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A novel group BWM approach to evaluate the implementation criteria of blockchain technology in the automotive industry supply chain

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ABSTRACT

The use of blockchain technology leads to improved operations and supply chain (SC) integration. Moreover, identifying and evaluating the blockchain technology application criteria in the logistics system is a Multi-Criteria Decision-Making (MCDM) challenge that requires taking into account the perspectives of experts with varying degrees of SC expertise. The purpose of this paper is to propose a novel group decision-making method based on the best-worst method (BWM) to evaluate the criteria of implementing blockchain technology in the SC. The proposed approach provides a mechanism whereby opinions of decision-makers (DMs) are aggregated in nine steps, first. Then, weights of criteria are determined using BWM individual decision-making models. Moreover, two individual decision-making methods called nonlinear goal programming based BWM II (NGPBWM II) and linear goal programming based BWM II (LGPBWM II) are extended in this study, which can be adopted in both individual and group decision-making problems. The NGPBWM II and LGPBWM II methods can be used for both individual and group decision-making. This study proposes a novel group decision-making framework. The framework has fewer constraints than previous group BWM models and can consider different best (worst) criteria by different DMs. The effectiveness of the proposed methodology is investigated employing eight numerical examples. The results reveal the high accuracy of the NGPBWM II in all eight examples. Therefore, a combination of the proposed group decision-making method and NGPBWM II is applied in a real case to evaluate the application criteria of the blockchain technology in the automotive industry SC, which was a new application for using blockchain technology in SC.

1. Introduction

The process of planning, manufacturing, processing, delivery, and operation from supplier to customer is referred to as the Supply Chain (SC) (Ronaghi, 2020). In SCs, such as the restaurant industry (Costa et al., 2013), drug and medicinal devices (Rotunno, Cesarotti, Bellman, Introna, & Benedetti, 2014), and high-value goods (Saberi, Kouhizadeh, Sarkis, & Shen, 2019), traceability is becoming an immediate necessity and a basic difference. Advanced emerging technologies can be utilized to improve models of SC operations and overcome the inefficient models in the domains of trust among SC segments, clarity and responsibility for the system (Morgan, Richey, & Ellinger, 2018), partnership (Tsanos & Zografos, 2016), information dissemination (Wagner & Bukó, 2005), and SC request and integrity (Stolze, Murfield, & Esper, 2015). Revolutions in and functions of technology brought about by the concept of blockchain make the improvements in the Supply Chain Management (SCM) more feasible institutionally, technically, and economically (Abeyratne & Monfared, 2016; Swan, 2015). The use of blockchain in the logistics system is one of the most well-known innovations (Kshetri, 2018; Viriyasitavat, Da Xu, Bi, & Sapsomboon, 2020). In technical terms, the application of blockchain technologies in distribution and distribution networks is brand new (Tian, 2016). Blockchain network relies on the intelligence network, and, more specifically, this network determines the data source and data owners, and contributes to considering and verifying transactions economically, and provides transparency alternatives in SCs (Ar et al., 2020). As a future technology, blockchain provides financial transactions and decentralization of processes by various stakeholders (Saberi et al., 2019). One of the key potential application domains for blockchain is logistics, which is described as a collection of operations that produces product development and knowledge flow across the SC (Ar et al., 2020). SC managers should use blockchain in their activities since, this way, all transactions, and exchanges would be more secure, visible, verifiable, and effective (Aste, Tasca, & Di Matteo, 2017; Kshetri, 2018). Studies exploring

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blockchain, its advantages, and different functions have highlighted its impact on the SCs. This literature addresses topics including, but not limited to, clarity and responsibility (Kshetri, 2018; Zhu, Song, Hazen, Lee, & Cegielski, 2018), Market analysis and record-keeping (Chowdhury, Ferdous, Biswas, Chowdhury, & Muthukkumarasamy, 2020), cyber security, and protection (Queiroz, Telles, & Bonilla, 2020). The technology can also be used to remake the relationship pattern among all segments of the SC (Aste et al., 2017; Viriyasitavat et al., 2020). Choosing whether or not to employ blockchain in the distribution chain, as well as what criteria to use in making the decision, is not only a difficult challenge but also a competitive one.

However, nowadays due to considering all socio-economic aspects, decision-making has become difficult and complicated (Kim & Ahn, 1999). The evaluation of the alternatives is the MCDM approach in which several alternatives are compared to each other based on a set of qualitative, quantitative, and even contradictory criteria (Omrani, Amini, & Alizadeh, 2020). The alternatives are weighed based on the expert's preferences (Mohammadi & Rezaei, 2020). To rank the alternatives, the criteria of the problem must be weighted. In some decision-making problems, one DM decides about the alternatives. But in many real-world problems, more than one DM is needed to evaluate the alternatives based on a set of criteria (Safarzadeh, Khansefid, & Rasti-Barzoki, 2018). In this case, if there are multiple DMs, they are required to consider all extracted priorities, and this is called group MCDM (Wu & Xu, 2016; Yan, Ma, & Huynh, 2017). In group decision-making problems, the DMs have different expertise and the opinions of each DM have a different effect on the result of the final decision (Yue, 2011). Therefore, it is necessary to use group decision-making since it takes several DMs' opinions into account. Many decision-making problems have been addressed using group MCDM approaches, including facility position selection (Dey, Bairagi, Sarkar, & Sanyal, 2017), provider selection (You, You, Liu, & Zhen, 2015), energy schedule selection (Chou & Ongkowijoyo, 2014), the evaluation of the sustainable alternatives in the construction industry (Heravi, Fathi, & Faeghi, 2017). Rezaei (2015) suggested BWM as a modern and precise approach for calculating the weights of criteria (Hafezalkotob & Hafezalkotob, 2017). In the BWM, a min-max model is provided to calculating the optimum weight of criteria for considering pairwise comparisons.

BWM based methods offer a structured way for making pairwise comparisons. This structure has several important advantages:

(i) The DM can have a proper grasp of the evaluation area before doing pairwise comparisons by determining the best and worst items. This awareness leads to more precise and efficient comparisons (Rezaei, 2020).
(ii) The BWM approach can be applied in several phases of solving MCDM problems. It can determine the weight of criteria and rank the alternatives (Rezaei, 2015). Most MCDM methods such as TOPSIS, ELECTRE, and VIKOR exclusively rank the alternatives. These methods are usually not used alone and are combined with methods that can determine the weight of the criteria, such as BWM.
(iii) DM's possible anchoring bias can be mitigated by using two pairwise comparison vectors based on two opposite references of best and worst. To counteract the anchoring bias, the opposite approach is used (Rezaei, 2020).
(iv) Pairwise comparison-based approaches come in different types. Some approaches such as Swing and SMART family, use a single vector. Some approaches such as AHP and ANP, make use of the full matrix (Rezaei, 2020). BWM based methods use two vectors. Although employing a single vector saves time and data, approaches based on a single vector cannot check the consistency of pairwise comparisons. In methods based on a full matrix, it is possible to calculate the consistency ratio. These techniques, however, need asking the DM many questions, which may cause the DM to become confused. Therefore, BWM is the most efficient approach, which can calculate the consistency of pairwise comparisons (Rezaei, 2020).
(v) When we need subjective evaluation, especially when objective values do not exist, the BWM is an effective approach as it is based on pairwise comparisons and can calculate the consistency ratio. In this framework, the reliability of results can be checked, which is not possible in most MCDM methods such as TOPSIS, TODIM, and VIKOR (Jozaghi, Alizadeh, Hatami, Flood, Khorrami, Khodaei, & Tousi, 2018; Liang, Brunelli, & Rezaei, 2020; Rezaei, 2015).
(vi) The rank reversal phenomenon has occurred in many MCDM methods, such as AHP, TOPSIS, and TODIM (Gomes, 1990; Wang & Luo, 2009). Rezaei (2015) showed that BWM provides a full ordinal consistency.

The BWM method has been used in various fields that can be pointed to assess sustainability (Zhao, Guo, & Zhao, 2018), areas related to aviation and airports (Rezaei, Hemmes, & Tavasszy, 2017), web services selection (Serrai, Abdelli, Mokdad, & Hammal, 2017), determining the appropriate location in the field of clean energy (Kalbasi et al., 2021; Mostafaeipour et al., 2021), equipment selection (Hafezalkotob, Hami-Dindar, Rabie, & Hafezalkotob, 2018), project outsourcing (Yadav, Mangla, Luthra, & Jakhar, 2018), etc. BWM method has also been developed in various researches which can be pointed to the linear mathematical model of BWM (Rezaei, 2016), the development of BWM in an intuitionistic fuzzy environment (Mou, Xu, & Liao, 2016), the development of the nonlinear mathematical model of the fuzzy version of BWM (Guo & Zhao, 2017), and the BWM's Z-number extension (Aboutorab, Saberi, Asadabadi, Hussain, & Chang, 2018), etc. In some research literature in the field of SC, sustainability issues and performance improvement using new technologies have been emphasized by researchers (Seuring, Brix-Asala, & Khalid, 2019; Yadav et al., 2020). Therefore, the application of blockchain technology in SC leads to improved performance and sustainability of SC. However, a review of the literature in the field of applications of the BWM method shows that there is a research gap in the use of blockchain technology in SC in real cases. On the other hand, determining the importance of criteria for using blockchain technology in SC is a decision issue. It is necessary to consider the opinions of a group of DMs in the form of a group decision-making process. In the previous studies on the development of the BWM, it was not possible to consider different criteria for best and worst by DMs, which in this regard, there is a lack of research. Therefore, in this study, a novel BWM group model is developed to determine the importance of criteria for the possibility of using blockchain technology in the SC.

Amiri and Emamat (2020) introduced the goal programming-based BWM (called GPBWM I hereafter). In the present research, two individual models which were the developed versions of the GPBWM I were presented (called GPBWM II hereafter). The proposed models were applied in three examples from Rezaei's study (2016) and in one example from Amiri and Emamat's study (2020), and the results were compared to the results obtained from the BWM, Linear BWM, Nonlinear GPBWM I (NGPBWM I), and Linear GPBWM I (LGPBWM I). Due to the high accuracy of the proposed models compared to the previous methods, a GPBWM II-based method was proposed to solve group problems. The proposed method is applied in four examples from the study of Safarzadeh et al. (2018), and the results obtained from the proposed method were compared to the models M1 and M2 proposed by Safarzadeh et al. (2018).

Because of the unique characteristics and dynamics of the automobile SC, which include the introduction of emerging technologies, cost savings, responsiveness to new consumer demands, and collaboration with numerous multinational corporations, constant performance management, and teamwork are critical. To improve performance, teamwork, decentralization, encrypted transfers, increase trust, and knowledge sharing, emerging technology such as blockchain and its use in logistics operations and between SC layers are critical. The use of blockchain for financial exchanges has enabled coordination and traceability, information sharing and coordination, information security, increasing trust between SC partners, decentralization, and the ability to operate around the world, especially for large automotive companies around the world. However, so far, no research has been done on the implementation of blockchain in the SC of the automotive industry. Researchers are using a new potential group approach to test the requirements for using blockchain in the Iranian automotive SC as a case study to close this research gap.

The present study is innovative in terms of the following items:

- Identifying the usability criteria of the blockchain in the SC;
- Developing the NGPBWM II and LGPBWM II models to identify the weight of the criteria in individual decision-making;
- Reducing the number of constraints of group models compared to group BWM methods proposed earlier;
- Combining NGPBWM II and the proposed group preference aggregation approach to identify the importance of the criteria in group decision-making.

The second section of this paper explores the studies on blockchain and its functions and on the development and use of the BWM. The third section describes the proposed individual models and the suggested framework for group decision-making. The fourth section presents the numerical examples for individual and group decision-making. In the fifth section, a real case is presented on blockchain usability in the automotive SC. Finally, the conclusions and executive and research suggestions are expressed in the sixth section.

2. Literature review

2.1. Blockchain technology and its functions

Blockchain is a distributed digital database of digitally signed transactions organized into blocks and once authenticated, each block is cryptographically connected to the one before it (Boubeta-Puig, Rosa-Bilbao, & Mendling, 2021; S. Kim, Park, & Lee, 2020). Blockchain enables the sharing and verification of a decentralized network with participants and it has received much interest as a technology that can resolve the problem of trust between different shareholders (Bamakan, Motavali, & Babaei Bondarti, 2020; Kim, Bock, & Lee, 2021). A data warehouse is much more vulnerable to theft, tampering, or harm than a distributed database (Tian, 2016). Therefore, due to being able to decentralize, blockchain technology is secure against hacking and damage. The blockchain can increase security since every transaction is verified by cryptography, and transaction records cannot be distorted in the blocks (Helo & Hao, 2019). In numerous researches, blockchain applications such as flexibility, visibility, encrypted data, reducing costs, and efficient manufacturing processes have been listed in various domains (Behnke & Janssen, 2020).

SCM and the use of emerging technology, such as data analytics, the internet – of – things, cloud technology, and blockchain, have been the subject of some studies in recent years (Duan, Edwards, & Dwivedi, 2019). Literature on the blockchain and the different advantages of this technology has confirmed its influence on the SC. This literature encompasses transparency and accountability (Kshetri, 2018), traceability and prevention of fake and counterfeit products (Chowdhury et al., 2020), cyber security and protection (Kshetri, 2017), etc. in the domain of SC. Blockchain technology can be applied to remake the relationship pattern among all members of the SC (Viriyasitavat et al., 2020). Blockchain is one of the most appropriate systems in the logistics and SCM processes for some of its fundamental elements because of data confidentiality and open operations (Perboli, Musso, & Rosano, 2018). The effectiveness of adopting blockchain to achieve clarity of data sharing across SC actors has been verified in many studies (Ho, Tang, Tsang, Tang, & Chau, 2021). Researchers have recently done a lot of researches in the field of blockchain. This section categorizes the researches conducted on the use of blockchain.

Some research, such as Roman-Belmonte, De la Corte-Rodriguez, and Rodriguez-Merchan (2018), Teufel, Sentic, and Barmet (2019), Anjum et al. (2020), Zou, Meng, Zhang, Zhang, and Li (2020), Kim et al. (2020), and Zheng and Lu (2021), are related to the vision of blockchain and the state of this technology in the future.

Some studies have emphasized the need to use blockchain in various applications. In these studies, various applications for this technology including finance (Chang et al., 2020; Khalil, Khawaja, & Sarfraz, 2021), education (Guustaaf, Rahardja, Aini, Maharani, & Santoso, 2021; Shah, Patel, Adesara, Hingu, & Shah, 2021), energy (Ahl, Yarime, Tanaka, & Sagawa, 2019; Yildizbasi, 2021), transportation (Khoshavi, Tristani, & Sargolzaei, 2021; Lei et al., 2017), Agriculture (Eluubek kyzy, Song, Vajdi, Wang, & Zhou, 2021; Pranto, Noman, Mahmud, & Haque, 2021), and Health (Pandey & Litoriya, 2021; Sharma & Joshi, 2021) were introduced. These studies present the applications of blockchain technology in different areas.

In some studies, decision-making in the blockchain field has been examined. Koens and Poll (2018), in a study, analyzed 30 projects in the field of blockchain in detail. In these analyzes, the discrepancies between these projects were examined and a plan for deciding on blockchain projects was presented. They stated that the planned new plan could determine the need for blockchain or alternative technologies. Wüst and Gervais (2018) first examined the suitability of blockchain technology. They also presented a methodical process for determining the best solution for permission-less and permission-ed blockchains. Also, three applications for blockchain technology were investigated in this study. Cash and Bassiouni (2018) compared the two kinds of permission-ed and permission-less blockchain and introduced the concept of dual blockchain for secure data sharing. The results showed that as the number of miners in a Proof-of-Work consensus increases, the total number of blocks in the permission-less blockchain increases. Prasad, Shankar, Gupta, and Roy (2018) identified a set of advanced determinants leading to the improvement of the operations of blockchain cloud services. Having examined the available literature and professional opinions, they identified nineteen important success factors. Tang, Shi, and Dong (2019) carried out a thorough analysis of the blockchain utilizing entropy and TOPSIS methods. They evaluated 30 blockchains by three criteria, including technology, recognition, and activity. The advantages and disadvantages of employing blockchain technology in operations management were outlined by Babich and Hilary (2020). Visibility, aggregation, validation, automation, and adaptability are strengths, while lack of confidentiality and uniformity, garbage in, garbage out, the black box effect, and inefficiency are weaknesses. Kamble, Gunasekaran, and Sharma (2020) identified the enablers of the blockchain and studied the way they communicated with several others utilizing the DEMATEL method. In this type of researches, the provision of a quantitative framework for decision-making and evaluation of factors was not considered and in a few types of research, quantitative methods were used.

Several studies have also emphasized the implementation of blockchain technology in the SC. Hackius and Petersen (2017) examined the viewpoints of logistics and SC specialists on the functions, barriers, and general outlook of the application of blockchain. They realized that the most important stakeholders emphasized the necessity of the application of blockchain. Kshetri (2018) investigated the influence of the blockchain on the increase of confidence and accountability in the SC. They presented various mechanisms to apply the blockchain in the SC. Min (2019) investigated the effect of blockchain technology on SC resilience. This study suggests using blockchain technology to increase SC resilience in situations of increased risk and uncertainty. Perboli et al. (2018) implemented blockchain technology in the food SC and considered the important factors in the implementation of this technology. The study also discussed the role of the blockchain in reducing logistics costs and optimizing operations. Rožman, Vrabič, Corn, Požrl, and Diaci (2019) created a system that enabled DMs to use blockchain and IoT in their SC procedures. Queiroz and Fosso Wamba (2019) emphasized that blockchain contributed to increasing customer trust, and the product's flow can be examined in the entire SC. Helo and Hao (2019) presented SC and blockchain-based transactions. As a result, various SC software applications were investigated and categorized using the blockchain. Finally, an operations monitoring system was demonstrated and implemented on the Ethereum network. Mistry, Tanwar, Tyagi, and Kumar (2020) looked at a G5 and blockchain-based IoT automation design. Moreover, the proposed programs were evaluated based on different criteria. Venkatesh, Kang, Wang, Zhong, and Zhang (2020) proposed a blockchain-driven SC architecture that is based on the concept of resilience. The study's findings showed that blockchain technology allows for social sustainability and the retention of qualified staff members in the SC. In real-case studies conducted by Choi, Guo, and Luo (2020), the performance of blockchain was investigated in improving the analysis of social networks to manage the SC operations. Moosavi, Naeni, Fathollahi-Fard, and Fiore (2021) reviewed the application of blockchain technology in the SC. In this study, the application areas of blockchain in the SC such as finance, logistics, and security were examined. The results of highly cited articles show that the blockchain can increase transparency, traceability, efficiency, and information security in SC management. In this group of researches, important factors for the implementation of blockchain technology in the SC have not been evaluated and quantitative methods have not been used for decision making.

2.1.1. Literature gaps in blockchain technology and its functions

A review of the literature and classification of research conducted in the field of blockchain showed that most research has introduced the advantages and applications of this technology in various industrial sectors and the SC in general. Also, some researchers have paid attention to the field of decision-making regarding blockchain technology in general. There is a research gap in terms of using quantitative approaches and providing a framework for identifying and evaluating criteria to implement blockchain in new industrial fields and SCs. Evaluating the usability criteria of the blockchain is a strategic decision, and different criteria need to be taken into account, which is an MCDM problem. According to the literature review, a limited number of real-case studies examined the utilization of blockchain in the SC to identify and evaluate the implication criteria of the blockchain using the MCDM. And despite its importance, there is a significant research gap in this domain.

2.2. BWM: Functions and developments

Rezaei (2015) introduced the BWM as a new MCDM approach in which the DM first selects the best and worst items, based on the least pairwise comparisons among criteria. This method was used in different studies to obtain the importance of each criterion: evaluation of the quality of public transport nodes (Groenendijk, Rezaei, & Correia, 2018), ranking edible oil suppliers (Rezaei, Nispeling, Sarkis, & Tavasszy, 2016), evaluation of urban sewage sludge technologies (Burnap et al., 2015), evaluation of online web services (Serrai, Abdelli, Mokdad, & Hammal, 2016), and site selection for cultural facilities (You, Chen, & Yang, 2016). This method, due to its advantages compared to other weighting methods, has recently drawn the attention of researchers, and the latest studies concerning the development and application of this technique are covered in the following paragraphs.

Rezaei (2015) proposed the BWM technique to solve MCDM problems. He used the BWM in a real case to select a smartphone. Rezaei (2016) suggested a BWM interval and linear model, each of which offers a unique solution. Mou et al. (2016) used intuitionistic fuzzy relations to develop group BWM. You et al. (2016) utilized group BWM to evaluate cultural centers in China. Yang, Zhang, You, and Chen (2016) proposed a new method to evaluate and classify overseas talents by the BWM under intuitionistic relations. Gupta and Barua (2016) evaluated thirteen innovation enablers in small and medium companies in India by the BWM. Salimi and Rezaei (2016) assessed University-Industry collaboration projects by the BWM. Rezaei et al. (2017) evaluated the alternatives of ground transport of air freights. In that study, the BWM was used to weigh three Key Process Indicators (KPI), i.e., cost, loading time, and quality. Salimi (2017) assessed the quality of scientific results (for instance, research papers, books, and reports) using the BWM. To consider uncertainties resulted from lack of knowledge due to qualitative assessment of the DMs, Guo and Zhao (2017) developed fuzzy BWM and conducted three case studies (selection of supplier, transportation method, and car) to demonstrate the effectiveness of the proposed fuzzy BWM. Hafezalkotob and Hafezalkotob (2017) suggested a new method based on individual and group judgment for the fuzzy BWM. The paradigm proposed to the senior DM assisted him in choosing between authoritarian political judgment models. Wan Ahmad, Rezaei, Sadaghiani, and Tavasszy (2017) evaluated the sustainable SC force in the gas and oil industry. The gathered data were assessed to identify the relative importance of force using the BWM. Van De Kaa, Scholten, Rezaei, and Milchram (2017) utilized group BWM to evaluate the criteria for choosing batteries and oil cell-driven electric cars. Stević, Pamučar, Zavadskas, Ćirović, and Prentkovskis (2017) evaluated wagons for domestic transportation using the BWM and rough numbers. Shojaei, Seyed Haeri, and Mohammadi (2018) assessed the performance and ranking of the airports using the Taguchi loss function and the BWM and VIKOR. Yadav et al. (2018) developed a decision-making framework to help managers to accept overseas outsourcing. In this study, the importance of offshore outsourcing-focused enablers was determined by the BWM. Ranking of organizations was also done by the ELECTRE method. Salimi and Rezaei (2018) proposed a multi-criteria framework to assess the research and development (R&D) performance of fifty small and medium businesses in the Netherlands. Furthermore, the BWM was used to identify the weight (importance) of R&D actions. Rezaei, Kothadiya, Tavasszy, and Kroesen (2018) evaluated the criteria of the SERVQUAL model to evaluate the condition of airline baggage managing systems and also used the BWM to weight criteria. Mahdiraji, Arzaghi, Stauskis, and Zavadskas (2018) evaluated the key indicators of sustainable architecture in Iran by the grey BWM. Safarzadeh et al. (2018) selected the best piping methods using developed group BWM. Tabatabaei et al. (2019) employed group BWM for two management problems, including evaluation of R&D and green SC. Mohammadi and Rezaei (2020) introduced the Bayesian BWM for group decision-making problems. Omrani et al. (2020) used developed group BWM to evaluate road safety in Iran. Amiri and Emamat (2020) developed goal programming models for individual BWM. The proposed models had fewer constraints compared to previous models. They also presented a numerical sample to examine the performance of the models. Amiri et al. (2021) developed a fuzzy BWM using possibilistic programming. They proposed a linear model based on possibility, necessity, and credibility. Using the developed model, DMs can have an optimistic, pessimistic, or mixed view about the problem. Pamučar, Puška, Stević, and Ćirović (2021) developed a novel BWM model based on the D numbers. The proposed model was applied to evaluate criteria in the field of healthcare waste management. In this study also a Multi-Attributive Border Approximation Area Comparison based on D numbers (MABAC-D) method was used to rank the alternatives. Wang, Ma, and Liu (2021) used *meta*-evaluation theory and methods to evaluate science and technology projects. The significance of the criteria was determined using IVIF-BWM methods in this study. The combination of criteria was determined using multi-objective optimization by ratio analysis plus the full multiplicative form (MULTIMOORA). The results confirmed the accuracy of the proposed model.

The Scopus and Google Scholar databases were reviewed by the authors. At this stage, by searching for the keywords "BWM" and "Best-Worst Method" in the abstract and text of the articles and considering indicators such as the English language of the article and the time from 2015 to 2021 and analyzing the relevance of studies within the present study, a list of articles was selected. These articles are compared in Table 1.

2.2.1. Literature gaps in BWM: Functions and developments

A review of research conducted in the field of BWM showed that most of the research was conducted on individual decision-making. There is a research gap for considering different best (worst) criteria by different DMs in group BWM methods. Also, these studies do not offer an approach to reduce computational complexity. On the other hand, there is a research gap on the application of the BWM method in real cases to improve SC performance using new technologies such as blockchain technology. Hence, in the current paper, in addition to identifying the implementation criteria of blockchain in the automotive SC, these criteria are weighted by the proposed group BWM. One of the most significant advantages of the proposed method is that it has fewer constraints than earlier models, resulting in lower computational complexity. The ability to consider different best (worst) criteria for different DMs is another advantage of the proposed group BWM in this study. Moreover, in the present research, the great accuracy of the proposed models is demonstrated in eight numerical examples. Also, the function of the proposed group method as the first research is examined in a case study concerning the use of blockchain in the automotive SC. To the best of the authors' knowledge, no paper so far has been carried out in the domain of the application of blockchain technology in the automotive SC.

3. The proposed approaches

3.1. Goal programming based BWM

In this section, the proposed models of the study are presented. These models have developed versions of the GPBWM I earlier proposed by Amiri and Emamat (2020). The developed models in this research, called GPBWM II, consist of linear and nonlinear models. The overall steps of the GPBWM I are as follows:

Step 1. Determining the set of decision criteria: In this step, n number of criteria are determined by the DM.

Step 2. Choosing the most significant criterion versus the least significant criteria.

Step 3. Examining the preference of the most significant criterion over other criteria: In this step, the favorite of the most suitable criterion over other criteria are determined by numbers 1 to 9 using the Best-to-Others (BO) vector depicted as $BO = (a_{B1}, \ldots, a_{Bj} \ldots, a_{Bn})$. In BO vector, a_{Bj} is the preference of the best criterion over criterion j.

Step 4. Determining the preferences of the other criteria over the worst criterion: In this step, the other criteria's preferences over the worst criterion are determined by numbers 1 to 9 using Others-to-Worst (OW) vector depicted as $OW = (a_{1w}, \ldots, a_{jw}, \ldots, a_{nw})^T$. in OW vector, a_{jw} is the preference of criterion j over the worst criterion.

Step 5. In this step, one of the models presented in sections 3.1 and 3.2 need to be used to determine final weights.

3.1.1. Nonlinear goal programming based BWM

In the BWM, the objective function seeks to minimize the deviation of $\frac{w_i}{w_j}$ from a_{ij}. If this deviation reaches zero, it means that there is no difference between the weight obtained by the model and the preference

Table 1
Separation of the study in the field of use and development of the BWM.

Articles	Method				Case study		Field of study
	Individual BWM	Group BWM	Developed Individual BWM	Developed group BWM	Real case	Numerical examples	
Rezaei (2015)	✓				✓	✓	Smartphone
Rezaei (2016)			✓			✓	-
Mou et al. (2016)		✓			✓	✓	Healthcare
You et al. (2016)		✓			✓		Cultural centre
Yang et al. (2016)			✓		✓		Overseas talent
Gupta and Barua (2016)		✓			✓		Technological innovation
Salimi and Rezaei (2016)	✓				✓		University-Industry collaboration
Rezaei et al. (2017)	✓				✓		Ground transport of air freights
Salimi (2017)	✓				✓		Scientific outputs
Guo and Zhao (2017)			✓		✓		Selection of supplier, transportation method and car
Hafezalkotob and Hafezalkotob (2017)				✓	✓		The policy-making process of a scientific journal, innovation projects selection
Wan Ahmad et al. (2017)		✓			✓		Sustainable SC
Van De Kaa et al. (2017)		✓			✓		Battery and fuel cell powered electric vehicles
Stević et al. (2017)			✓		✓		The internal transport
Shojaei et al. (2018)		✓			✓		Airports
Yadav et al. (2018)	✓				✓		Offshore outsourcing adoption
Salimi and Rezaei (2018)		✓			✓		R&D
Rezaei et al. (2018)		✓			✓		Airline baggage handling systems
Mahdiraji et al. (2018)	✓				✓		Sustainable architecture
Safarzadeh et al. (2018)				✓	✓	✓	Piping methods
Tabatabaei et al. (2019)				✓			R&D and green SC
Mohammadi and Rezaei (2020)				✓		✓	-
Amiri and Emamat (2020)			✓			✓	-
Omrani et al. (2020)				✓	✓		Road Safety
Amiri et al. (2021)			✓			✓	-
Pamučar et al. (2021)				✓	✓		Healthcare waste management
Wang et al. (2021)			✓		✓		Science and technology project review experts
This paper			✓	✓	✓	✓	Use of blockchain technology in the automotive SC

stated by the DM. This occurs when there is full-system consistency. However, slight inconsistency is normally inevitable in real-world systems, and the model should be designed in a way that occurring some deviations is imaginable. In such a case, among all the proposed models, the one capable of minimizing this deviation is more accurate. The model should calculate the weights of criteria in a way that has the highest consistency with the preference stated by the DM. Otherwise, the obtained weights are unreal and misleading.

The NGPBWM I is demonstrated in Eq. (1). In this model, the deviation between $\frac{w_B}{w_j}$ and a_{Bj} and the deviation between $\frac{w_j}{w_W}$ and a_{jW} is depicted using free variables, i.e., $y_j = y_j^+ - y_j^-$ and $z_j = z_j^+ - z_j^-$. In the original BWM, absolute values were used in the constraints of the model, but in the NGPBWM I, using free variables, absolute values were eliminated from the model and the complexity of the model was less.

$$\min z = \sum_j (y_j^+ + y_j^-) + \sum_j (z_j^+ + z_j^-)$$

$$s.t.$$

$$\frac{w_B}{w_j} - a_{Bj} = y_j^+ - y_j^-, \mathit{for\ all\ j}$$

$$\frac{w_j}{w_W} - a_{jW} = z_j^+ - z_j^-, \mathit{for\ all\ j}$$

$$\sum_j w_j = 1$$

$$w_j, y_j^+, y_j^-, z_j^+, z_j^- \geq 0, \mathit{for\ all\ j} \tag{1}$$

Eq. (1) can be transformed to Eq. (2). The model presented in Eq. (2), called NGPBWM II, minimizes the maximum total deviation of BO preferences and maximum total deviation of OW preferences.

$$\min z = \varepsilon$$

$$s.t.$$

$$\sum_j (y_j^+ + y_j^-) \leq \varepsilon$$

$$\sum_j (z_j^+ + z_j^-) \leq \varepsilon$$

$$\frac{w_B}{w_j} - a_{Bj} = y_j^+ - y_j^-, \mathit{for\ all\ j}$$

$$\frac{w_j}{w_W} - a_{jW} = z_j^+ - z_j^-, \mathit{for\ all\ j}$$

$$\sum_j w_j = 1$$

$$w_j, y_j^+, y_j^-, z_j^+, z_j^- \geq 0, \mathit{for\ all\ j} \tag{2}$$

3.1.2. Linear goal programming based BWM

NGPBWM I was a nonlinear model. Instead of $\frac{w_i}{w_j} - a_{ij}$, $w_i - a_{ij}.w_j$ can be used in the constraints to linearize this model. This transformation simplifies the model since the model will no longer be nonlinear. Other parts of the LGPBWM I are similar to NGPBWM I. It is worth mentioning that Rezaei (2016) had already used the same way to linearize the original BWM. The NGPBWM I model is based on Eq. (3).

$$\min z = \sum_j (y_j^+ + y_j^-) + \sum_j (z_j^+ + z_j^-)$$

$$s.t.$$

$$w_B - a_{Bj}.w_j = y_j^+ - y_j^-, \mathit{for\ all\ j}$$

$$w_j - a_{jW}.w_W = z_j^+ - z_j^-, \mathit{for\ all\ j}$$

$$\sum_j w_j = 1$$

$$w_j, y_j^+, y_j^-, z_j^+, z_j^- \geq 0, \mathit{for\ all\ j} \tag{3}$$

Eq. (3) can be transformed to Eq. (4). The model presented in Eq. (4), called LGPBWM II, minimizes the maximum total deviation of BO preferences and maximum total deviation of OW preferences.

$$\min z = \varepsilon$$

$$s.t.$$

$$\sum_j (y_j^+ + y_j^-) \leq \varepsilon$$

$$\sum_j (z_j^+ + z_j^-) \leq \varepsilon$$

$$w_B - a_{Bj}.w_j = y_j^+ - y_j^-, \mathit{for\ all\ j}$$

$$w_j - a_{jW}.w_W = z_j^+ - z_j^-, \mathit{for\ all\ j}$$

$$\sum_j w_j = 1$$

$$w_j, y_j^+, y_j^-, z_j^+, z_j^- \geq 0, \mathit{for\ all\ j} \tag{4}$$

3.1.3. Consistency ratio

Although full system consistency is always favorable, inconsistency inevitably exists in real-world systems. Therefore, to prevent extreme deviation between the preferences stated by the DM and the obtained weights after solving the model, it is necessary to be able to trace this deviation. The consistency ratio (CR) can be calculated using Eq. (5). The closer CR is to zero, the better.

$$CR = \frac{d}{CI} \tag{5}$$

d is calculated through Eq. (6).

$$d = \max_j \left\{ y_j^+ + y_j^-, z_j^+ + z_j^- \right\} \tag{6}$$

Consistency index (CI) can be calculated based on Table 2 presented by Rezaei (2015).

3.2. Group best-worst method (GBWM)

Most of the time, decisions are made in groups. Therefore, it is important to develop a method that can collect the opinions of experts and present final weights. In what follows, the steps of the suggested approach are presented.

Step 1. Determining the members of the decision team: first, those who are supposed to participate in decision-making are determined.

Step 2. Determining the importance of each member: In this step, if the importance of members' opinions and their expertise level are different, a certain weight is allocated to each member. To this end, the weighting methods such as the GPBWM I, GPBWM II, or other weighting methods can be used. Also, a number between 0 and 1 can be selected as the expert weight vector in a way that the total weight of members equals one. The importance of expert k is shown as W^K.

Step 3: Determining the best and worst criteria by each expert: Each expert selects the best and worst criteria from their perspective in the

Table 2
Consistency index.

a_{BW}	1	2	3	4	5	6	7	8	9
CI	0.00	0.44	1.00	1.63	2.30	3.00	3.73	4.47	5.23

process. The best criterion is shown as C_P, while the worst criterion is shown as C_V.

***Step 4. Determining Best-to-Other's vector*:** In this step, each expert evaluates the best criterion over all the other criteria, and eventually, the BO vector is developed. The preference of the best criterion over criterion j by expert k is demonstrated as b^k_{Pj}.

***Step 5. Determining Others-to-Worst vector*:** In this step, each expert evaluates all the other criteria over the worst criterion, and eventually, the OW vector is formed. The preference of criterion j over the worst criterion by expert k is depicted as b^k_{jV}.

***Step 6. Determining reference best and worst criteria*:** In this step, it is required to determine reference best and worst criteria for this problem. Reference best criterion is demonstrated as C_B and references worst criteria as C_W. Assume the set of best criteria determined by all experts is shown as FP. $U(C_P)$ equals to total weight of experts whose selected best criterion was C_P. $U(C_P)$ is calculated using Eq. (7). The maximum amount of $U(C_P)$ determines the reference best criterion.

$$U(C_P) = \sum_k S^k(C_P).w^k, \forall P \in FP \tag{7}$$

In the above Eq., $S^k(C_P)$ is obtained by Eq. (8).

$$S^k(C_P) = \begin{cases} 1 & \text{if expert } k \text{ selects } C_P \text{ as the best criterion} \\ 0 & \text{otherwise} \end{cases} \tag{8}$$

Suppose the set of worst criteria determined by all experts is depicted as FV. $U(C_V)$ equals to total weight of experts whose selected worst criterion was C_V. $U(C_V)$ is calculated by Eq. (9). The maximum of $U(C_V)$ determines the reference worst criterion.

$$U(C_V) = \sum_k S^k(C_V).w^k, \forall V \in FV \tag{9}$$

In the above Eq., $S^k(C_V)$ is calculated based on Eq. (10)

$$S^k(C_V) = \begin{cases} 1 & \text{if expert } k \text{ selects } C_v \text{ as the worst criterion} \\ 0 & \text{otherwise} \end{cases} \tag{10}$$

***Step 7. Determining the preference of reference best criterion to other criteria for each expert*:** The preference of the reference best criterion to other criteria based on expert k's opinion is shown as a^k_{Bj} and is calculated by Eq. (11).

$$a^k_{Bj} = b^k_{BP}.b^k_{Pj} = \frac{b^k_{Pj}}{b^k_{PB}} \tag{11}$$

***Step 8. Determining the preferences of others to reference the worst criterion for each expert*:** The preferences of others to reference the worst criterion based on the opinion of expert k is depicted as a^k_{jW} and is obtained by Eq. (12).

$$a^k_{jW} = b^k_{jV}.b^k_{VW} = \frac{b^k_{jV}}{b^k_{WV}} \tag{12}$$

***Step 9. Determining global reference pairwise comparison vectors*:** To gather the experts' opinions to determine the entries of global reference best to others vector, Eq. (13) is used.

$$a_{Bj} = \prod_k \left(a^k_{Bj}\right)^{w^k} \tag{13}$$

To gather the experts' opinions to determine the entries of global reference others to worst vector, Eq. (14) is used.

$$a_{jW} = \prod_k \left(a^k_{jW}\right)^{w^k} \tag{14}$$

***Step 10. Determining the weights of criteria*:** in this step, to calculate the weights of criteria, every individual BWM model can be used. Nevertheless, regarding the comparisons made in this study and the accuracy observed in the results obtained from the GPBWM II compared to other methods, the use of GPBWM II could be a good option. In Fig. 1, the framework of the proposed method for the GBWM is presented.

3.2.1. Consistency ratio

Often, before the aggregation of the opinions of DMs, the consistency ratio of each DM needs to be determined. To this end, Eq. (15) can be used to calculate the consistency ratio (Liang et al., 2020). Calculating CR before solving this model enables us to put aside questionnaires with unsuitable CR or ask the DM to revise their questionnaire, before solving the model.

$$CR^k = \max_j CR^k_j \tag{15}$$

CR^k_j is obtained by Eq. (16).

$$CR^k_j = \begin{cases} \dfrac{\left|b^k_{Pj} \times b^k_{jV} - b^k_{PV}\right|}{b^k_{PV} \times b^k_{PV} - b^k_{PV}} & b^k_{PV} > 1 \\ 0 & b^k_{PV} = 1 \end{cases} \tag{16}$$

CR^k can be calculated for all DMs. The closer the amount is to zero, the better.

Group consistency ratio can be calculated after solving the model. But it should be noted that, in group decision-making, after aggregating the opinions of DMs, a_{BW} might not equal to an integer number and hence a decimal number is achieved. In this case, Table 2 cannot be used to obtain CI, since, in this Table, only integer numbers 1 to 9 are mentioned for a_{BW}. CI of intermediate values can be obtained by Eq. (17). The maximum value of ε is considered for the CI (Rezaei, 2015).

$$\varepsilon^2 - (1 + 2a_{BW})\varepsilon + \left(a_{BW}{}^2 - a_{BW}\right) = 0 \tag{17}$$

Now that the CI value is obtained, CR can be calculated using Eq. (5).

4. Numerical studies

4.1. Numerical examples for individual decision-making

In this section, the results of the BWM, LBWM, NGPBWM I, LGPBWM I, NGPBWM II, and LGPBWM II are compared according to the examples presented in earlier studies. To this end, having solved each model and determined the weights of criteria, the authors calculated total deviation (TD). The smaller the TD, the better the results are. In the present paper, TD is viewed as a criterion to compare the models. TD is obtained by Eq. (18) (Mohtashami, Aghsami, & Jolai, 2020).

$$TD = \sum_i \sum_{\substack{j \\ j \neq i}} \left(a_{ij} - \frac{w_i}{w_j}\right)^2 \tag{18}$$

It should be noted that Eq. (19) is usually utilized for PC-based methods. This Eq. changes according to Eq. (8) to be more consistent with the BWM.

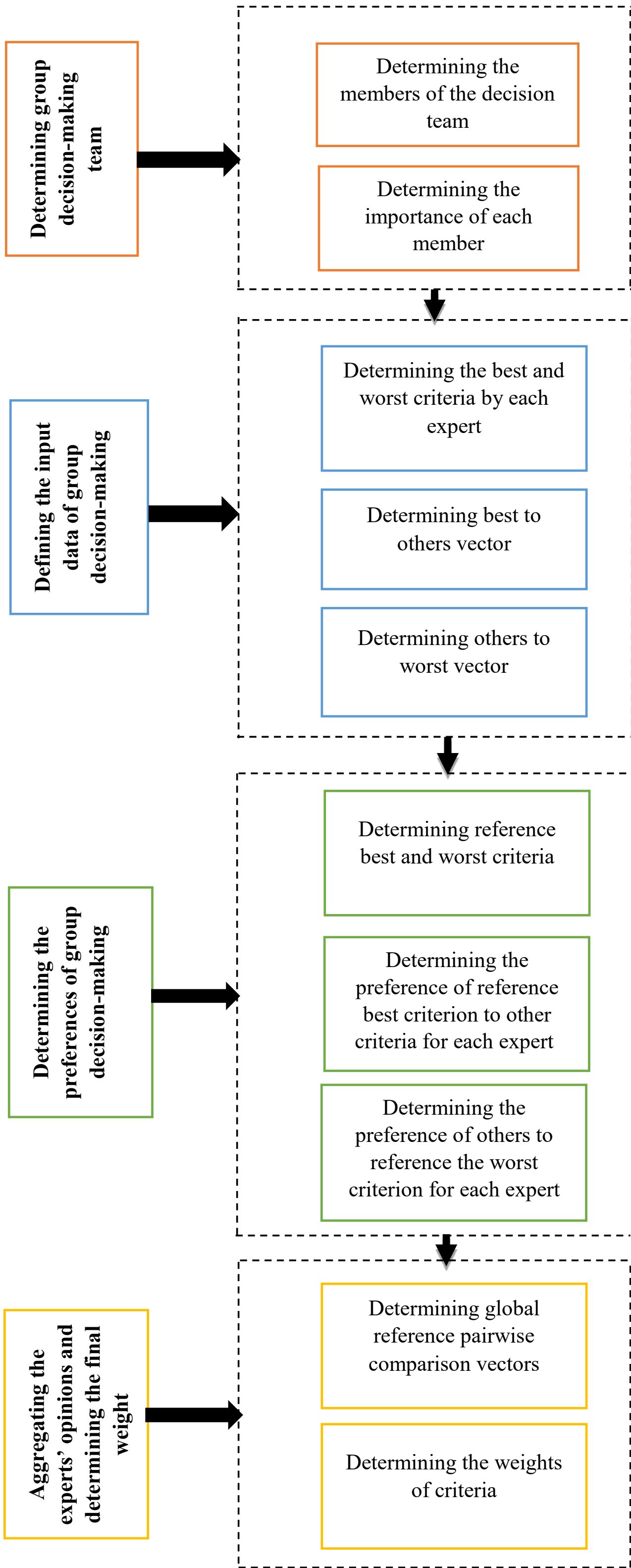

Fig. 1. The GBWM framework.

$$TD = \sum_j ((a_{Bj} - \frac{w_B}{w_j})^2 + (a_{jW} - \frac{w_j}{w_W})^2) - (a_{BW} - \frac{w_B}{w_W})^2 \tag{19}$$

Example 1. *In this section, numerical examples presented by Rezaei (2016) are taken into account. In this example, to purchase a car, five criteria such as quality* (C_1)*, price* (C_2)*, comfort* (C_3)*, safety* (C_4)*, and style* (C_5) *are considered by the buyer. This example is examined by three different data set. In the following, the results obtained from different methods are compared based on all of these examples.*

Example 1.1. *In this example, the buyer presented pairwise comparison vectors according to Table 3. This example considers a condition in which the comparison system is fully consistent. Having this example in mind, the results of the comparison of different methods are demonstrated in Table 4. Table 4 shows the results, all methods present the same results, considering Example* 1.1 *data. In this example, TD is in the best possible condition* (*zero*) *for all methods.*

Example 1.2. *It was observed in Example* 1.1 *that all methods produced the same results. Although complete consistency is always favorable, in the real world, some inconsistency normally exists in primary data, which is inevitable. Hence, comparing the methods is more challenging when there are some inconsistencies in the data set. In Example* 1.2*, the comparison system is not fully consistent. In this example, the buyer presented pairwise comparison vectors based on Table 5. As can be seen in Table 6, by employing different methods, different weights are obtained for criteria. The quantities of TD are now analyzed to evaluate the effects. The results reveal that, among all models, the least TD belongs to GPBWM II models in a way that the NGPBWM II, compared to other nonlinear models such as the BWM and NGPBWM I, presented better results. Also, the LGPBWM II presented the best results compared to other linear models, including the LBWM and LGPBWM I. The NGPBWM II having TD* = 0.0589 *demonstrates the minimum deviation of preferences of DMs among all models.*

Example 1.3. *In Example* 1.3*, the inconsistency value is considered slightly more than in Example* 1.2*. In this example, the buyer presented pairwise comparison vectors based on Table 7. Considering the data of this example, the results of the comparison of different methods are shown in Table 8. As can be observed, in this example, like the previous one, the GPBWM II models presented the minimum TD. The NGPBWM II, compared to other nonlinear models such as the BWM and NGPBWM I, produced better results. Moreover, the LGPBWM II presented the best results compared to other linear models, including the LBWM and LGPBWM I. The LGPBWM II having TD* = 3.3047 *demonstrates the minimum deviation of preferences of DM among all models.*

Example 2. *In this section, the numerical example presented by Amiri and Emamat (2020) is taken into account. This example is also concerned with a car purchase, however, in this example, eight criteria such as quality* (C_1)*, price* (C_2)*, comfort* (C_3)*, safety* (C_4)*, style* (C_5)*, speed* (C_6)*, fuel consumption* (C_7)*, and after-sale service* (C_8) *are considered. There are multiple best criteria in this example. That is, both quality* (C_1) *and price* (C_2) *are evalu-*

Table 3
Pairwise comparison vectors: Example1.1.

Best criterion	Worst criterion	Quality	Price	Comfort	Safety	Style
Price		2	1	4	2	8
	Style	4	8	2	4	1

Table 4
Comparison of the results of different models: Example1.1.

Criteria	Original BWM		GPBWM I		GPBWM II	
	BWM	LBWM	NGPBWM I	LGPBWM I	NGPBWM II	LGPBWM II
Quality	0.2105	0.2105	0.2105	0.2105	0.2105	0.2105
Price	0.4211	0.4211	0.4211	0.4211	0.4211	0.4211
Comfort	0.1053	0.1053	0.1053	0.1053	0.1053	0.1053
Safety	0.2105	0.2105	0.2105	0.2105	0.2105	0.2105
Style	0.0526	0.0526	0.0526	0.0526	0.0526	0.0526
TD	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 5
Pairwise comparison vectors: Example1.2.

Best criterion	Worst criterion	Quality	Price	Comfort	Safety	Style
Price		2	1	4	3	8
	Style	4	8	2	3	1

ated as the best criteria by the buyer. In other words, these two criteria have the same preference for the buyer. According to Rezaei (2015), when there are multiple best (worst) criteria in the problem, one of them should be selected arbitrarily. In this example, quality (C_1) is considered as the best criterion and after-sale service (C_8) as the worst criterion. Here, the comparison system is not fully consistent, and pairwise comparison vectors are presented in Table 9. Table 10 shows the weights obtained from different models. The examination of the TD achieved from the results of the models demonstrates that, in this example, the GPBWM II models also produced the best results.

The NGPBWM II, compared to other nonlinear models, including the BWM and NGPBWM I yielded better results. Furthermore, the LGPBWM II, compared to other linear models such as the LBWM and LGPBWM I, presented a better TD. In this example, the minimum amount of TD is calculated to be 0.9534 for the NGPBWM II.

Fig. 2 depicts the comparison of individual models based on TD. The examination of all examples revealed that the results obtained from two models NGPBWM II and LGPBWM I, considering TD criterion, presented more accurate results compared to earlier models.

Table 6
Comparison of results of different models: Example1.2.

Criteria	Original BWM		GPBWM I		GPBWM II	
	BWM	LBWM	NGPBWM I	LGPBWM I	NGPBWM II	LGPBWM II
Quality	0.2258	0.2295	0.2264	0.2264	0.2244	0.2254
Price	0.4516	0.4481	0.4528	0.4528	0.4487	0.4507
Comfort	0.1089	0.1148	0.1132	0.1132	0.1122	0.1127
Safety	0.1582	0.1530	0.1509	0.1509	0.1586	0.1549
Style	0.0554	0.0546	0.0566	0.0566	0.0561	0.0563
TD	0.0917	0.1464	0.1111	0.1111	0.0589	0.0708

Table 7
Pairwise comparison vectors: Example1.3.

Best criterion	Worst criterion	Quality	Price	Comfort	Safety	Style
Price		2	1	4	3	8
	Style	4	8	4	2	1

Table 8
Comparison of the results of different models: Example1.3.

Criteria	Original BWM		GPBWM I		GPBWM II	
	BWM	LBWM	NGPBWM I	LGPBWM I	NGPBWM II	LGPBWM II
Quality	0.2278	0.2462	0.2264	0.2264	0.2122	0.2198
Price	0.4557	0.4308	0.4528	0.4528	0.4244	0.4396
Comfort	0.1519	0.1231	0.1132	0.1132	0.1688	0.1392
Safety	0.1139	0.1538	0.1509	0.1509	0.1415	0.1465
Style	0.0506	0.0462	0.0566	0.0566	0.0531	0.0549
TD	4.3125	7.4636	4.4444	4.4444	3.3209	3.3047

Table 9
Pairwise comparison vectors: Example 2.

Best criterion	Worst criterion	Quality	Price	Comfort	Safety	Style	Speed	Fuel consumption	After sale service
Price		1	1	3	3	2	3	2	6
	Style	6	6	2	3	4	2	3	1

Table 10
Comparison of the results of different models: Example 2.

Criteria	Original BWM		GPBWM I		GPBWM II	
	BWM	LBWM	NGPBWM I	LGPBWM I	NGPBWM II	LGPBWM II
Quality	0.2318	0.2308	0.2308	0.2400	0.2289	0.2338
Price	0.1994	0.2308	0.2308	0.2400	0.2289	0.2338
Comfort	0.0882	0.0839	0.0769	0.0800	0.0763	0.0779
Safety	0.0912	0.0839	0.0769	0.0800	0.0844	0.0779
Style	0.1411	0.1259	0.1538	0.1200	0.1526	0.1429
Speed	0.0882	0.0839	0.0769	0.0800	0.0763	0.0779
Fuel consumption	0.1241	0.1259	0.1154	0.1200	0.1145	0.1169
After sale service	0.0359	0.0350	0.0385	0.0400	0.0382	0.0390
TD	1.9076	2.1459	1.2547	2.0000	0.9534	1.2433

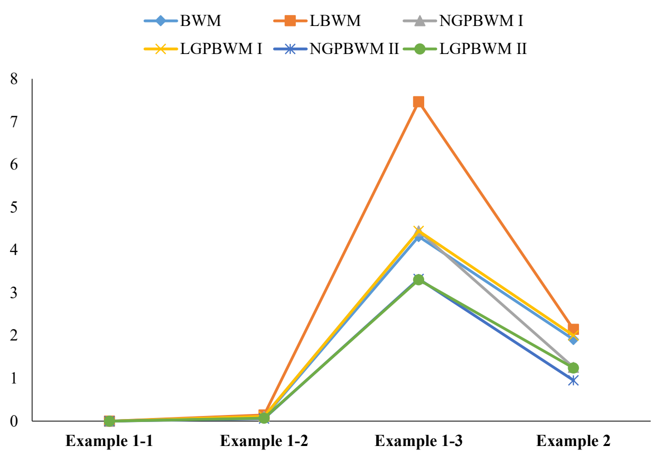

Fig. 2. Comparison of individual models based on TD.

Table 11
Pairwise comparison vectors: Example 1.

Decision makers	Best criterion	Worst criterion	C_1	C_2	C_3	C_4
D_1	C_1	–	1	2	9	3
	–	C_3	9	4	1	2
D_2	C_1	–	1	2	8	2
	–	C_3	8	4	1	2

Table 12
Comparison of the results of different models: Example 1.

Criteria	M1	M2	NGPBWM II	LGPBWM II
C_1	0.5280	0.5120	0.5225	0.5091
C_2	0.2220	0.2460	0.2463	0.2400
C_3	0.0650	0.0630	0.0616	0.0600
C_4	0.1850	0.1790	0.1696	0.1908
TD	3.9367	2.9848	2.8420	3.8728

Table 13
Pairwise comparison vectors: Example 2.

Decision makers	Best criterion	Worst criterion	C_1	C_2	C_3	C_4
D_1	C_1	–	1	2	9	3
	–	C_3	9	4	1	2
D_2	C_1	–	1	2	8	4
	–	C_3	8	4	1	2
D_3	C_1	–	1	2	8	4
	–	C_3	8	3	1	2

Table 14
Comparison of the results of different models: Example 2.

Criteria	M1	M2	NGPBWM II	LGPBWM II
C_1	0.5510	0.5530	0.5470	0.5378
C_2	0.2270	0.2260	0.2379	0.2508
C_3	0.0650	0.0660	0.0660	0.0649
C_4	0.1570	0.1550	0.1491	0.1466
TD	3.2925	3.1754	2.4860	2.3873
WTD	1.0943	1.0358	0.8173	0.8190

4.2. Numerical examples for group decision-making

The suggested group decision-making structure is implemented in this section. And in the last step of this framework, the NGPBWM II and LGPBWM II models are used. The results eventually are compared to the models suggested by Safarzadeh et al. (2018). Thus, four examples presented by Safarzadeh et al. (2018) are taken into account, and after solving each model and obtaining the weights of criteria, TD is calculated and considered as a criterion of comparison of the models.

Example 1. *In this example, two experts intending to evaluate four criteria (C_1, C_2, C_3, C_4) are considered. Both experts determined C_1 as the best and C_3 as the worst criterion. In this example, the weight of experts is considered the same ($w^1 = w^2 = 0.5$). Table 11 shows the pairwise comparison for both experts. After solving the models, the weights of criteria were achieved according to Table 12. As can be seen, the minimum TD belongs to the NGPBWM II.*

Example 2. *In this example, four criteria (C_1, C_2, C_3, C_4) are measured by three experts. Similar to the previous example, C_1 is determined as the best and C_3 as the worst criterion. In this example, the weights of experts are $w^1 = w^2 = 0.3$ and $w^3 = 0.4$. A pairwise comparison for three experts is demonstrated in Table 13. After solving the models, the weights of criteria were obtained as depicted in Table 14. In this example, in addition to TD, weighted total deviation (WTD) was also calculated, since the experts' weights are different in this example. Therefore, it is required to allocate more weight to*

Table 15
Pairwise comparison vectors: Example 3.

Decision makers	Best criterion	Worst criterion	C_1	C_2	C_3	C_4	C_5
D_1	C_1	–	1	2	9	4	2
	–	C_3	9	4	1	2	4
D_2	C_1	–	1	2	8	4	2
	–	C_3	8	4	1	2	4
D_3	C_1	–	1	2	8	4	3
	–	C_3	8	3	1	2	4
D_4	C_1	–	1	2	9	4	2
	–	C_3	9	5	1	3	3

Table 16
Comparison of the results of different models: Example 3.

Criteria	M1	M2	NGPBWM II	LGPBWM II
C_1	0.4211	0.4211	0.4386	0.4311
C_2	0.2105	0.2105	0.2035	0.2140
C_3	0.0526	0.0526	0.0517	0.0523
C_4	0.1053	0.1053	0.1097	0.1078
C_5	0.2105	0.2105	0.1966	0.1948
TD	7.0000	7.0000	5.4436	5.7080

deviations of experts having more weights. Generally, WTD can be calculated according to Eq. (20). But this Eq. is normally used in PC-based methods. To be more consistent with the BWM, Eq. (21) was utilized. As observed in Table 14, TD and WTD of GPBWM II models are less than M1 and M2 models. Also, considering WTD, the NGPBWM II yielded more accurate results compared to all models.

$$WTD = \sum_i \sum_{\substack{j \\ j\neq i}} \sum_k w^k \left(b_{ij}^k - \frac{w_i}{w_j}\right)^2 \tag{20}$$

$$WTD = \sum_k \sum_j w^k \left(\left(b_{Bj}^k - \frac{w_B}{w_j}\right)^2 + \left(b_{jW}^k - \frac{w_j}{w_W}\right)^2\right) - \sum_k w^k \left(b_{BW}^k - \frac{w_B}{w_W}\right)^2 \tag{21}$$

Example 3. *In this example, five criteria (C_1, C_2, C_3, C_4, C_5) are evaluated by four experts. In this example, the weights of experts are considered the same, and similar to the previous example, C_1 was selected as the best and C_3 as the worst criterion. Pairwise comparison for four experts is shown in Table 15. Table 16 demonstrates the weights of criteria obtained from different models. As can be seen in Table16, TDs of the GPBWM II models are less than M1 and M2 models. And the NGPBWM II produced the best results compared to other models.*

Example 4. *In this example, five criteria are assessed by ten experts. In this example, similar to the previous example, the importance of experts is considered the same, and C_1 was determined as the best and C_3 as the worst criterion. A pairwise comparison for ten experts is depicted in Table 17. After solving the models, weights of criteria were achieved according to Table 18. As can be observed, the TD of the GPBWM II is less than M1 and M2 models, and the minimum TD belongs to the NGPBWM II.*

Fig. 3 represents the comparison of the GPBWM II models with M1 and M2 models. As can be seen, considering all examples, the NGPBWM II model has achieved the best TD value.

In the present study, a total of eight numerical examples were selected from Rezaei (2016), Amiri and Emamat (2020), and Safarzadeh et al. (2018), four of which were for individual decision-making, and four were for group decision-making. In this research, TD, and WTD were used as criteria of comparison for the results obtained from the models. Considering all the numerical examples, the NGPBWM II produced impressive results in a way that, in all of these examples, this model had a better performance compared to previous models and was more consistent with DM's preferences than other methods. In addition to the remarkable performance of the NGPBWM II, the LGPBWM II presented a better performance in 7 out of 8 examples compared to earlier models which demonstrated the acceptable accuracy of this linear model. If the results obtained from the NGPBWM II and LGPBWM II are compared, it is revealed that the NGPBWM II had a better performance in seven examples compared to the LGPBWM II. Also, in Example 1.3, where the LGPBWM II performed better than the NGPBWM II, the difference was extremely trivial. Therefore, considering all the achieved results, it can be stated that the NGPBWM II has produced the best results.

Table 17
Pairwise comparison vectors: Example 4.

Decision makers	Best criterion	Worst criterion	C_1	C_2	C_3	C_4	C_5
D_1	C_1	–	1	2	9	4	2
	–	C_3	9	4	1	2	4
D_2	C_1	–	1	2	8	4	2
	–	C_3	8	4	1	2	4
D_3	C_1	–	1	2	8	4	3
	–	C_3	8	3	1	2	4
D_4	C_1	–	1	2	9	4	2
	–	C_3	9	5	1	3	3
D_5	C_1	–	1	3	8	4	2
	–	C_3	8	5	1	3	3
D_6	C_1	–	1	2	8	4	2
	–	C_3	8	4	1	3	3
D_7	C_1	–	1	2	8	4	2
	–	C_3	8	4	1	2	3
D_8	C_1	–	1	2	8	4	2
	–	C_3	8	4	1	3	2
D_9	C_1	–	1	2	9	4	2
	–	C_3	9	5	1	2	3
D_{10}	C_1	–	1	2	9	4	2
	–	C_3	9	4	1	3	3

Table 18
Comparison of the results of different models: Example 4.

Criteria	M1	M2	NGPBWM II	LGPBWM II
C_1	0.4283	0.4737	0.4427	0.4334
C_2	0.2240	0.2105	0.2194	0.2148
C_3	0.0502	0.0526	0.0528	0.0517
C_4	0.1236	0.1053	0.1107	0.1083
C_5	0.1738	0.1579	0.1745	0.1918
TD	20.0431	31.6250	17.6353	18.4909

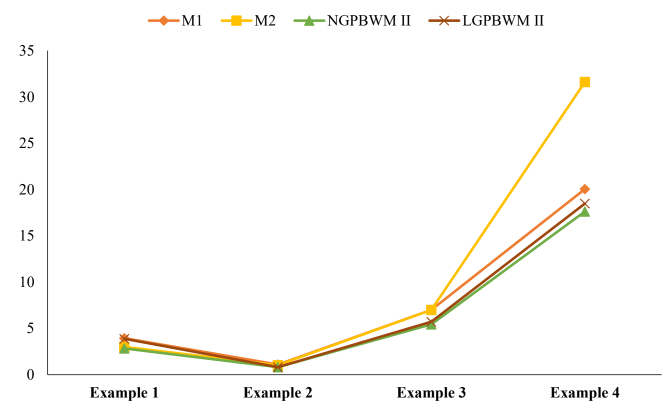

Fig. 3. Comparison of group models based on TD.

Table 19
Different instances for analyzing DMs' weights.

Instance number	w^1	w^2
1	0	1
2	0.1	0.9
3	0.2	0.8
4	0.3	0.7
5	0.4	0.6
6	0.5	0.5
7	0.6	0.4
8	0.7	0.3
9	0.8	0.2
10	0.9	0.1
11	1	0

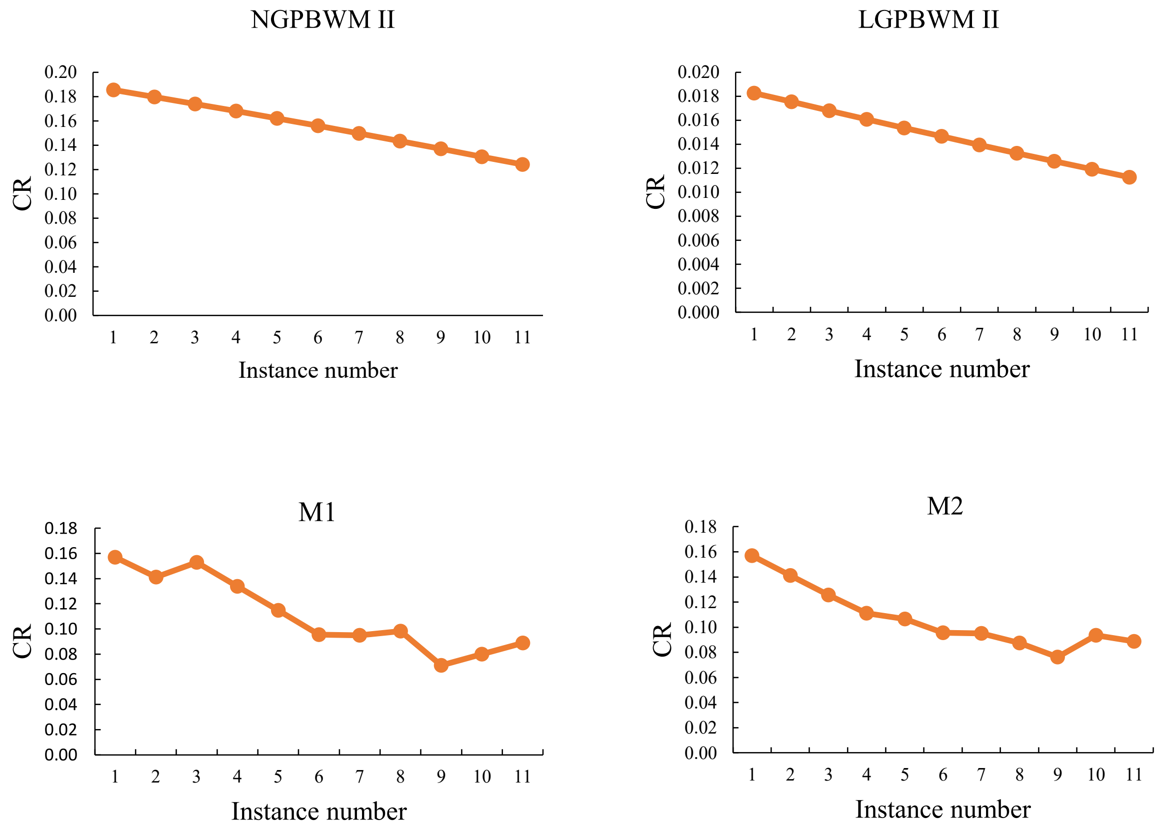

Fig. 4. The effect of DMs' weight change on the CR.

4.3. Sensitivity analysis

The weights of DMs, or, in other words, the DMs' level of expertise play a significant role in the results. In this section, considering different weights for the DMs, the results are evaluated. Example 1 was used to carry out sensitivity analysis. In this analysis, the effect of DMs' weight change is examined on the results of four methods, including the NGPBWM II, LGPBWM II, M1, and M2. To perform sensitivity analysis, first, eleven instances based on Example 1 as depicted in Table 19 are introduced.

Then, four models are solved for each instance, and the consistency ratio of each model was obtained. Fig. 4 represents the impact of DMs' weight change on the CR. Eq. (17) is used to determine the consistency ratio of each expert, the first expert equals 0.1111 and the second one is calculated at 0.1429. Moreover, the CR obtained for the first and eleventh instance confirms in all models that the CR of the first expert is better than the second one since in the first instance, the first expert's weight is 0 and the second expert's weight is 1. Also, in instance 11, the weight of the first expert is 1 and the weight of the second one is 0. Consequently, the first instance demonstrates the results of the second expert, and the eleventh instance shows the results of the first expert.

According to Fig. 4, it can be stated that group NGPBWM II and LGPBWM II models, compared to M1 and M2, are more sensitive to DMs' weight change, and their CR has changed in line with DMs' weight change. Among all models, M1 shows the maximum fluctuations, and instances 3, 8, 9, and 10 demonstrate the change in the direction of the Figure in this model. Although the CR of M2 is more stable than that of M1, the maximum stability of the CR is seen in the NGPBWM II and LGPBWM II models. In these two models, the amounts of CR for all instances have constantly changed from high CR (the source of which is the second DM) to low CR (the source of which is the first DM), and the change in direction or fluctuation is not seen in the Figure. In the next section, a case study is presented for better understanding and more clarification regarding the use of the GBWM in real-world problems.

5. A real case study

In the present segment, a case study is conducted on blockchain usability in the SC. Blockchain utilizes cryptography to provide security in transactions. Despite banking systems having a certain place and being centralized, the data center in which there are blockchains, are totally decentralized and distributed around the world. Therefore, in addition to being secure, blockchain is usable worldwide. Hence, active big enterprises in the world seek to implement blockchain in their SC. In line with this, a case study is carried out on the SC of an automotive company in Iran. This company produces and assembles cars in Iran and the Middle-East countries and collaborates in partnership with various countries. It also undertakes logistics operations such as raw material transportation, storage, process, transportation, fleet management, navigation of transportation vehicles, and product lifecycle management in different cities. This company is one of the pioneers of research and development and possesses advanced infrastructures in the field of Information Technology. Because this SC is formed in collaboration with several multinational companies, the implementation of blockchain is essential to increase cooperation, coordination, improve transactions, share information, and track the various components of the SC. Therefore, the effective criteria in the implementation of blockchain in the automotive SC are identified and these criteria are evaluated by a novel group BWM approach.

5.1. Identification of criteria

In the present study, first, a list of the most important criteria used by the researchers was identified, considering the literature on the blockchain. Then, the identified criteria were evaluated and confirmed by the decision-making team. In this study, questionnaires were distributed to

Table 20
Criteria for selecting the blockchain technology in the SC.

Code	Criterion	Description	Reference
C_1	Easy data sharing and collaboration	Blockchain programs tend to be capable of collaboration and creating a space in which different blockchains communicate easily. The capability of easy information sharing is necessary for all blockchain and collaboration networks.	Ar et al. (2020), Casino, Dasaklis, and Patsakis (2019), Dujak and Sajter (2019), Lu (2018)
C_2	Demand response	Blockchain technology solves accountability, data transparency, and tracking problems. Data and demand response, especially for smart contracts, are paramount.	Ar et al. (2020), Casino et al. (2019), Dujak and Sajter (2019), Hofmann, Strewe, and Bosia (2018), Kamble et al. (2020)
C_3	traceability and visibility	Blockchain traceability leads to decentralization, lack of tracking and authentication. Gaining information about the flow of products from the primary source to the end consumer is possible by applying blockchain technology, and this criterion is vital for planning in SC.	Ar et al. (2020), Casino et al. (2019), Dujak and Sajter (2019), Hastig and Sodhi (2020), Makhdoom, Abolhasan, Abbas, and Ni (2019), Saberi et al. (2019)
C_4	Level of trust and correct transactions	Correct transmit of transactions between business partners in the blockchain system is possible. Trust is necessary among the users who make transactions in a secure method through the infrastructures of the blockchain.	Ar et al. (2020), Makhdoom et al. (2019)
C_5	Factor of safety	Since the data is collected as blockchain payments, blockchain must have a high degree of protection. Security and safety are necessary for blockchain transactions as confirmed exchanges.	Ar et al. (2020), Reyna, Martín, Chen, Soler, and Díaz (2018), Saberi et al. (2019)
C_6	Privacy protection	Blockchain can decrease privacy. Since financial information is saved in the blockchain and might be seen by users, privacy protection is vital.	Ar et al. (2020), Casino et al. (2019), Dujak and Sajter (2019), Kamble et al. (2020)
C_7	Open access	Blockchain may be open to anyone or a small number of users, based on the type of knowledge. This free access to information in the SC will have a lot of advantages, including making the operation easier, reducing the number of direct contacts, and giving the final user more knowledge.	Dujak and Sajter (2019)

the experts in the automotive industry to weight criteria and rank them. Purposive (judgmental) sampling was utilized to select the experts since the judgments of the experts directly contribute to the results of the study, and expert selection is one of the basic steps of the present study. Therefore, a decision-making team of eight members, including the CEO, R&D manager, IT manager, financial manager, logistics manager, and academic experts in IT, computer engineering, and SC was organized. The experts in the decision-making team had more than seven years of experience in the logistics and automotive industry SC and were knowledgeable of the blockchain and its functions in the SC. Furthermore, they were given numerous explanations on the opportunities, features, drawbacks, limits, and benefits of implementing blockchain in the SC. Eventually, a set of seven criteria was identified and confirmed by the decision-making team, presented in Table 20.

Table 21
Importance and role of DMs.

Decision makers	Role	w^k
D_1	CEO	0.22
D_2	R&D manager	0.19
D_3	IT manager	0.15
D_4	Financial manager	0.12
D_5	Logistics manager	0.10
D_6	Academic expert in IT	0.08
D_7	Academic expert in computer engineering	0.07
D_8	Academic expert in SC	0.06

5.2. Weighting the criteria

At this stage, the weight of the DM is first estimated. The weights of the DMs are determined by the senior DM. A weight-based on Table 21 is assigned to each participant by their level of expertise.

To begin, every expert determined which criteria were the best and worst in their opinion. Then, using the numbers 1 to 9 on the questionnaire, they determined the best criterion's preference over all other criteria, followed by the preferences of others over the worst criterion. Table 22 represents the best and worst criteria of each expert and the value of preferences determined by the experts. It should be mentioned that the consistency ratio of each expert's questionnaire is also obtained by Eq. (17) and reported in Table 22. The closer the amount is to zero, the better. The reported CRs in this problem does not show high values and are acceptable.

Now, reference the best criterion and reference the worst criterion need to be determined so that in the next stages, the obtained results could be aggregated. Table 23 depicts the utility of criteria for selecting the best (worst) criterion for all the criteria of the problem.

According to Table 23, C5 has the highest utility among all criteria to be selected as the reference best criterion. Also, C_7 has the highest utility among all criteria to be selected as the reference worst criterion. Then, reference BO and OV vectors need to be determined for each expert, using Eqs. (13) and (14). In Table 24, the best and worst criteria for all DMs are unified, and preferences are updated accordingly. By these transformations, it is possible to aggregate preferences of DMs by Eqs. (15) and (16). The results of the aggregation of DMs' preferences are demonstrated in Table 25.

Based on the data in Table 25, the NGPBWM II is applied to calculate the importance of the criteria. The ultimate weights of the criteria are shown in Table 26.

In Fig. 5, the findings of calculating the weight of the criteria using the proposed novel group method are plotted.

5.3. Results and discussion

Coordination and traceability, knowledge sharing and coordination, data management, the trust between SC members, decentralization, and the ability to work globally have all been facilitated using blockchain for payment systems, particularly for major automotive companies around the world. There has been relatively little study into the use of blockchain in the automotive SC so far. The researchers proposed a novel group approach to test the requirements for using blockchain in the Iranian automotive SC as a case study to close this research gap. Experts used different criteria as the best and worst criteria. The importance of the criteria could not be determined using the group methods described

Table 22
Pairwise comparison vectors.

Decision makers	Best criterion	Worst criterion	C_1	C_2	C_3	C_4	C_5	C_6	C_7	CR^k
D_1	C_5	–	4	3	2	2	1	4	7	0.0476
	–	C_7	2	3	4	4	8	2	1	
D_2	C_5	–	3	2	4	2	1	5	8	0.0357
	–	C_7	3	5	2	4	9	2	1	
D_3	C_5	–	2	2	6	2	1	4	9	0.0417
	–	C_7	5	6	2	6	8	3	1	
D_4	C_3	–	4	4	1	3	2	3	9	0.0972
	–	C_7	4	3	9	2	6	5	1	
D_5	C_6	–	2	3	2	4	2	1	7	0.0714
	–	C_7	4	3	5	2	4	8	1	
D_6	C_3	–	2	5	1	3	3	6	9	0.0833
	–	C_7	6	3	9	5	4	2	1	
D_7	C_6	–	2	4	2	9	2	1	4	0.0972
	–	C_4	5	4	7	1	6	8	3	
D_8	C_5	–	4	3	5	8	1	2	3	0.0714
	–	C_4	3	4	2	1	8	5	4	

Table 23
Utility of criteria for selecting the best (worst) criterion.

U(Cp)		U(C_V)	
U(C_1)	0	U(C_1)	0
U(C_2)	0	U(C_2)	0
U(C_3)	0.2	U(C_3)	0
U(C_4)	0	U(C_4)	0.14
U(C_5)	0.63	U(C_5)	0
U(C_6)	0.17	U(C_6)	0
U(C_7)	0	U(C_7)	0.86
U(C_8)	0	U(C_8)	0

in the literature. As a result, the weight of the criteria was measured using the novelty developed group BWM. The results of the weighting of the criteria revealed that the most significant criteria were a factor of safety, Demand response, and traceability and visibility, respectively. According to the findings, increasing safety in financial transactions between business partners around the world in the automotive SC is very significant. Accountability, data transparency, and tracking are also critical for smart contracts between partners and levels of the SC, leading to increased coordination and collaboration. Blockchain traceability leads to decentralization, tracking, authentication, and increases data accuracy in the automated SC. Safe exchanges, transparency, and accuracy of data to satisfy the needs and the ability to track and determine the source of each operation provide a significant role in the development of blockchain in the automotive SC.

5.3.1. Management implications

The results of this study help the managers to successfully implement blockchain technology in the automotive SC. According to the results of this study, to properly implement blockchain technology in the SC, it is

Table 26
The weight and ranking of criteria.

Criteria	Weight of criteria	Ranking of criteria
C_1	0.1399	4
C_2	0.1541	2
C_3	0.1530	3
C_4	0.1268	5
C_5	0.2647	1
C_6	0.1135	6
C_7	0.0480	7

Table 24
Reference BO and OV vectors for each DM.

Decision makers	Best criterion	Worst criterion	C_1	C_2	C_3	C_4	C_5	C_6	C_7
D_1	C_5	–	4	3	2	2	1	4	7
	–	C_7	2	3	4	4	8	2	1
D_2	C_5	–	3	2	4	2	1	5	8
	–	C_7	3	5	2	4	9	2	1
D_3	C_5	–	2	2	6	2	1	4	9
	–	C_7	5	6	2	6	8	3	1
D_4	C_5	–	2	2	0.5	1.5	1	1.5	4.5
	–	C_7	4	3	9	2	6	5	1
D_5	C_5	–	1	1.5	1	2	1	0.5	3.5
	–	C_7	4	3	5	2	4	8	1
D_6	C_5	–	0.6667	1.6667	0.3333	1	1	2	3
	–	C_7	6	3	9	5	4	2	1
D_7	C_5	–	1	2	1	4.5	1	0.5	2
	–	C_7	1.6667	1.3333	2.3333	0.3333	2	2.6667	1
D_8	C_5	–	4	3	5	8	1	2	3
	–	C_7	0.75	1	0.5	0.25	2	1.25	1

Table 25
Aggregated BO and OV vectors.

Reference best criterion	Reference worst criterion	C_1	C_2	C_3	C_4	C_5	C_6	C_7
C_5	–	2.1204	2.1306	1.8407	2.0880	1	2.3317	5.2639
–	C_7	2.9138	3.2090	3.1860	2.6073	5.7060	2.6847	1

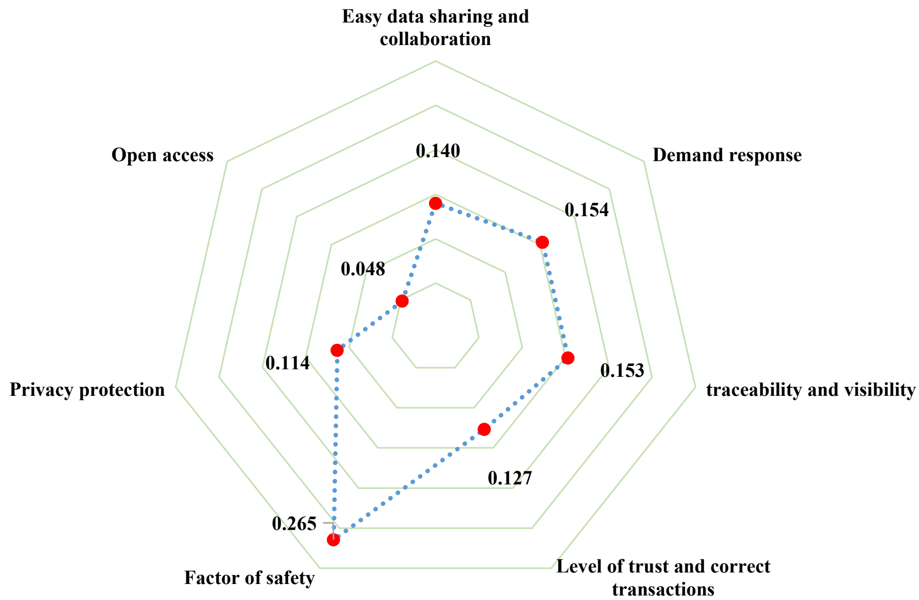

Fig. 5. The findings of calculating the weight of the criteria.

necessary to consider the factor of safety in financial transactions and information exchange at different levels of the SC. By increasing safety in SC while successfully implementing blockchain technology, the ability to manipulate information and malicious attacks on the system is minimized and provides accurate data access for decision making. On the other hand, financial transactions are done with accuracy and transparency, and cooperation and coordination in SC are improved. Also, according to the demand response criterion, information on customer demands can be shared at different levels of the SC with the help of blockchain technology. Therefore, coordination and cooperation in the SC of the automobile can be improved and help meet market demand. Research and development activities at SC automotive are also accelerated by access to customer information. On the other hand, according to the traceability and visibility criteria, while observing and tracking orders at different levels of the car SC, it is possible to complete and produce orders on time and minimize delays in order estimation. By implementing traceability and visibility, the production process can be monitored at each stage, and if a problem is seen at any stage, it can be fixed quickly, which will advance the overall performance of the automotive SC. Therefore, the use of blockchain in the automotive industry leads to improved efficiency, coordination, cooperation, information sharing, and cost reduction. By eliminating centralization, cooperation with automotive companies around the world is provided and the growth and development of this industry increase. So, the implementation of blockchain will cause a great revolution in the automotive industry.

6. Conclusions

Nowadays, globalization and the emergence of new technologies and various human behaviors in the networks of SC have highlighted the necessity of exploiting modern technologies more than ever. The use of advanced technologies such as blockchain contributes to the improvement of the models of SC and logistics management operations in the domains of trust, transparency and accountability, collaboration, information sharing, financial transactions, and SC integrity. Blockchain uses cryptography to provide security in transactions. Despite banking systems having a certain place and being centralized, the data center in which there are blockchains, are decentralized and distributed all over the world. Therefore, in addition to being secure, blockchain is usable worldwide. Hence, active big enterprises in the world seek to implement blockchain in their SC. However, the use of blockchain in the SC to evaluate selection criteria and application of the blockchain in real cases using the MCDM is observed in a handful of papers, and regarding the importance of blockchain technology, this domain requires serious attention. Thus, in the present manuscript, in addition to identifying criteria for selecting and adopting blockchain technology in automotive SC, these criteria are weighted.

Furthermore, in this study, two NGPBWM II and LGPBWM II models were developed for individual decision-making. Plus, a new approach was proposed to facilitate the participation of DMs in the decision-making process and to solve group decision-making problems. This approach allowed DMs to consider different best and worst criteria, and there was no need for all DMs to adopt the same best and worst criteria. The mechanism of the proposed group method operated in a way that, first, it aggregated the opinions of the DMs, then, it calculated the weights of criteria using each individual model. The suggested individual models in this study had fewer constraints compared to the BWM. Therefore, computational complexities decreased in the proposed methods. Moreover, in the previous group BWM methods, as the number of DMs increased, the number of constraints increased as well, while in the proposed group model of this study, since the experts' opinions were combined prior to solving the model, the final model had far fewer complexities and involved fewer calculations. To examine the efficiency of the findings obtained from the proposed methods and to explain how a decision analyst can utilize the proposed methods, a comprehensive numerical study including eight examples was presented. With regard to the results achieved from this study and the high accuracy of the NGPBWM II, it was recommended that the opinions of DMs were first combined, using the proposed GBWM method in this research, for group decision-making problems. And eventually, the final weights of criteria were calculated by the NGPBWM II. Therefore, considering the high accuracy of the proposed GBWM method, this approach was applied in a real case in the domain of using blockchain in the automotive SC. The results of weighting the criteria showed that the factor of safety, demand response, traceability, and visibility were introduced as the most important criteria, respectively. The results of blockchain implementation in the automotive industry can improve efficiency, coordination, cooperation, information sharing, and cost reduction, which eliminates decentralization and provides a basis for cooperation with automotive companies around the world, and the growth and development of this industry.

6.1. Limitations and future research directions

According to the lack of complete information in real-world problems and also qualitative judgments of pairwise comparisons in BWM, there are uncertainties in comparisons (Mohtashami, 2021). One of the limitations of the proposed model is that pairwise comparisons in this model are based on crisp values. One important development on BWM based methods is to deal with fuzzy data (Wang et al., 2021). This study can be a basis for future developments to address uncertainty in expert judgment. The development of proposed methods in this study, in fuzzy, gray, and intuitive fuzzy decision-making space, is proposed by authors for future research. This study was conducted to present a new application of blockchain technology in automobile SC. However, there are still new areas for the utilization of blockchain technology in SC and logistics, which can be used to help develop this technology in various fields. Identifying and evaluating strategies to address the implementation of blockchain technology barriers in SC was outside the scope of the present study and will be suggested for future research. Also, the identified criteria in this study were appropriate to the field of automotive SC, and researchers can identify and evaluate more comprehensive criteria in new industrial areas and other SCs in future research. How to implement blockchain technology in logistics operations in different SCs was not investigated in this study, which researchers can investigate in future studies.

Declaration of Competing Interest

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

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