI in administrative issues can increase efficiency in healthcare system because a nurse in US spends almost 25% of the worktime on such activities (Commins 2010). However, AI is expected to cause a substantial displacement of the workforce. A Deloitte LLP report in 2015 in collaboration with Oxford Martin Institute suggest that 35% of jobs will be automated in the next 20 years (Deloitte LLP 2015). So, it is not wrong to expect that a group in the healthcare supply chain community can be hesitant to accept the implementation of AI techniques.

2.3 Research gaps

Although there exist a few studies in analyzing the diffusion of AI in practice (Almaiah et al. 2022; Gardas 2022; Kumar et al. 2023a), the literature is open to multidimensional comprehensive studies in testing the successful implementation of AI technologies in different countries and in different industries. This study aims to use a multi-criteria decision-making method to analyze the model in the study. Then, a case study is used to test the method and the model.

3 Problem definition

In the case study, Türkiye's healthcare supply chain is taken into consideration. Türkiye is one of the fast-growing emerging economies in developing world. The healthcare industry's share in Turkish economy is accelerated in the recent years as the industry grows with its services that lead growing health tourism. Turkish government is ambitious in technology adoption with growing subsidies provided to the organizations in health, defense and automotive industry (Cetin and Tokgoz 2022). Therefore, healthcare industry in Türkiye is an interesting case to study especially in supply chain management. The implementation of AI in supply chain and administration is relatively higher in compared to other uses. The public administration system e-Pulse Healthcare System is publicly financed AI-based system which is used by more than 10 million. Türkiye which is a highly populated country of almost 85 million has a general healthcare system and insurance covering all citizens. Thus, further use of AI in the public sector is in the future prospects of the authorities. Both in public and

private healthcare sector in Türkiye, expert systems, genetic algorithm, fuzzy logic and artificial neural networks are major AI methods used (Canbolat and Toker 2021). Especially, after the COVID-19 break, the healthcare workforce of Türkiye was proven its sufficiency and quality. Yet, efficiency can be improved through implementation of AI technologies to reallocate the resources and workforce deployment. Obviously, Türkiye's healthcare system could get full advantages of AI implementation. However, some obstacles can prevent the diffusion process. The paper aim to find out these barriers and obstacles in the process. So that a smooth and quick transformation process can follow the successful implementation of AI technologies. Experts from the field are questioned for the factors listed in the developed model. The importance of factors is tested with the novel method that is created for this complex analysis.

3.1 Identification of the factors in the diffusion process of AI

The literature review provides the necessary dimensions and the factors that should be taken into consideration in analyzing the diffusion of AI to develop a resilient healthcare supply chain. The model of this study follows the diffusion of innovation theory by Rogers (Rogers 2010) and some models derived from the theory. Therefore, the model in the current study is based on four dimensions: technical infrastructure (MC₁), business environment (MC₂), macroeconomic system (MC₃), social acceptance (MC₄). The model evaluates 22 factors (Kumar et al. 2023a, b) that may influence diffusion of AI in healthcare supply chain management in each dimension. The dimensions and factors are explained and evidence from literature is provided below.

(1) MC₁: Technical Infrastructure:

C₁: Technology intensity: It refers to the availability and quality of technological requirements such as hardware or software (Cannavale et al. 2022; Bleher and Braun 2022; Perera et al. 2023; Sisodia and Jindal 2021).

C₂: Observability: Observability of the technology is useful to use the network externality in the community. It creates stronger communication as the use of technology is observed and interchangeably realized (Cain and Mittman 2002; Uraikul et al. 2007; Almaiah et al 2022).

C₃: Trialability: Being able to try the new technology before full adoption let adopters to test the activities. Tests increases the efficiency of the systems for later adoption (Sun et al. 2020; Cain and Mittman 2002).

C₄: Expected returns: It motivates the adopters to meet requirements of adoption process (Sun et al. 2020; Cain and Mittman 2002; Damoah et al. 2021).

C₅: Data reliability and sustainability: Reliability and sustainability of data is a major concern for adopters in adoption process. Both for persuading the patients to use the systems and to be able trust on the system efficiency (Cain and Mittman 2002; Damoah et al. 2021; Ahmad et al. 2021).

(2) MC₂: Business Environment

C₆: Firm size and structure: The firm size is important to issue the financial needs, dealing with the potential risks and efficiently managing human capital resources (Kinkel et al. 2022; Kwon et al. 2016; Kaminski 2011; Sun et al. 2020).

C₇: Firm agility: It refers to the responsiveness of firm to the dynamic business environment. The firm's ability to adapt to changes and market uncertainties increases the success rate of technology adaptation (Bai et al. 2023; Yang et al. 2015).

C₈: Investment capacity: Being independent of firm size, firms' in-house investment creation or their ability to find required financial resources is highly effective in their technology adaptation decision and the success of the process (Gardas 2022; Correa et al. 2010).

C₉: Business networks: Possible coalitions of firms are determined through the structure of business network. As the probability of alignments among firms increases, they can tolerate costs of adoption of new technologies in the process (Babu and Weber 2019). Moreover, the existence of communication networks can increase the possibility of strategic alliances making firms stronger against market uncertainties (Jatoba et al. 2022).

C₁₀: Opinion leaders in the business: It refers to the existence of reliable leader firms, organizations or individuals such as managers or scientists who are influential on the adopters so that adopters can follow their lead in the technology adaptation process (Cain and Mittman 2002; Rogers 2010; Gardas 2022).

C₁₁: Internal and External Economies of Scale: Economies of scale refers to decreasing average costs as the production increases. The availability of internal economies of scale provides firms a competitive advantage while external economies of scale provide the whole industry competitive advantage. In both case, technology adoption becomes easier for the adopter who have already competitive advantage relatively to others (Foster and Fernandez 2010; Smidt and Jokonya 2022).

C₁₂: Customs and norms in the Business: It refers to the values that the adopters share, how they interact and collaborate and coordinate. The pace of diffusion is highly related to the acceptance of the new technology based on how it can serve to the values and norms shared in the business environment (Rogers 2010; Kaminski 2011; Gardas 2022).

(3) MC₃: Macroeconomic System

C₁₃: Government support and policies: The subsidies or supports provided by the government or policy framework that is driven to accelerate the technology diffusion has positive effects on the process (Almaiah et al. 2022; Parente and Prescott 1994; Sun and Medaglia 2019).

C₁₄: Industry-specific pressure: Healthcare supply chain is highly effective in healthcare costs and the success of the services. Therefore, secured supply resilience is demanded by patients, payers and physicians and managers of the organizations. The adoption of new technologies is subject to demand and other industry-specific factors (Mathur et al. 2018; Pournader et al. 2021; Kwon et al. 2016).

C₁₅: Peer pressure: As the competition in the industry cut throats, the adoption of new technologies can be enforced especially in the supply chain dimension not to be departed from the rest of the industry (Mathur et al. 2018; Pournader et al. 2021; Almaiah et al. 2022).

C₁₆: Inclusiveness: The technological adoption process affects shareholders of the industry in different ways. With an inclusive approach, technology adopters include the shareholders and partners in a collaborative way to the adaptation process. Otherwise, strong objections from different parts of the community can slow down the pace of diffusion (Isik et al. 2023; Rogers 2010; Kaminski 2011).

C₁₇: Environmental Concerns and Actions: The sustainability issues and climate actions taken by the regulatory authorities enforce firms and organizations to take drastic measures in many dimensions including adoption of new technologies in running the business. It creates an interactive relation among shareholders as well as vertical integrations (Isik et al. 2023; Peltier et al. 2012; Kwon et al. 2016).

(4) MC₄: Social Acceptance

C₁₈: Workforce transformation: It refers to the changing labor demand of the industry with the adoption of new technologies. Some jobs destructed as AI substitutes the human work, whereas new jobs are created to use and improve the new techniques and methods (Deloitte LLP 2015; Commins 2010).

C₁₉: Takeoff phase: It refers to the starting phase of the implementation. How much the community is ready to meet and try a new technology is important for the rest of the process (Rogers 2010; Geroski 2000).

C₂₀: Adopters' acceptance rate: The adopters in the community can have different adaptation skills to continuously using the new practices. As the consumer of the technology is more open to use of the new ways of doing the business, the adoption pace accelerates (Rogers 2010; Geroski 2000).

C₂₁: Human capital: The know-how of the new technology is important for the adaptation process. As the workforce in the industry has the required skills and talents or is ready to get these skills and talents, the pace of

adoption accelerates (Gardas 2022; Geroski 2000; Rogers 2010).

C₂₂: Future prospects on the use of AI: The successful implementation of adoption of new technologies is highly correlated with the future plans of adopters in further use of these technologies. Having such plans is the proof of successful implementation and integration of the new technologies with the existing ones (Gardas 2022; Geroski 2000; Rogers 2010).

4 Methodology

In this section, the preliminaries and basic notations of the used model including fuzzy Aczel–Alsina norms/conorms are presented.

4.1 Aczel–Alsina norms

This section provided the preliminaries and basic operations of Aczel–Alsina norms under triangular fuzzy numbers (TRNs).

Definition 1 (Aczel and Alsina 1982): Suppose that φ_1 and φ_2 are real numbers, then the Aczel–Alsina T-norm and T-conorm can be expressed by:

$$\mathbb{R}^{\zeta} = \begin{cases} \mathbb{R}(\varphi_1, \varphi_2) & \text{if } \zeta = 0, \\ \min(\varphi_1, \varphi_2) & \text{if } \zeta = \infty, \\ e^{-((- \ln(\varphi_1))^{\zeta} + (- \ln(\varphi_2))^{\zeta})^{1/\zeta}} & \text{otherwise} \end{cases} \quad (1)$$

$$\mathbb{R}_c^{\zeta} = \begin{cases} \mathbb{R}_c(\varphi_1, \varphi_2) & \text{if } \zeta = 0, \\ \min(\varphi_1, \varphi_2) & \text{if } \zeta = \infty, \\ 1 - e^{-((- \ln(1 - \varphi_1))^{\zeta} + (- \ln(1 - \varphi_2))^{\zeta})^{1/\zeta}} & \text{otherwise.} \end{cases} \quad (2)$$

where $\mathbb{R}^{\zeta}$ and $\mathbb{R}_c^{\zeta}$ denote T-norm and T-conorm, respectively, and $(\varphi_1, \varphi_2) \in [0, 1]$, $\zeta \in (0, \infty]$.

Definition 2 Let's suppose that $\tilde{\varphi}_1 = (\varphi_1^{(\alpha)}, \varphi_1^{(\beta)}, \varphi_1^{(\pi)})$ and $\tilde{\varphi}_2 = (\varphi_2^{(\alpha)}, \varphi_2^{(\beta)}, \varphi_2^{(\pi)})$ are TRNs. Additionally, let it be $\eta, \zeta \in (0, \infty]$ if $f(\varphi_i) = \varphi_i / \sum_{i=1}^2 \varphi_i$, then the arithmetic operators can be defined as follows:

(1) Addition “ $\oplus$ ”

$$\tilde{\varphi}_1 \oplus \tilde{\varphi}_2 = \left(\begin{array}{l} 1 - e^{-((- \ln(1 - f(\varphi_1^{(\alpha)}))^{\zeta} + (- \ln(1 - f(\varphi_2^{(\alpha)}))^{\zeta})^{1/\zeta}}, \\ 1 - e^{-((- \ln(1 - f(\varphi_1^{(\beta)}))^{\zeta} + (- \ln(1 - f(\varphi_2^{(\beta)}))^{\zeta})^{1/\zeta}}, \\ 1 - e^{-((- \ln(1 - f(\varphi_1^{(\pi)}))^{\zeta} + (- \ln(1 - f(\varphi_2^{(\pi)}))^{\zeta})^{1/\zeta}} \end{array} \right) \quad (3)$$

(2) Multiplication “ $\otimes$ ”

$$\tilde{\varphi}_1 \otimes \tilde{\varphi}_2 = \left(\begin{array}{l} e^{-((- \ln(f(\varphi_1^{(\alpha)}))^{\zeta} + (- \ln(f(\varphi_2^{(\alpha)}))^{\zeta})^{1/\zeta}}, \\ e^{-((- \ln(f(\varphi_1^{(\beta)}))^{\zeta} + (- \ln(f(\varphi_2^{(\beta)}))^{\zeta})^{1/\zeta}}, \\ e^{-((- \ln(f(\varphi_1^{(\pi)}))^{\zeta} + (- \ln(f(\varphi_2^{(\pi)}))^{\zeta})^{1/\zeta}} \end{array} \right) \quad (4)$$

(3) Scalar multiplication

$$\eta \tilde{\varphi}_1 = \left(\begin{array}{l} 1 - e^{-((\eta(- \ln(1 - f(\varphi_1^{(\alpha)}))^{\zeta})^{1/\zeta}}, \\ 1 - e^{-((\eta(- \ln(1 - f(\varphi_1^{(\beta)}))^{\zeta})^{1/\zeta}}, \\ 1 - e^{-((\eta(- \ln(1 - f(\varphi_1^{(\pi)}))^{\zeta})^{1/\zeta}} \end{array} \right) \quad (5)$$

(4) Power

$$\tilde{\chi}_1^{\eta} = \left(\begin{array}{l} e^{-((\eta(- \ln(f(\varphi_1^{(\alpha)}))^{\zeta})^{1/\zeta}}, \\ e^{-((\eta(- \ln(f(\varphi_1^{(\beta)}))^{\zeta})^{1/\zeta}}, \\ e^{-((\eta(- \ln(f(\varphi_1^{(\pi)}))^{\zeta})^{1/\zeta}} \end{array} \right) \quad (6)$$

To better understand arithmetic operations with the fuzzy Aczel–Alsina norm, additional basic settings are expressed by:

- (1) $\tilde{\varphi}_1 \oplus \tilde{\varphi}_2 = \tilde{\varphi}_2 \oplus \tilde{\varphi}_1$ and $\tilde{\varphi}_1 \otimes \tilde{\varphi}_2 = \tilde{\varphi}_2 \otimes \tilde{\varphi}_1$;
- (2) $\eta(\tilde{\varphi}_1 \oplus \tilde{\varphi}_2) = \eta \tilde{\varphi}_1 \oplus \eta \tilde{\varphi}_2$ and $(\eta_1 + \eta_2) \tilde{\varphi}_1 = \eta_1 \tilde{\varphi}_1 \oplus \eta_2 \tilde{\varphi}_1$;
- (3) $(\tilde{\varphi}_1 \otimes \tilde{\varphi}_2)^{\eta} = \tilde{\varphi}_1^{\eta} \otimes \tilde{\varphi}_2^{\eta}$ and $\tilde{\varphi}_1^{\eta_1} \otimes \tilde{\varphi}_1^{\eta_2} = \tilde{\varphi}_1^{(\eta_1 + \eta_2)}$.

4.2 Determining criteria weights—fuzzy Aczel–Alsina function-based LMAW

This section presents the steps of fuzzy Aczel–Alsina LMAW model (Deveci et al. 2023). The concept of the traditional LMAW is developed by Pamucar et al. (2021) and the Aczel–Alsina T-norm and T-conorms is introduced by Aczel and Alsina (1982). Aczel–Alsina norms have been introduced to overcome the shortcomings of the min–max operators, which are generally implemented to fuzzy sets (Zadeh 1965). The advantages of Aczel–Alsina operators are as follows: (i) the determination of the result by only one variable, which is the essential feature of the min–max operator due to all its axiomatic properties, is eliminated; (ii) min–max operators are non-analytical and their second derivatives are not continuous, which is eliminated by the application of the Aczel–Alsina operator (Pamucar et al. 2021; Deveci et al. 2023). The steps of fuzzy Aczel–Alsina's are given by:

Step 1 Expressing the priority vector. Suppose that s experts participate and it is $1 \leq r \leq s$, then we a priority vector ($\mathbb{Q}$) can be expressed for each expert as follows:

$$\mathbb{Q}^r = (\tilde{\chi}_{A_1}^r, \tilde{\chi}_{A_2}^r, \dots, \tilde{\chi}_{A_n}^r), \quad (7)$$

where $\tilde{\chi}_{A_1}^r = (\chi_{A_1}^{r(\alpha)}, \chi_{A_1}^{r(\beta)}, \chi_{A_1}^{r(\pi)})$ denotes the expert's preference for criterion A_1 and it is stated based on a linguistic scale.

Step 2 Definition of the absolute anti-ideal point (θ) (AAIP) using Eq. (8).

$$\theta < \min_{\substack{1 \leq j \leq n, \\ 1 \leq r \leq h}} (\tilde{\chi}_{A_j}^r), \quad (8)$$

where $\tilde{\chi}_{A_j}^r$ denotes the element of the vector.

Step 3 Expressing a ratio vector. It shows the relationship between the criteria within the priority vector. The elements of the ratio vector $\mathbb{C}^r = (\tilde{\psi}_{A_1}^r, \tilde{\psi}_{A_2}^r, \dots, \tilde{\psi}_{A_n}^r)$ are described by Eq. (9):

$$\tilde{\psi}_{A_j}^r = \frac{\tilde{\chi}_{A_j}^r}{\theta}, \quad (9)$$

where $\tilde{\chi}_{A_j}^r \in \mathbb{Q}^r$, $\tilde{\chi}_{A_1}^r = (\chi_{A_1}^{r(\alpha)}, \chi_{A_1}^{r(\beta)}, \chi_{A_1}^{r(\pi)})$ and $1 \leq r \leq h$.

Step 4 To get the score values, we use Eqs. (10) and (11) as follows:

$$\tilde{\vartheta}_j^r = \frac{\ln(\tilde{\psi}_{A_j}^r)}{\ln(\tilde{\delta}_j^r)} = \left(\frac{\ln(\psi_{A_j}^{r(\alpha)})}{\ln(\delta_j^{r(\alpha)})}, \frac{\ln(\psi_{A_j}^{r(\beta)})}{\ln(\delta_j^{r(\beta)})}, \frac{\ln(\psi_{A_j}^{r(\pi)})}{\ln(\delta_j^{r(\pi)})} \right), \quad (10)$$

We obtain the element $\tilde{\delta}_j^r = (\delta_j^{r(\alpha)}, \delta_j^{r(\beta)}, \delta_j^{r(\pi)})$ by applying Eq. (11).

$$\tilde{\delta}_j^r = \left(\delta_j^{r(\alpha)}, \delta_j^{r(\beta)}, \delta_j^{r(\pi)} \right) = \left(\sum_{j=1}^n \psi_j^{r(\alpha)} \left(e^{-\left(\sum_{i=1}^n \frac{1}{n} (-\ln(f(\psi_j^{r(\alpha)})))^\zeta \right)^{1/\zeta}} \right), \sum_{j=1}^n \psi_j^{r(\beta)} \left(e^{-\left(\sum_{i=1}^n \frac{1}{n} (-\ln(f(\psi_j^{r(\beta)})))^\zeta \right)^{1/\zeta}} \right), \sum_{j=1}^n \psi_j^{r(\pi)} \left(e^{-\left(\sum_{i=1}^n \frac{1}{n} (-\ln(f(\psi_j^{r(\pi)})))^\zeta \right)^{1/\zeta}} \right) \right), \quad (11)$$

where $\zeta > 0$, and $f(\tilde{\psi}_j^r) = \tilde{\psi}_j^r / \sum_{j=1}^n \tilde{\psi}_j^r$.

The aggregated coefficients are expressed using Eq. (12).

$$\tilde{\vartheta}_j = \left(\vartheta_j^{(\alpha)}, \vartheta_j^{(\beta)}, \vartheta_j^{(\pi)} \right) = \left(\sum_{k=1}^h \vartheta_{j(k)}^{(\alpha)} \left(1 - e^{-\left(\sum_{k=1}^h \frac{1}{h} (-\ln(1 - f(\vartheta_{j(k)}^{(\alpha)})))^\tau \right)^{1/\tau}} \right), \sum_{k=1}^h \vartheta_{j(k)}^{(\beta)} \left(1 - e^{-\left(\sum_{k=1}^h \frac{1}{h} (-\ln(1 - f(\vartheta_{j(k)}^{(\beta)})))^\tau \right)^{1/\tau}} \right), \sum_{k=1}^h \vartheta_{j(k)}^{(\pi)} \left(1 - e^{-\left(\sum_{k=1}^h \frac{1}{h} (-\ln(1 - f(\vartheta_{j(k)}^{(\pi)})))^\tau \right)^{1/\tau}} \right) \right), \quad (12)$$

where $\tau > 0$, $f(\tilde{\vartheta}_{j(k)}) = \tilde{\vartheta}_{j(k)} / \sum_{k=1}^h \tilde{\vartheta}_{j(k)}$, and h denotes a number of experts.

5 Experimental results

In this section, the experimental results obtained are presented. The flowchart of the used model is shown in Fig. 1. The used model is proposed by Deveci et al. (2023). A questionnaire is conducted to evaluate the criteria. Each criterion is scored by the experts. The questionnaires are sent to three experts. The results are gathered.

Twenty-two criteria $A_j (j = 1, 2, \dots, 22)$ are evaluated by a set of experts $s_l (l = 1, 2, 3)$ with the help of Table 1 which presents the linguistic scale to obtain the experts' opinions.

Three experts participated in the survey and provided their opinions on the importance of the criteria. The assessments of the criteria are reported in Table 2.

Step 1 Three decision-makers (experts) provided their preferences within the fuzzy priority vector with the help of Table 1. The significance of the criteria is given in Table 3.

Steps 2 and 3 Using Eq. (8) and expressing the relationship vector, the value of AAIP $\varepsilon = (0.4, 0.5, 0.6)$ is integrated. Later, AAIP is implemented to obtain the ratio vector by Eq. (9). The results are given in Table 4.

For example, the ratio vector for C_1 is calculated by Eq. (9) as follows:

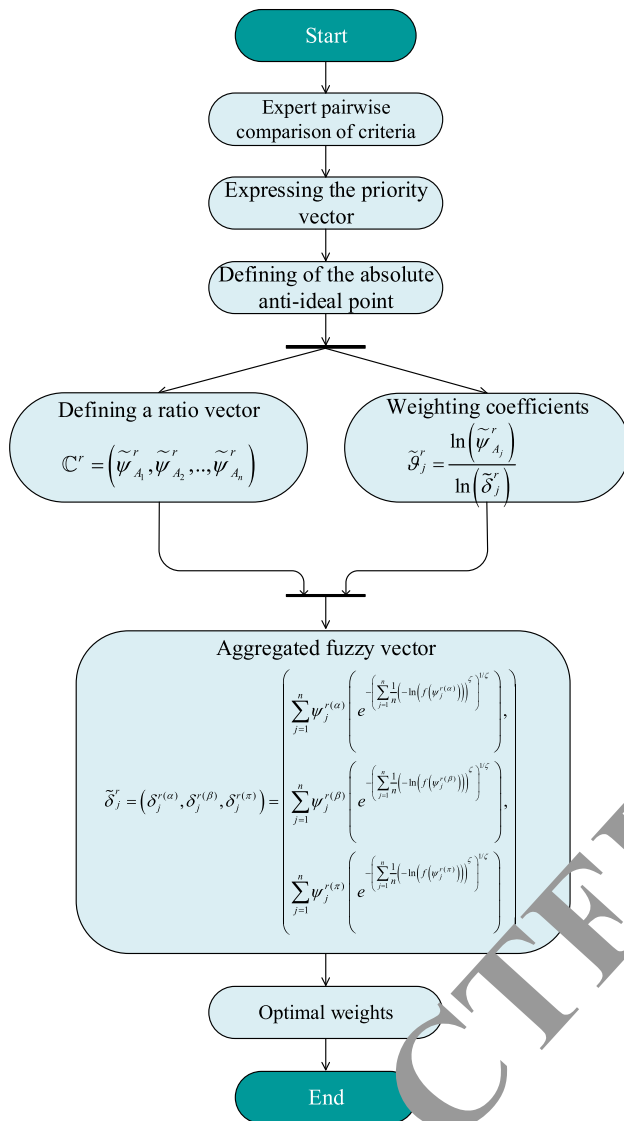


Fig. 1 Fuzzy Aczel–Alsina LMAW model

Table 1 Fuzzy linguistic scale (Gokhmagulov et al. 2019)

Linguistic terms	Membership function
Absolutely low (AL)	(1, 1, 1)
Very low (VL)	(1, 2, 3)
Low (L)	(2, 3, 4)
Medium low (ML)	(3, 4, 5)
Equal (E)	(4, 5, 6)
Medium high (MH)	(5, 6, 7)
High (H)	(6, 7, 8)
Very high (VH)	(7, 8, 9)
Absolutely high (AH)	(8, 9, 9)

Table 2 The criteria list of AI technologies

Main-criteria	Sub-criteria
Technical infrastructure (MC₁)	
C ₁	Technology intensity
C ₂	Observability
C ₃	Trialability
C ₄	Expected returns
C ₅	Data reliability and sustainability
Business environment (MC₂)	
C ₆	Firm size and structure
C ₇	Firm agility
C ₈	Investment capacity
C ₉	Business networks
C ₁₀	Opinion leaders in the business
C ₁₁	Internal and external economies of scale
C ₁₂	Customs and norms in the business
Macroeconomic system (MC₃)	
C ₁₃	Government support and policies
C ₁₄	Industry-specific pressure
C ₁₅	Peer pressure
C ₁₆	Inclusiveness
C ₁₇	Environmental Concerns and Actions
Social acceptance (MC₄)	
C ₁₈	Workforce transformation
C ₁₉	Takeoff phase
C ₂₀	Adopters' acceptance rate
C ₂₁	Human capital
C ₂₂	Future prospects on the use of AI

$$\tilde{\psi}_{A_1}^1 = \tilde{\psi}_{A_1}^2 = \frac{(8, 9, 9)}{(0.4, 0.5, 0.6)} = (11.33, 18, 22.5);$$

$$\tilde{\psi}_{A_1}^3 = \frac{(7, 8, 9)}{(0.4, 0.5, 0.6)} = (11.67, 16, 22.5).$$

Step 4 The final vector of weighting coefficients is calculated by Eqs. (10)–(11) using Table 4. The score values and rank of the criteria are presented in Table 5.

The score values of the AI success factors are illustrated in Fig. 2 and reported in Table 5. It can be seen that the technology intensity (C₁), trialability (C₃), and government support and policies have most important AI success factors. It is also seen that the internal and external economics of scale (C₁₁) and the opinion leaders in the business (C₁₀) have the least impact.

For example, C₁ can be calculated as follows:

Table 3 Criteria priority vectors

AI factors	E_1	E_2	E_3	AI factors	E_1	E_2	E_3
C_1	(8,9,9)	(8,9,9)	(7,8,9)	C_{12}	(3,4,5)	(1,1,1)	(3,4,5)
C_2	(4,5,6)	(4,5,6)	(3,4,5)	C_{13}	(7,8,9)	(6,7,8)	(8,9,9)
C_3	(7,8,9)	(8,9,9)	(6,7,8)	C_{14}	(3,4,5)	(1,2,3)	(2,3,4)
C_4	(1,2,3)	(2,3,4)	(3,4,5)	C_{15}	(5,6,7)	(6,7,8)	(5,6,7)
C_5	(6,7,8)	(5,6,7)	(6,7,8)	C_{16}	(6,7,8)	(8,9,9)	(3,4,5)
C_6	(1,2,3)	(1,2,3)	(2,3,4)	C_{17}	(1,2,3)	(1,1,1)	(4,5,6)
C_7	(2,3,4)	(4,5,6)	(1,2,3)	C_{18}	(2,3,4)	(2,3,4)	(3,4,5)
C_8	(4,5,6)	(3,4,5)	(8,9,9)	C_{19}	(4,5,6)	(6,7,8)	(5,6,7)
C_9	(2,3,4)	(1,1,1)	(3,4,5)	C_{20}	(6,7,8)	(5,6,7)	(3,4,5)
C_{10}	(1,1,1)	(2,3,4)	(1,2,3)	C_{21}	(2,3,4)	(7,8,9)	(4,5,6)
C_{11}	(1,2,3)	(1,1,1)	(1,1,1)	C_{22}	(5,6,7)	(4,5,6)	(5,6,7)

Table 4 Criteria ratio vectors

AI factors	E_1	E_2	E_3
C_1	(13.33,18,22.5)	(13.33,18,22.5)	(11.67,16,22.5)
C_2	(6.67,10,15)	(6.67,10,15)	(5.8,12.5)
C_3	(11.67,16,22.5)	(13.33,18,22.5)	(10,14,20)
C_4	(1.67,4,7.5)	(3.33,6,10)	(5.8,12.5)
C_5	(10,14,20)	(8.33,12,17.5)	(10,14,20)
C_6	(1.67,4,7.5)	(1.67,4,7.5)	(3.33,6,10)
C_7	(3.33,6,10)	(6.67,10,15)	(1.67,4,7.5)
C_8	(6.67,10,15)	(5.8,12.5)	(13.33,18,22.5)
C_9	(3.33,6,10)	(1.67,2,2.5)	(5.8,12.5)
C_{10}	(1.67,2,2.5)	(3.33,6,10)	(1.67,4,7.5)
C_{11}	(1.67,4,7.5)	(1.67,2,2.5)	(6.67,10,15)
C_{12}	(5.8,12.5)	(1.67,2,2.5)	(5.8,12.5)
C_{13}	(11.67,16,22.5)	(10,14,20)	(13.33,18,22.5)
C_{14}	(5.8,12.5)	(1.67,4,7.5)	(3.33,6,10)
C_{15}	(8.33,12,17.5)	(10,14,20)	(8.33,12,17.5)
C_{16}	(10,14,20)	(13.33,18,22.5)	(5.8,12.5)
C_{17}	(1.67,4,7.5)	(1.67,2,2.5)	(6.67,10,15)
C_{18}	(3.33,6,10)	(3.33,6,10)	(5.8,12.5)
C_{19}	(6.67,10,15)	(10,14,20)	(8.33,12,17.5)
C_{20}	(10,14,20)	(8.33,12,17.5)	(5.8,12.5)
C_{21}	(3.33,6,10)	(11.67,16,22.5)	(6.67,10,15)
C_{22}	(8.33,12,17.5)	(6.67,10,15)	(8.33,12,17.5)

Table 5 The fuzzy vector of weight coefficients

AI factors	Fuzzy value	Score	Rank
C_1	(0.09,0.12,0.18)	0.126	1
C_2	(0.06,0.1,0.15)	0.100	12
C_3	(0.09,0.12,0.17)	0.123	2
C_4	(0.04,0.08,0.13)	0.079	16
C_5	(0.08,0.11,0.17)	0.115	4
C_6	(0.03,0.07,0.12)	0.068	17
C_7	(0.05,0.08,0.13)	0.084	14
C_8	(0.07,0.1,0.16)	0.107	10
C_9	(0.04,0.07,0.11)	0.069	19
C_{10}	(0.03,0.06,0.1)	0.060	21
C_{11}	(0.02,0.04,0.08)	0.043	22
C_{12}	(0.04,0.07,0.12)	0.074	18
C_{13}	(0.09,0.12,0.17)	0.123	3
C_{14}	(0.04,0.08,0.13)	0.078	15
C_{15}	(0.08,0.11,0.16)	0.113	5
C_{16}	(0.08,0.11,0.16)	0.114	6
C_{17}	(0.04,0.06,0.11)	0.067	20
C_{18}	(0.05,0.08,0.13)	0.084	13
C_{19}	(0.08,0.11,0.16)	0.111	7
C_{20}	(0.07,0.1,0.16)	0.108	8
C_{21}	(0.07,0.1,0.15)	0.104	11
C_{22}	(0.07,0.1,0.16)	0.108	9

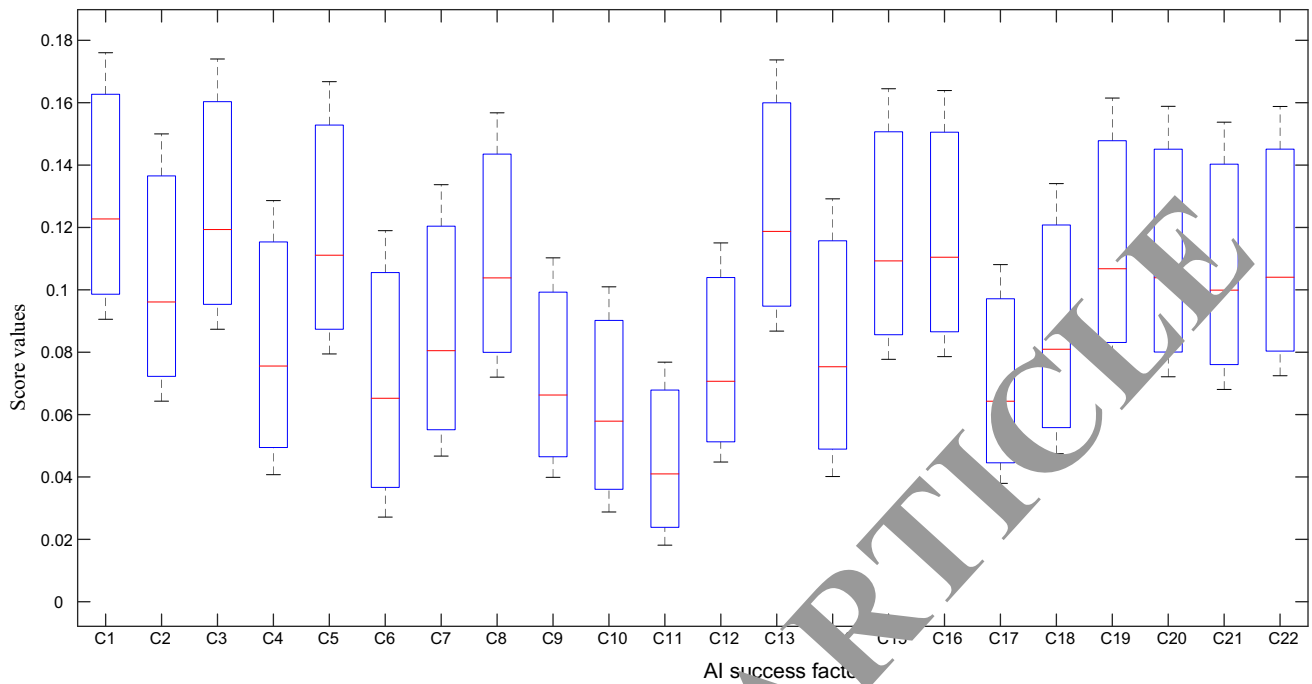


Fig. 2 Fuzzy weight coefficients of criteria

$$\begin{aligned} \tilde{\delta}_{C1} &= (\delta_{C1}^{(\alpha)}, \delta_{C1}^{(\beta)}, \delta_{C1}^{(\pi)}) \\ &= \begin{cases} \delta_{C1}^{(\alpha)} = 0.27 \cdot \left(1 - e^{-(0.333 \cdot (-\ln(1-0.33))^1 + 0.333 \cdot (-\ln(1-0.36))^1 + 0.333 \cdot (-\ln(1-0.31))^1)^{1/1}} \right) = 0.091; \\ \delta_{C1}^{(\beta)} = 0.37 \cdot \left(1 - e^{-(0.333 \cdot (-\ln(1-0.34))^1 + 0.333 \cdot (-\ln(1-0.36))^1 + 0.333 \cdot (-\ln(1-0.31))^1)^{1/1}} \right) = 0.123; \\ \delta_{C1}^{(\pi)} = 0.53 \cdot \left(1 - e^{-(0.333 \cdot (-\ln(1-0.34))^1 + 0.333 \cdot (-\ln(1-0.36))^1 + 0.333 \cdot (-\ln(1-0.31))^1)^{1/1}} \right) = 0.176; \end{cases} \\ &= (0.091, 0.123, 0.126). \end{aligned}$$

The remaining weights from Table 5 are calculated similarly.

6 Results and Discussion

The results of testing the model reveal that among eleven success factors, technology intensity, trialability, and government support and policies are the most important ones. It is also seen that the internal and external economies of scale and the opinion leaders in the business have the least impact. These results are highly correlated with the technology diffusion theories. The technical infrastructure is significantly important in the diffusion phase. The existing technologies and their intensity prepare the users for the new technologies. The trialability of the new technology prevent the avoidance of the users due to

their potential risk averse behaviors. It is also financially important to try and test the new technology before adopting it for good. Also, especially in the developing countries where the private sector may not ready to take the financial burden of the use of new technologies, governments' push plays a crucial role in the adoption process. Governments can invest on the infrastructure that is required but cannot be provisioned by private sector. The importance of the peer pressure is significant in the results. Therefore, existing networks can provide a background for the spillover of technology among business partners.

Results show that governments' role in the diffusion process is significant. A big push that supports the existing technical infrastructure as well as social and business networks can speed up the diffusion process of AI technologies in supply chain management of healthcare industries. Therefore, while the governments are expected to start a

big push, the business partners and shareholders are expected to use the opportunities created by the new technologies as they became more inclusive and uplifting for the adopters.

7 Conclusion

The aim of this study is to investigate the barriers and obstacles in the healthcare supply chain process. Therefore, a smooth and quick transformation process can follow the successful implementation of AI technologies. In this study, twenty-two criteria are examined and determined the importance of the AI success factors with the help of fuzzy Aczel–Alsina LMAW model. The used model assesses 22 factors that can influence diffusion of AI in healthcare supply chain management in each dimension. According to the results, the most effective criteria are the technology intensity (C_1), trialability (C_3), and government support and policies, respectively, while the most ineffective criteria are the internal and external economics of scale (C_{11}) and the opinion leaders in the business (C_{10}).

The study has some limitations. Some biases of the survey results may still exist, one of which is due to insufficient experts and other criteria. In future studies, type-2 neutrosophic fuzzy sets can be used to capture the uncertainty of the subjective judgments of experts. Also, fuzzy Einstein or dombi operators can be implemented to provide the flexibility in decision-making. These operators can provide some important advantages.

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Data availability Enquiries about data availability should be directed to the authors.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

Ethical approval This article does not contain any studies with animals performed by any of the authors.

Informed consent Informed consent was obtained from all individual participants included in the study.

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