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A fuzzy BWM and MARCOS integrated framework with Heronian function for evaluating cryptocurrency exchanges: a case study of Türkiye

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Abstract

Crypto assets have become increasingly popular in recent years due to their many advantages, such as low transaction costs and investment opportunities. The performance of crypto exchanges is an essential factor in developing crypto assets. Therefore, it is necessary to take adequate measures regarding the reliability, speed, user-friendliness, regulation, and supervision of crypto exchanges. However, each measure to be taken creates extra costs for businesses. Studies are needed to determine the factors that most affect the performance of crypto exchanges. This study develops an integrated framework, i.e., fuzzy best–worst method with the Heronian function—the fuzzy measurement of alternatives and ranking according to compromise solution with the Heronian function (FBWM'H–FMARCOS'H), to evaluate cryptocurrency exchanges. In this framework, the fuzzy best–worst method (FBWM) is used to decide the criteria's importance, fuzzy measurement of alternatives and ranking according to compromise solution (FMARCOS) is used to prioritize the alternatives, and the Heronian function is used to aggregate the results. Integrating a modified FBWM and FMARCOS with Heronian functions is particularly appealing for group decision-making under vagueness. Through case studies, some well-known cryptocurrency exchanges operating in Türkiye are assessed based on seven critical factors in the cryptocurrency exchange evaluation process. The main contribution of this study is generating new priority strategies to increase the performance of crypto exchanges with a novel decision-making methodology. "Perception of security," "reputation," and "commission rate" are found as the foremost factors in choosing an appropriate cryptocurrency exchange for investment. Further, the best score is achieved by Coinbase, followed by Binance. The solidity and flexibility of the methodology are also supported by sensitivity and comparative analyses. The findings may pave the way for investors to take appropriate actions without incurring high costs.

Keywords: Cryptocurrency, Cryptocurrency platform, Cryptocurrency exchange selection, Investment decisions, MCDM, Fuzzy sets

Introduction

Cryptocurrency, which means crypto money, was coined by combining the words "crypto" and "currency." Cryptocurrencies refer to digital money that does not physically exist. These coins are also referred to as virtual currencies. As can be understood from its definition, the foremost feature of cryptocurrencies is an encryption system (Nakamoto 2008). In this way, transactions can be made more reliably. Unlike currencies in the classical sense, a central authority does not issue cryptocurrencies (Blasco et al. 2022). With this feature, cryptocurrencies have attracted the attention of investors considerably. Bitcoin, Ethereum, Cardano, and Tether are among the most popular types of cryptocurrencies (Aspris et al. 2021).

Cryptocurrencies have several advantages. First, they are not affiliated with any country's central bank. Therefore, it is not affected by the negativities experienced in a country's economy (Gu et al. 2022). Flexibility is one of the advantages associated with cryptocurrencies. It is straightforward to own cryptocurrencies and make transactions between countries with these currencies. Transactions with cryptocurrencies can be concluded within a short time (Ma and Tanizaki 2022). In particular, the rapid transfer of money allows businesses to experience some financial conveniences (Brauneis et al. 2022). According to Böyükaslan and Ecer (2021), one of the most crucial advantages of cryptocurrencies is that they are safe. Due to the password system used, cryptocurrency is much more secure than ordinary electronic transactions (Böyükaslan and Ecer 2021).

Cryptocurrency exchanges are platforms people use to buy, sell, and store their crypto assets. Binance, FTX, Coinbase, and other cryptocurrency exchanges try to attract customers to use their platforms. These platforms make money through trading fees (commissions), margin borrow interests, futures trading, etc. (Faghih Mohammadi Jalali and Heidari 2020). Moreover, crypto exchanges do not require an intermediary institution (Zulfiqar and Gulzar 2021). This situation is an essential difference between cryptocurrency exchanges. Hence, cryptocurrency exchanges play a vital role in increasing the use of cryptocurrencies. In summary, when these exchanges operate effectively, they can increase the use of cryptocurrencies (Fang et al. 2022).

To ensure security in transactions, cryptocurrencies use various mathematical codes and encryption protocols (Narayanan et al. 2016; Ecer et al. 2022). These protocols can hide the identities of cryptocurrency users, thus preventing other organizations from accessing user information (Liu et al. 2022a). As soon as cryptocurrencies became involved in financial transactions, radical changes occurred in the financial sector (Davison et al. 2022). However, it may take time for society to trust such novel financial instruments (Shahzad et al. 2018; Arias-Oliva et al. 2019). Currently, there is a lack of reliable research that can guide investors. Although there is no obstacle to ordinary customers using cryptocurrency exchanges, they are concerned about the reliable exchange to choose when trading. This issue has been neglected in studies on cryptocurrency exchanges. Therefore, this study has the potential to meet a need in the cryptocurrency exchange domain, which would contribute to society's adoption of the decentralized digitalization age.

Although the technical and financial aspects of cryptocurrencies have been studied by many papers, performance measuring of cryptocurrency exchanges is overlooked in the literature (Böyükaslan and Ecer 2021). Thus, practical and robust analysis techniques are needed to determine the most essential drivers affecting the performance of cryptocurrency exchanges. The foremost reason is that the stock exchanges depend on numerous factors that can cause high financial costs (Cui and Maghyereh 2022). There is a need for a mathematical tool that can comprehensively and reliably measure the performance of cryptocurrency exchanges. Many factors may affect the performance of these exchanges, and it is significant to identify the most critical issues. This situation helps to provide specific strategies to improve the performance of these exchanges efficiently.

This study aims to fill this gap in the relevant field and support society and investors in evaluating cryptocurrency exchanges. To prioritize the critical factors and evaluate cryptocurrency exchanges, we develop a decision support mechanism based on two multi-criteria decision-making (MCDM) approaches and an aggregation operator. First, the factors that affect the performance of cryptocurrency exchanges are prioritized using the fuzzy best–worst method with the Heronian function (FBWM'H). Second, the fuzzy measurement of alternatives and ranking according to compromise solution with the Heronian function (FMARCOS'H) is used to rank alternatives. The approach offered is a recommender tool and a decision support mechanism for cryptocurrency traders, customers, and investors to decide on a proper cryptocurrency exchange. Furthermore, the introduced framework would help investors in choosing a cryptocurrency exchange for trading, allow them to make essential considerations in their exchange selection decisions, and broaden researchers' perspectives on cryptocurrency exchanges. Once the data change, the proposed framework may suggest a different cryptocurrency exchange for traders, meaning that the framework has an innovative and updatable decision support mechanism. The following research questions are answered:

1. Which factors should you consider when selecting the most proper cryptocurrency exchange?
2. Which factor is more crucial in the selection process?
3. Which cryptocurrency exchange is preferable for investment and trading?
4. What factors should be focused on to increase the performance of crypto exchanges?

Motivations of the study

The following issues summarize the fundamental motivations for conducting this study.

1. Today, investing in cryptocurrencies is attracting increasing interest. Investors desire to trust their preferred cryptocurrency exchanges. Thus, evaluating cryptocurrency exchanges is a critical issue but, unfortunately, has been neglected in the literature.
2. Investors face many difficulties when deciding on the factors they should consider when selecting a cryptocurrency exchange. Therefore, clarifying the factors that can be used in assessing such exchanges is necessary.
3. Due to the vagueness and uncertainty of expressions and associated factors (criteria) in the decision-making process, experts usually have difficulty expressing their judgments and experiences with crisp numbers. The fuzzy set area allows us to convert vagueness and ambiguity in linguistic variables to numbers so that we can cope with uncertainty better. Therefore, there is a need for a mathematical tool that can numer-

ically express the opinions and judgments of decision-makers for solving real-world problems.

4. Heronian functions help handle multi-criteria problems as they reveal interactions between attributes. However, traditional functions cannot eliminate the influence of awkward data. Hence, there is a need to extend the Heronian function in the fuzzy context.

Contributions of this study

The primary aim of the study is to determine the factors used in evaluating cryptocurrency exchanges and measure the performance of these exchanges. To achieve this goal, a decision support tool is developed to assist investors, scholars, and others, revealing another critical research aim. The present study contributes to financial management and decision science in the following ways:

1. A detailed factors list that affects the performance of cryptocurrency exchanges is generated.
2. The most influential factors for improving the performance of cryptocurrency exchanges are determined. Thus, it would help in creating effective and efficient strategies.
3. A fresh decision-making frame is introduced by improving the FBWM and FMARCOS methods with the Heronian operator for addressing investment decisions and other financial issues.
4. The factor weight values are decided through FBWM, and alternatives are ranked with FMARCOS. The framework introduced performs the fuzzy Heronian operator to aggregate experts' judgments, making it more effective, and satisfactory.
5. For another critical scientific contribution, this study offers a measurement system for recommending a suitable cryptocurrency exchange for society, investors, and traders.
6. Cryptocurrencies and cryptocurrency exchanges are new financial instruments offered by Industry 4.0. In summary, this study would contribute to and support society's adoption of the digitalization era.

Novelties of the research

Evaluation of cryptocurrency exchanges is an MCDM problem based on many conflicting criteria. The best–worst method (BWM) is an easy-to-understand but effective subjective weighting method that allows comparison of the most and least preferred criteria with other criteria. It helps to obtain more consistent results; thus, it is suitable for this study. Although measurement of alternatives and ranking according to compromise solution (MARCOS) is in its infancy, it has gained the appreciation of many researchers, who have used it in many fields in a short time due to its ease to use and producing effective results. However, crisp MCDM methods are insufficient in the analysis as qualitative criteria are included in the evaluation process. Difficult problems can be solved because of the fuzzy extension MCDM methods developed based on the potential of fuzzy logic to incorporate human thoughts and ideas into an analysis. Using this approach, fuzzy extensions of both BWM and MARCOS have been developed in the literature (Hashemkhani Zolfani et al. 2022; Ecer and Pamucar 2021; Stankovic et al. 2020).

Aggregation operators or functions can eliminate some of the disadvantages of MCDM methods and thus contribute to more practical and effective usage of these methods. Recently, the use of the Einstein function (Rani and Mishra 2021), the Dombi function (Yaran Ögel et al. 2022), the Hamacher function (Faizi et al. 2021), the Bonferroni function (Böyükaslan and Ecer 2021), and the Heronian function (Kayapinar Kaya et al. 2022) with various MCDM methods have received increasing attention. One of the significant criticisms of FBWM and FMARCOS is that they neglect the interrelationships and interplay between attributes. To reveal the interactions among various attributes, decision-making methods need a rational tool. The fuzzy Heronian operator allows aggregation based on the relationships between objects, thus eliminating an essential shortcoming of BWM and MARCOS. Therefore, this study integrates BWM, and MARCOS methodologies modified with fuzzy Heronian function, i.e., FBWM'H-FMARCOS'H, to incorporate the ambiguities, and uncertainties of decision-makers' judgments on assessing criteria and alternatives. The fuzzy Heronian function is employed after the criterion weights are found with FBWM, and it is performed in the analysis of the FMARCOS model to aggregate elements of the fuzzy weighted-normalized matrix. Thus, the proposed methodology can deal with the interrelationships between the drivers and eliminate the influence of awkward data. To clarify the feasibility of the proposed model, five cryptocurrency exchanges (two international and three Turkish) are analyzed. To the best of the authors' knowledge, no research has combined the fuzzy Heronian function with the BWM and MARCOS methods simultaneously. Similarly, the present study is the first to use fuzzy MCDM models to assess cryptocurrency exchanges.

Crypto exchanges are digital asset exchanges that allow users to buy and sell crypto assets. The performance of crypto exchanges affects the liquidity and prices of crypto assets. Crypto exchanges enable users to buy and sell crypto assets and thus determine the demand and supply of crypto assets. Therefore, crypto exchanges should offer a reliable, fast, and user-friendly platform. This increases users' trust in these exchanges, contributing to an increase in the liquidity of crypto assets. Therefore, it is necessary to take adequate measures regarding the reliability, speed, user-friendliness, regulation, and supervision of crypto exchanges. However, taking each measure creates extra costs for businesses. Because of this, for countries to take necessary actions efficiently, the more important factors should be identified. In this study, a priority analysis is conducted for the indicators of crypto exchanges. The analysis results pave the way for investors to implement appropriate actions without incurring high costs.

Structure of the research

The next section presents a detailed literature review on the topic and the methods used. Next, the research methodology is introduced in "Method and data" Section. Afterward, the application, and results are presented in "Evaluation of cryptocurrency exchanges through the proposed methodology" section. The findings are reinforced with discussion and implications in "Discussion" section. Finally, a conclusion is presented, which includes a general assessment, future studies, and limitations.

Literature review

To evaluate cryptocurrency exchanges, we perform FBWM, and FMARCOS methodologies with a fuzzy Heronian function. This part of the paper summarizes studies that discuss cryptocurrency exchanges, and studies related to the approaches performed in this work are mentioned.

Factors influencing the performance of cryptocurrency exchanges

As predicted, there are relevant studies on the effectiveness of cryptocurrency exchanges. Some of these works focused on how to improve the performance of cryptocurrency exchanges.

Security is one of the most emphasized issues in this regard. According to Mensi et al. (2021), it is a vital issue that affects investors' decisions. Ensuring technological and financial security in crypto transactions makes these exchanges more preferred. Financial investors prefer to complete their transactions securely (Floros 2020). If a platform is unsafe, the exchange will lose its competitiveness significantly (Arslanian 2022). Therefore, necessary measures must be put in place to increase security on an exchange platform. The security of the technological infrastructure of an exchange is a prominent issue in this process. Taking necessary precautions against hacking attacks will increase investors' confidence (Gomzin 2022). However, it is essential to take necessary precautions against personnel-based mistakes (Xu et al. 2019; Chaganti et al. 2022). Having a double confirmation mechanism in transactions will contribute significantly to solving such problems. Aysan et al. (2021) evaluated crypto exchanges, discussing that security is a critical issue in improving the performance of these exchanges. Similarly, Fantazzini and Calabrese (2021) focused on the relationship between crypto exchanges and credit risks. They concluded that necessary precautions should be taken against hacking attacks to increase investors' confidence. When analyzing cryptocurrency exchanges, Suga et al. (2020), Takahashi and Lakhani (2019), and Johnson et al. (2018) discussed security issues for cryptocurrency exchanges.

The *popularity* of crypto exchanges is also another consideration for performance improvement. Investors prefer the most popular cryptocurrency exchanges (Shibano and Mogi 2022). The fact that there are many exchanges where crypto transactions can be made leads to an increase in competition (Trigka et al. 2022). Thus, investors may also be undecided in their choice of crypto exchange. It is possible to discuss some factors that affect investors' decisions (Bouraga 2021). The popularity of crypto exchanges is also one of the considerations in this process (Kim 2020). The increasing popularity of crypto exchanges increases investors' confidence (Kethineni and Cao 2020). Increased reliability also contributes to the competitiveness of stock markets (de Azevedo Sousa et al. 2021), and it is much easier to improve the performance of stock markets that investors prefer. Zafar et al. (2021) investigated the key indicators of an effective blockchain system, finding that the popularity of crypto exchanges plays a key role. Rahouti et al. (2018) also stated that increasing popularity has a powerful impact on the performance of crypto exchanges.

The user-friendliness of a platform is another element that can increase the performance of crypto exchanges. Investors want to buy or sell very quickly on these exchanges. Therefore, the platform should be easy to use (Fratrič et al. 2022). For crypto exchanges to be highly competitive, they must be preferred by many investors (Kou et al. 2021; Jain et al. 2022; Desai et al. 2021). Thus, the exchange must be easy for investors who are elderly or have a low level of education (Jørgensen and Beck 2022). Many investors will be lost on a platform developed only for young people or those with a high level of education (Suratkar et al. 2020). Hence, to increase the performance of crypto exchanges, it is crucial to create exchanges that are easy to use for different customer groups (Dupuis and Gleason 2020). Knewtson and Rosenbaum (2020) tried to evaluate the fintech industry. They found that crypto exchanges should be user-friendly. Moreover, Lacity (2020) also revealed that the different expectations of various investors should be considered when designing currency exchange platforms.

Transaction costs or commission rates are another vital issue in improving the performance of crypto exchanges. Here, the cost of using an exchange is essential. Investors buy crypto products to make a profit (Shahab and Allam 2020). The profit margin of investors will decrease significantly if the cost of trading on these exchanges is high (Scheid et al. 2019). Therefore, the fees for transactions made on a platform must be reasonable (Marchesi et al. 2020). Considering the increasing number of exchanges where crypto transactions are carried out (Osmani et al. 2020; Kou et al. 2022a), exchanges will lose some customers if transaction costs are high (Krause and Tolaymat 2018), which will make them lose their competitive advantage significantly. Dyhrberg et al. (2018) evaluated BTC markets and argued that transaction costs have to be fair to attract investors. Jabbar and Dani (2020) focused on the BTC market and concluded that transaction fees on currency exchange platforms must be reasonable.

In some studies, it has been emphasized that the *volume* issue in crypto transactions is effective in the performance of these indices. Li and Wang (2017) utilized trading volume for their analysis. Bianchi et al. (2022) and Milunovich and Lee (2022) stated that the high daily trading volumes of these products attract the attention of investors. According to Gu et al. (2022) and Chan et al. (2022), this also helps increase the performance of crypto exchanges. Here, the *diversity of cryptocurrencies* is essential. Having many financial products attracts the attention of more investors. Crypto exchanges can increase their trading volumes through different and innovative financial products (Tan et al. 2022). Hence, the performance of the stock markets can be improved more successfully (Ronaghi 2022). Crypto exchanges must prioritize offering more products to improve their performance compared with that of their competitors. The *number of registered users* is another issue in increasing the performance of cryptocurrency exchanges as more users will lead to more transactions. Thus, a dramatic increase in cryptocurrency exchange users will lead to a considerable increase in the trading volumes of exchanges (Chelladurai and Pandian 2022). This will also improve performance (Lu et al. 2022).

After a detailed state-of-art review, we identify seven criteria (Table 1) and determine their significance levels. We also focus on five cryptocurrency exchanges—Binance, Coinbase, BTCTurk, Paribu, and Bitexen—and conduct their performance rankings.

Table 1 Evaluation criteria for crypto exchanges and their explanations

Criteria	Description	Source
Perception of security (C1)	It means how secure the exchange is concerning the decision-makers	Kolb et al. (2020), Davison et al. (2022), Mashatan et al. (2022), Kou et al. (2022b)
Reputation (C2)	It refers to how reputable and well-known the exchange is regarding the decision-makers	Sebate and Puente (2003)
User-friendliness (C3)	It refers to having a website and a mobile application that is easy to use	Liu et al. (2021), Davison et al. (2022), Namahoot and Rattanawiboonsom (2022),
Commission rates (C4)	It means a commission rate taken from the transactions while buying, selling, sending, and withdrawing money and crypto assets	Pérez-Solà et al. (2019), Davison et al. (2022), Liu et al. (2021), Ajienka et al. (2020)
Number of cryptocurrencies (C5)	It refers to the number of cryptocurrencies allowed to be bought and sold within the exchange	Casino et al. (2019), Davison et al. (2022), Swan (2015)
Number of registered users (C6)	It means the number of registered users using the exchange for their transactions	Liu et al. (2022b)
24-h trading volume (C7)	It refers to daily cryptocurrency trading volume in USD	Davison et al. (2022), Bouri et al. (2019)

Studies on FBWM and FMARCOS

BWM has gained the attention of researchers since its introduction by Rezaei (2015). To handle uncertainty and vagueness more practically, its uncertain extensions have been used by researchers worldwide in a variety of studies with various purposes, such as supplier selection (Amiri et al. 2021) and the ship recycling process (Soner et al. 2022). Xu et al. (2021) studied initial water rights in a river basin. Guo and Zhao (2017) introduced an improved BWM with fuzzy sets. Khan et al. (2021) and Moslem et al. (2020) evaluated driver behavior factors related to road safety. Amiri et al. (2021) solved a sustainable supplier selection problem. Soner et al. (2022) assessed several ecological effects of the ship recycling process. Rowshan et al. (2020) identified factors for outsourcing in public hospitals. Kumar et al. (2022) solved a flowline problem.

Although MARCOS is relatively new in the MCDM field, it has become a preferred method in challenging works. Its advantages over the other MCDM methods and its usability with different approaches make it an ideal tool (Büyüközkan et al. 2021). To cope with uncertain and imprecise data, MARCOS has been extended with fuzzy information. For instance, organizational structure selection for hospitals was examined by Khosravi et al. (2022). Stankovic et al. (2020) considered a road traffic risk analysis. Puška et al. (2021) proposed a sustainable supplier selection. Büyüközkan et al. (2021) determined a suitable digital transformation strategy for airlines. Tadić et al. (2022) focused on the sustainability assessment of city logistics initiative categories.

However, only a few scholars have integrated FBWM and FMARCOS models. For instance, Du et al. (2022) conducted a regional distribution network outage loss assessment.

Research gaps in the relevant literature

The literature review reveals that scholars have focused on crypto exchanges, especially in the last few years. They mainly focused on the critical determinants of the performance improvement of these systems. Only a few studies evaluated the main criteria that affect the performance of these platforms. Moreover, none considered human thought, judgment, and experience through fuzzy set theory or other uncertainty theories. Because of this, there is a need for a robust and practical evaluation tool that makes a priority analysis of these items and the ranking process of crypto exchanges. Through this, more effective strategies can be provided to crypto exchange platforms to improve their performance.

Further, as pointed out in the previous subsection, a limited number of studies have used the FBWM and FMARCOS approaches together. This study improves FBWM and FMARCOS models by integrating them with the fuzzy Heronian function. We apply FBWM'H (FBWM with Heronian) to weigh the decision-making criteria of experts' opinions. To compare alternatives of these criteria and derive the final ranking, we perform FMARCOS'H (FMARCOS with Heronian). To the best of the authors' knowledge, only one study evaluating cryptocurrency exchanges was studied by Davison et al. (2022). They compared cryptocurrency exchanges using the analytical hierarchy process. However, they considered neither uncertainty and imprecision nor the interactions between criteria. Hence, this study is also the first to use FBWM and FMARCOS approaches with the fuzzy Heronian function to evaluate alternative cryptocurrency exchanges. This study is unique in that it models the ambiguity in human judgments with the aid of fuzzy sets and uses the Heronian function to determine the interrelations between the evaluation criteria. This study would contribute to the literature and provide information about the effective decision-making process of cryptocurrency exchange selection to investors and researchers.

Method and data

In this study, we perform an improved FBWM and FMARCOS methodology based on the Heronian operator to rank cryptocurrency exchanges. BWM and MARCOS methods are new, effective, and reliable methods. BWM provides consistent results with very few pairwise comparisons. MARCOS can consider many criteria and alternatives in a decision problem and resist the rank reversal problem. Moreover, the Heronian function helps to make a more flexible decision by revealing the interactions between attributes. Therefore, the superiorities of BWM, MARCOS, Heronian function, and fuzzy set theory are unified in the proposed model to produce consistent results and solve challenging decision-making problems. First, in this section, fuzzy sets are briefly presented. FBWM'H and FMARCOS'H models are explained in Appendix 1.

Evaluation of cryptocurrency exchanges through the proposed methodology

In this work, FBWM, and FMARCOS integrated model improved with the fuzzy Heronian function is utilized to evaluate cryptocurrency exchanges. FBWM'H is employed to compute the relative weight coefficients of the cryptocurrency exchange

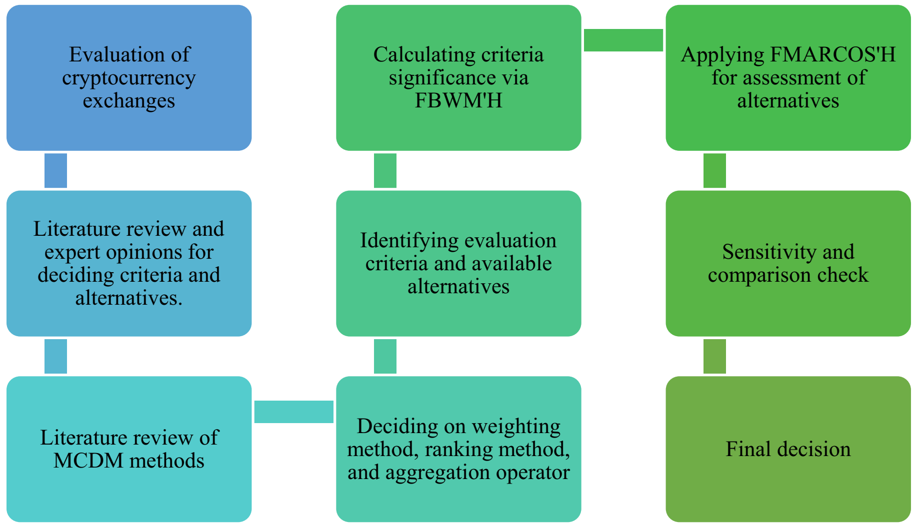


Fig. 1 Flowchart of the proposed framework

evaluation criteria, whereas FMARCOS'H is used to select the most promising cryptocurrency exchange. The methodology flowchart is depicted in Fig. 1.

This study involves six decision-makers as experts to assess the evaluation criteria and alternatives. The evaluation criteria belong to the benefit criteria, whereas the commission rate (C4) is a cost criterion. In Appendix 1, Table 8 is performed to evaluate the criteria, whereas Table 9 is considered to assess alternatives of each criterion.

The experts include a portfolio manager, two brokers working in a financial firm, a bank teller, and two academicians working in finance. Each expert has enough experience and knowledge of cryptocurrency investments. Furthermore, they have been investing in cryptocurrencies for at least three years and using multiple cryptocurrency exchanges for different cryptocurrency investments. This study is based on seven decision-making criteria and five alternative solutions. The decision-making criteria used were determined based on the relevant literature and experts' opinions.

Identifying a safe exchange is the first and critical stage in utilizing cryptocurrencies. Interestingly, over 34,000 cryptocurrency exchanges have active markets worldwide (Davison et al. 2022). However, only a few of these cryptocurrency platforms are familiar to the general community. Thus, five well-known cryptocurrency exchanges worldwide and in Türkiye are identified based on the factors considered in this study. The views of decision-makers (experts) were considered in selecting the alternative exchanges. Here, for a successful analysis, a decision-maker should know about all the cryptocurrency exchanges included in the evaluation. However, there is a limitation that an expert can only have an opinion on a certain number of cryptocurrency exchanges. Therefore, the current study analyzes five cryptocurrency exchanges selected for convenience—two are international cryptocurrency exchanges and the rest are Turkish cryptocurrency exchanges.

Binance (A1) is one of the first cryptocurrency exchanges that come to mind. It was launched in 2017, and after 180 days, it became the largest cryptocurrency exchange in the world (Binance 2022). It also provides spot and derivative trading, offering its customers crypto loans and various services. *Coinbase (A2)*, one of the world's first cryptocurrency exchanges, was founded in 2012. It has over 103 million users, and the exchange is used in over 100 countries with over 217B USD quarterly trading volume (Coinbase 2022). *BTCTurk (A3)* is the first cryptocurrency exchange in Türkiye and the fourth in the world, with over 4 million users (BTCTurk 2022). *Paribu (A4)*, founded in 2017, is another major cryptocurrency exchange in Türkiye. The company currently provides services to over 4.5 million users (Paribu 2022). *Bitexen (A5)* is another Turkish digital asset exchange that offers both spot and derivative trading, and the platform supports the trading of over 100 crypto assets (Bitexen 2022).

Table 2 presents the linguistic evaluations of the criteria analyzed by each expert. It also includes triangular fuzzy number (TFN) correspondences of linguistic variables. Table 3 presents the results of the calculations conducted using FBWM'H. The step-by-step calculations of the FBWM'H framework are presented in Appendix 2.

Table 2 Linguistic assessments of experts for criteria and their TFN correspondences

Expert	Best	C1	C2	C3	C4	C5	C6	C7
#1	C2	WI	EI	AI	WI	FI	FI	VI
#2	C1	EI	AI	AI	WI	FI	WI	WI
#3	C1	EI	VI	AI	WI	FI	FI	VI
#4	C1	EI	FI	VI	VI	FI	AI	VI
#5	C7	WI	WI	AI	FI	VI	AI	EI
#6	C2	WI	EI	FI	VI	AI	VI	AI
	Worst	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**
#1	C3	VI	AI	EI	VI	FI	FI	WI
#2	C2	AI	EI	WI	WI	WI	FI	VI
#3	C3	AI	WI	EI	AI	VI	FI	WI
#4	C6	AI	VI	WI	WI	VI	EI	VI
#5	C6	VI	VI	WI	FI	WI	EI	AI
#6	C7	AI	AI	VI	FI	WI	WI	EI
TFN correspondences for linguistic variables								
Expert	**Best**	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**
#1	C2	(0.67, 1, 1.5)	(1, 1, 1)	(3.5, 4, 4.5)	(0.67, 1, 1.5)	(1.5, 2, 2.5)	(1.5, 2, 2.5)	(2.5, 3, 3.5)
#2	C1	(1, 1, 1)	(3.5, 4, 4.5)	(3.5, 4, 4.5)	(0.67, 1, 1.5)	(1.5, 2, 2.5)	(0.67, 1, 1.5)	(0.67, 1, 1.5)
#3	C1	(1, 1, 1)	(2.5, 3, 3.5)	(3.5, 4, 4.5)	(0.67, 1, 1.5)	(1.5, 2, 2.5)	(1.5, 2, 2.5)	(2.5, 3, 3.5)
#4	C1	(1, 1, 1)	(1.5, 2, 2.5)	(2.5, 3, 3.5)	(2.5, 3, 3.5)	(1.5, 2, 2.5)	(3.5, 4, 4.5)	(2.5, 3, 3.5)
#5	C7	(0.67, 1, 1.5)	(0.67, 1, 1.5)	(3.5, 4, 4.5)	(1.5, 2, 2.5)	(2.5, 3, 3.5)	(3.5, 4, 4.5)	(1, 1, 1)
#6	C2	(0.67, 1, 1.5)	(1, 1, 1)	(1.5, 2, 2.5)	(2.5, 3, 3.5)	(3.5, 4, 4.5)	(2.5, 3, 3.5)	(3.5, 4, 4.5)
	Worst	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**
#1	C3	(2.5, 3, 3.5)	(3.5, 4, 4.5)	(1, 1, 1)	(2.5, 3, 3.5)	(1.5, 2, 2.5)	(1.5, 2, 2.5)	(0.67, 1, 1.5)
#2	C2	(3.5, 4, 4.5)	(1, 1, 1)	(0.67, 1, 1.5)	(0.67, 1, 1.5)	(0.67, 1, 1.5)	(1.5, 2, 2.5)	(2.5, 3, 3.5)
#3	C3	(3.5, 4, 4.5)	(0.67, 1, 1.5)	(1, 1, 1)	(3.5, 4, 4.5)	(2.5, 3, 3.5)	(1.5, 2, 2.5)	(0.67, 1, 1.5)
#4	C6	(3.5, 4, 4.5)	(2.5, 3, 3.5)	(0.67, 1, 1.5)	(0.67, 1, 1.5)	(2.5, 3, 3.5)	(1, 1, 1)	(2.5, 3, 3.5)
#5	C6	(2.5, 3, 3.5)	(2.5, 3, 3.5)	(0.67, 1, 1.5)	(1.5, 2, 2.5)	(0.67, 1, 1.5)	(1, 1, 1)	(3.5, 4, 4.5)
#6	C7	(3.5, 4, 4.5)	(3.5, 4, 4.5)	(2.5, 3, 3.5)	(1.5, 2, 2.5)	(0.67, 1, 1.5)	(0.67, 1, 1.5)	(1, 1, 1)

EI equally important, *WI* weakly important, *FI* fairly important, *VI* very important, *AI* absolutely important

Table 3 FBWM'H results and final fuzzy weights of criteria

	Ex#1	Ex#2	Ex#3	Ex#4
w1	(0.166, 0.173, 0.230)	(0.236, 0.280, 0.280)	(0.206, 0.249, 0.283)	(0.265, 0.265, 0.281)
w2	(0.222, 0.224, 0.255)	(0.070, 0.087, 0.087)	(0.072, 0.082, 0.097)	(0.122, 0.186, 0.186)
w3	(0.061, 0.061, 0.069)	(0.052, 0.058, 0.058)	(0.058, 0.058, 0.065)	(0.066, 0.081, 0.081)
w4	(0.194, 0.194, 0.230)	(0.122, 0.156, 0.162)	(0.203, 0.255, 0.286)	(0.065, 0.099, 0.127)
w5	(0.091, 0.132, 0.148)	(0.084, 0.100, 0.103)	(0.137, 0.155, 0.181)	(0.120, 0.210, 0.238)
w6	(0.091, 0.132, 0.163)	(0.122, 0.156, 0.162)	(0.096, 0.122, 0.136)	(0.055, 0.055, 0.061)
w7	(0.068, 0.079, 0.067)	(0.149, 0.192, 0.192)	(0.072, 0.082, 0.082)	(0.105, 0.121, 0.157)
	Ex#5	**Ex#6**	**Final weights with the Heronian function**	
w1	(0.162, 0.223, 0.223)	(0.220, 0.230, 0.265)	(0.203, 0.229, 0.253)	
w2	(0.195, 0.223, 0.223)	(0.276, 0.276, 0.308)	(0.161, 0.181, 0.194)	
w3	(0.051, 0.057, 0.069)	(0.149, 0.161, 0.192)	(0.073, 0.080, 0.090)	
w4	(0.087, 0.130, 0.148)	(0.078, 0.106, 0.130)	(0.124, 0.154, 0.178)	
w5	(0.064, 0.074, 0.091)	(0.062, 0.066, 0.085)	(0.092, 0.122, 0.140)	
w6	(0.058, 0.067, 0.069)	(0.078, 0.080, 0.094)	(0.079, 0.097, 0.109)	
w7	(0.220, 0.248, 0.248)	(0.062, 0.062, 0.071)	(0.110, 0.126, 0.132)	

Ex# denotes expert, while w denotes weight

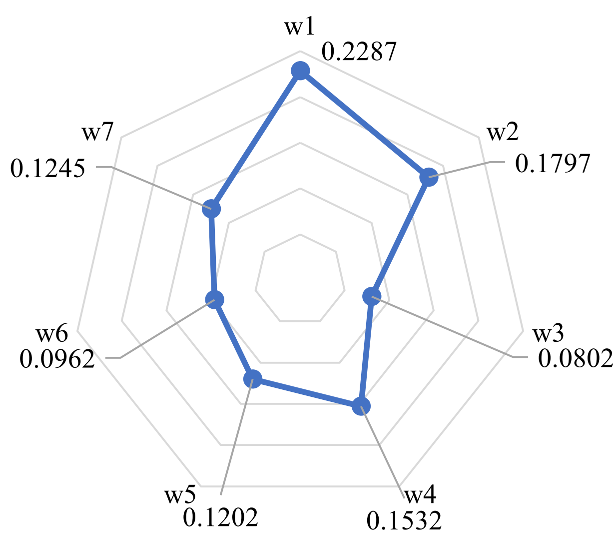


Fig. 2 Final weight values of criteria (Note: w's indicate criterion weight)

The consistency ratio for each pairwise comparison is less than 0.10, indicating that the obtained results are acceptable. The Heronian function is applied for the aggregation of fuzzy weight values. The crisp weights of seven criteria are depicted in Fig. 2. Moreover, graded mean integration representation is employed to transform the fuzzy weights of the criteria to exact weights.

Regarding the findings of the FBWM'H approach, perception of security (C1), recognition (C2), and commission rates (C4) are the most critical factors in deciding the most proper cryptocurrency exchanges.

Table 4 Experts' linguistic evaluation of alternatives to the criteria

	A1	A2	A3	A4	A5
C1	VG, VG, EG, G, EG, VG	MG, VG, G, M, MG, M	VG, VG, EG, G, EG, VG	M, MG, MG, MP, M, M	M, MG, M, MP, M, MP
C2	EG, EG, EG, VG, EG, VG	MG, EG, EG, MP, MP, M	EG, EG, EG, M, EG, VG	MP, M, MG, MP, MP, M	MP, M, M, MP, P, MP
C3	MP, VG, M, MG, G, MG	G, MG, EG, G, VG, G	VG, VG, G, G, VG, VG	G, MG, M, MG, G, G	MG, MG, M, M, G, G
C4	VG, EG, VG, G, VG, EG,	MG, G, MG, MP, MP, MP	P, M, MP, VP, VP, VP	MP, MG, MP, P, P, VP	MP, MG, G, MP, P, VP
C5	EG, EG, EG, VG, EG, EG	P, MP, M, M, P, P	G, G, G, MG, MG, G	MP, MP, MP, P, VP, P	VP, P, P, VP, EP, VP
C6	EG, EG, EG, VG, EG, VG	MP, M, M, MP, M, P	EG, VG, EG, G, EG, EG	MP, MP, MG, MP, MP, P	MP, P, P, VP, P, VP
C7	EG, EG, EG, VG, G, G	MP, MP, M, P, M, MP	G, VG, G, EG, VG, VG	MP, P, MP, P, P, MP	MP, P, P, P, VP, VP

EP extremely poor, *VP* very poor, *P* poor, *MP* medium poor, *M* medium, *MG* medium good, *G* good, *VG* very good, *EG* extremely good

Table 5 Results of the FMARCOS'H approach and final ranking of cryptocurrency exchanges

	Aggregated matrix			$\tilde{K}_i^-$			$\tilde{K}_i^+$			$\tilde{T}_i$		
A1	0.105	0.125	0.129	1.550	2.206	3.141	0.692	0.896	1.140	2.242	3.102	4.280
A2	0.065	0.085	0.092	0.957	1.502	2.250	0.427	0.610	0.817	1.384	2.112	3.067
A3	0.107	0.131	0.145	1.579	2.327	3.522	0.705	0.945	1.278	2.285	3.272	4.800
A4	0.057	0.074	0.092	0.842	1.312	2.227	0.376	0.533	0.808	1.218	1.844	3.035
A5	0.045	0.063	0.076	0.663	1.116	1.845	0.296	0.453	0.670	0.960	1.570	2.515
	$f\left(\tilde{K}_i^-\right)$			$f\left(\tilde{K}_i^+\right)$			K_i^-	K_i^+	$f(K_i^-)$	$f(K_i^+)$	K_i	Rank
A1	0.206	0.266	0.339	0.461	0.656	0.934	2.252	0.902	0.268	0.670	0.748	2
A2	0.127	0.181	0.243	0.285	0.447	0.669	1.536	0.614	0.183	0.457	0.323	3
A3	0.210	0.281	0.380	0.470	0.692	1.048	2.402	0.961	0.286	0.714	0.862	1
A4	0.112	0.158	0.240	0.250	0.390	0.662	1.386	0.552	0.164	0.412	0.258	4
A5	0.088	0.135	0.199	0.197	0.332	0.549	1.162	0.463	0.138	0.346	0.178	5

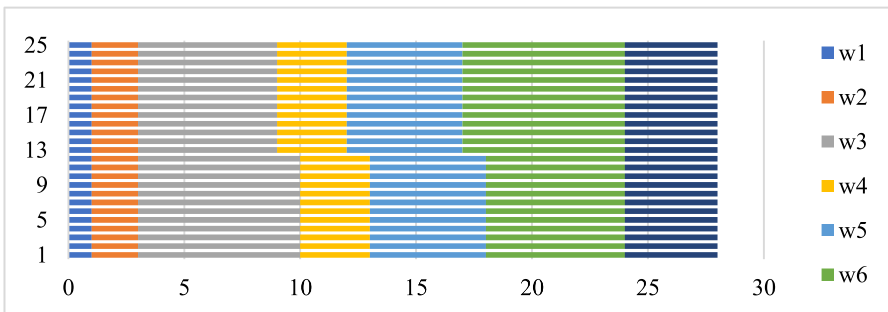
A1: Binance; A2: BTCTurk; A3: Coinbase; A4: Paribu; A5: Bitexen

In the second step of the analysis, FMARCOS'H is employed to rank the alternatives. After assessing the alternatives, the correspondence matrices of the experts are generated (Table 4).

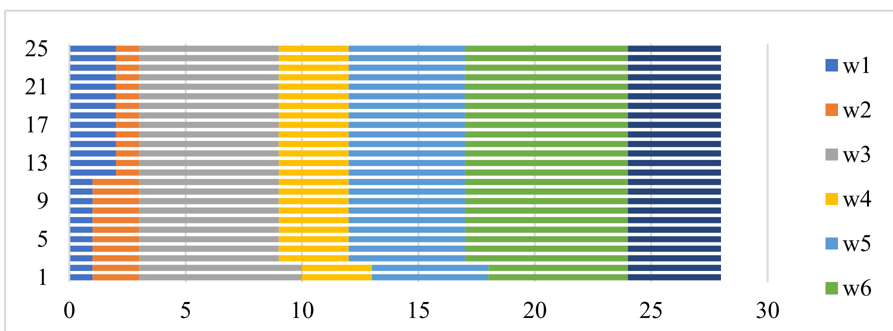
After determining the average performance ratings and reference values, fuzzy normalized decision matrix, and fuzzy weighted-normalized decision matrix, the aggregated matrix is constructed by aggregating the values of the fuzzy weighted-normalized decision matrix using the Heronian function [Eq. (9) in Appendix 1]. The summarized findings are presented in Table 5. The step-by-step calculations of the FMARCOS'H approach are presented in Appendix 3.

According to Table 5, the best cryptocurrency exchange is A3 (Coinbase), followed by A1 (Binance) and A2 (BTCTurk).

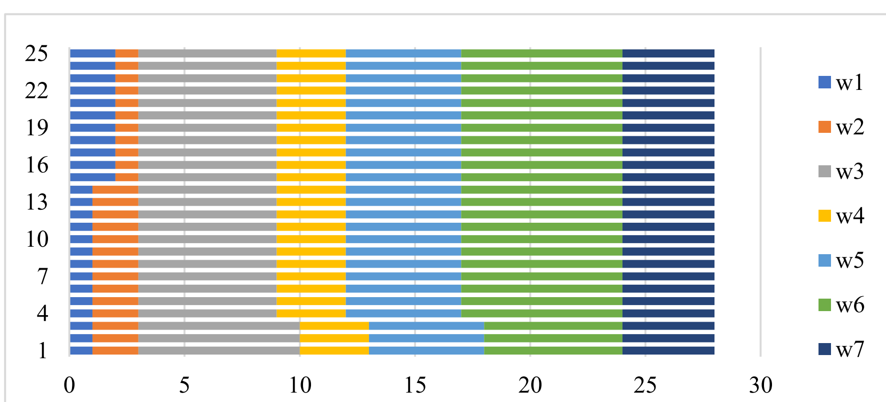
To check the stability and effectiveness of the proposed framework, sensitivity, and comparison analyses consisting of three stages are conducted. First, the effect of a change in the weighting coefficients of the criteria on the criteria ranking outcomes is analyzed. In the Heronian function, the effect of the alteration of p and q on the ranking outcomes is investigated. In this study, three experiments are conducted to achieve this goal. In the first experiment (Experiment 1), the effect of a change in q ($1 \leq q \leq 25$) on a change in the ranking orders of options while the value of p remains the same ($p = 1$) through all 25 scenarios is analyzed. In Experiment 2, q remained the same ($q = 1$) through all 25 scenarios, whereas the effect of the change of p ($1 \leq p \leq 25$) on the change of ranking orders of options is studied. In the last experiment (Experiment 3), the same value is assigned to the parameters p and q in all scenarios, i.e., $1 \leq p = q \leq 25$. As depicted in Fig. 3, the criteria ranking is steady, excluding a slight change in w1 and w2 in the first and third experiments as well as in w3 and w6 in the second experiment. Such an analysis demonstrates that p and q in the Heronian operator influence a change in the



a) $p = 1, 1 \leq q \leq 25$



b) $q = 1, 1 \leq p \leq 25$



c) $1 \leq p = q \leq 25$

Fig. 3 Impact of p and q values on a change in the criteria rankings (Note: w's indicate criterion weight)

Table 6 Rankings obtained after eliminating the worst alternative from the system

Alternative	Original rank	Scenario #1	Scenario #2	Scenario #3
A1	2	2	2	2
A2	3	3	3	Removed
A3	1	1	1	1
A4	4	4	Removed	Removed
A5	5	Removed	Removed	Removed

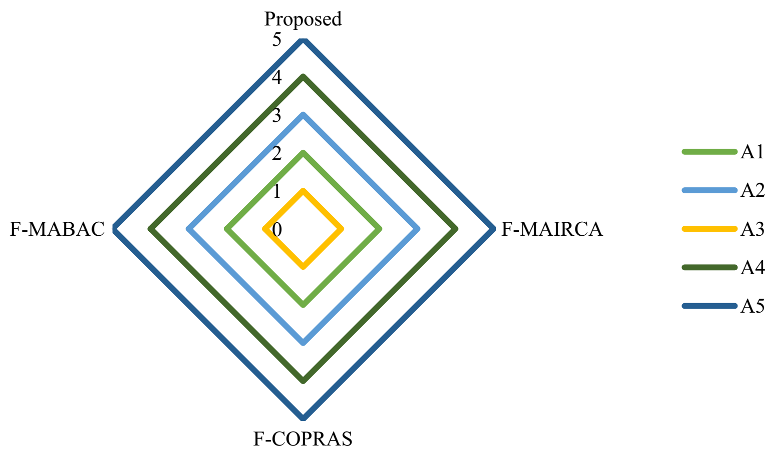


Fig. 4 Final rankings of alternatives using various fuzzy sets-based methodologies

criteria weights and thus criteria ranking, indicating that the framework is sensitive to parameter modifications.

The second stage of the sensitivity check—the rank reversal issue and a change in the alternatives' ranking order when there is an addition or subtraction of any alternative—is investigated. The ranking of cryptocurrency exchanges is A3 > A1 > A2 > A4 > A5. Thus, A5 is the worst alternative. When alternative A5 is eliminated, the rankings of the other alternatives would remain the same. Therefore, this is a novel decision matrix that removes the worst option in each scenario and continues till the last option remains. The newest rankings obtained in the current study are presented in Table 6. Based on Table 6, first, the worst option (A5) is excluded from the analysis. Then, the other options are ranked based on Scenario 1, and the worst option (A4) in the new ranking is removed. The analysis ends in Scenario 3. The ranking order of alternatives is stable, proving that the framework has no rank reversal problem.

In this study, we also conduct rank reversal analysis for the suggested framework by removing a random alternative, say A4, from the model.

Current ranking: A3 > A1 > A2 > A4 > A5.

Revised ranking (after removing A4 from the system): A3 > A1 > A2 > A5.

This result proves once again that the model proposed has no rank reversal problem.

Last, the solidity of the outcomes is compared with the outcomes of some well-known and strong fuzzy multi-criteria approaches, i.e., fuzzy multi-attributive ideal-real comparative analysis (F-MAIRCA), fuzzy complex proportional assessment (F-COPRAS),

Table 7 Comparison of suggested vs. other fuzzy-based models

	Proposed framework	F-MABAC	F-COPRAS	F-MAIRCA
Attributes interaction	Yes	No	No	No
Eliminating the influence of awkward data	Yes	No	No	No
Aggregation function structure	Nonlinear	Linear	Linear	Linear
Calculation time	Acceptable	Long	Short	Middle
Nature of criteria	Considered	Considered	Not considered	Considered
Flexibility in real-world problems	Yes	Partially	Partially	Partially
Creating reliable ranking	Fairly	Yes	Yes	Yes

and fuzzy multi-attributive border approximation area comparison (F-MABAC). The results of all approaches, including the proposed model, are the same. Put differently, A3 is the best alternative, followed by A1, A2, A4, and A5 (Fig. 4). Overall, the sensitivity control proves the robustness of the FBWM'H-FMARCOS'H framework and suggests that alternative A3 is trustworthy as a cryptocurrency exchange.

The sensitivity check reveals that the ranking results of cryptocurrency exchange found by the suggested methodology are consistent with other well-known fuzzy methodologies, such as F-MABAC, F-COPRAS, and F-MAIRCA. Among them, F-MABAC, and F-MAIRCA are models based on linear normalization, while F-COPRAS uses additive normalization. The fact that the proposed model yields the same ranking results as models with different structures emphasizes its flexibility and consistency. Table 7 presents various features of the suggested and existing approaches from the application perspective. The information aggregation functions of F-MABAC, F-COPRAS, and F-MAIRCA are linear, whereas a nonlinear aggregation function is used in the proposed model. The Heronian function in the suggested model allows considering interrelationships between initial matrix values; thus, flexible decision-making is realized. Other models do not have such a capability. However, using fuzzy sets increases the model's mathematical complexity. Applying the fuzzy set theory to other fuzzy models increases the mathematical processing load and complexity. Fortunately, the mathematical procedures of the proposed model do not influence its efficiency. These problems can be easily solved with user-friendly computer software and programs, which will shorten the processing time and reduce the mathematical complexity of the process.

Discussion

This study is distinct from other studies as it is a novel study to measure cryptocurrency exchange performance based on fuzzy MCDM methods and the Heronian function. It finds seven evaluation criteria based on experts' opinions and relevant studies on cryptocurrency investment exchange features. The criteria are the security perception, reputation, user-friendliness of the mobile application and the website, commission rates, number of cryptocurrencies that can be traded, number of registered users, and 24-h trading volume. Our analysis revealed that the most critical decision-making driver is the perception of security (C1: 0.2287), followed by the reputation of the exchange (C2: 0.1797) and commission rates (C4: 0.1532). Cryptocurrencies are highly volatile investment tools, so investors' consideration for a secure platform is not surprising. We focused on five cryptocurrency exchanges—Binance, Coinbase, BTCTurk Pro, Paribu, and Bitexen. Our findings indicate that Coinbase is the most preferred exchange, followed by Binance, and BTCTurk. Paribu and Bitexen are the least preferred exchanges.

In their study, Davison et al. (2022) examined six cryptocurrency exchange evaluation criteria (security perception, trading fee, user-friendliness, support services, number of tradable cryptocurrencies, and trading volume) and six alternative exchanges, including Binance, and Coinbase. They found that the perception of security is the foremost factor for selecting a cryptocurrency exchange, which is entirely consistent with our findings. They further emphasized that Binance and Coinbase are the best exchanges, which aligns with our results. Some authors have also addressed the security perception issues of these platforms (Kolb et al. 2020; Mashatan et al. 2022).

Consistent with our findings, some scholars have emphasized how vital the commission rate is in cryptocurrency investments. For instance, Pérez-Solà et al. (2019) argued that sometimes the transaction fee is higher than the output value. Liu et al. (2021) stated that intensity influences the commission rate. Ajienka et al. (2020) noted that a high commission fee keeps investors away from a platform. We found that a user-friendly exchange is essential for investors. Consistent with the current study, Namahoot and Rattanawiboonsom (2022) provided a strong correlation between traders' finding a cryptocurrency exchange user-friendly and having a proper perception of it. Further, Liu et al. (2021) emphasized that a user-friendly exchange will encourage users to create more new accounts. This study revealed the importance of the number of cryptocurrencies traded on a cryptocurrency exchange. Consistent with the study by Casino et al. (2019), we find that trading more cryptocurrencies on a cryptocurrency exchange can be perceived positively by investors. However, many cryptocurrencies also bring with them the problem of latency (Swan 2015). Further, Yli-Huumo et al. (2016) concluded that the attention paid to other factors than security and privacy was very limited. Undoubtedly, the number of cryptocurrencies traded and the number of users registered are also other crucial drivers for assessing a cryptocurrency exchange. It is a valuable contribution to the literature that these two factors are included in this study.

Security measures are of great importance in increasing the performance of crypto assets. Transactions with cryptocurrencies are protected by encryption. However, it is appropriate to take additional security measures to protect cryptocurrencies and other crypto assets (van der Linden and Shirazi 2023). Theft of users' accounts and fraud are the main security risks in cryptocurrency transactions (Çağlayan Aksoy 2023). In this framework, it is possible to increase the performance of crypto assets through security measures (Anderie 2023). Issues such as antivirus software and multi-factor authentication are essential measures to secure users' accounts (Appel 2023). In addition to these issues, a wallet's security is also very important for the effective storage of these assets (Olbrecht and Pieters 2023). In summary, increasing the value of crypto assets is easier by ensuring the security of users' accounts and wallets (Ghosh and Banerjee 2023). This will increase investors' confidence so that crypto assets would be preferred more.

Conclusion

This study conducts a cryptocurrency exchange performance evaluation of seven criteria with a new framework—an improved version of FBWM and FMARCOS—based on the Heronian function (FBWM'H-FMARCOS'H). To the best of the authors' knowledge, this integrated methodology has not been developed before, indicating the originality of the work. As most of the drivers considered in selecting cryptocurrency exchanges are qualitative, this fuzzy-based framework is invaluable for cryptocurrency investors when making decisions. While FBWM'H is used to rank the decision-making criteria, FMARCOS'H is employed to assess the five alternative solutions. Our analysis reveals that security perception is the foremost driver, while Coinbase, and Binance are the top cryptocurrency exchanges. This result is not surprising because of the high-security perceptions of these exchanges. Naturally, the primary concern of investors regarding financial instruments is the safety and security of their investments. Cryptocurrency investors are no exception to this fundamental concern. In fact, cryptocurrencies are highly volatile by their nature; thus, compared to other financial market investors, cryptocurrency investors might demand extra security. Therefore, it is recommended that crypto exchanges should pay more attention to security to prevent investors from encountering problems that have been frequently encountered in recent years such as hacking.

Ordinary customers worry about the cryptocurrency exchange they can reliably choose, which has been neglected by researchers. The fact that it has the potential to meet this critical need in the cryptocurrency domain emphasizes the significance of this study. Some key scientific contributions of the study are as follows: (1) the factors affecting the performance of cryptocurrency exchanges are clarified; (2) a fuzzy performance measurement tool is proposed to aid in choosing the cryptocurrency exchange to be used for cryptocurrency transactions; and (3) in the era of decentralized digitalization, society can be helped to adopt cryptocurrency. Further, the primary novelties of the study are as follows: (1) it allows investors to identify cryptocurrency exchanges where they can earn more and feel safe, and (2) it provides scholars and researchers with a trustworthy decision support mechanism. This study's observations are helpful in different ways for professionals from diverse backgrounds. Our results provide an essential starting point for academicians, decision-making guidance for financial experts and investors, and a focal point for policymakers. First, researchers may benefit from our findings when exploring the professional investors' decision-making process and factors that affect this process. Second, investors and those who want to invest can use our findings to choose the proper cryptocurrency exchange for their investment by focusing on the appropriate decision-making criteria, comparing different alternatives, and deciding on the ideal option. Third, policymakers may use our findings as guidance in policymaking for cryptocurrency exchanges as our findings reveal the most important factors, so policies regarding these factors can be prioritized.

As expected, this study has some limitations. First, the results are based on the opinion of six experts who have been investing in cryptocurrencies for at least three years and have used multiple cryptocurrency exchanges for their investments. Second, the analysis does not include other popular cryptocurrency exchanges such as Kraken because the platform was not popular among Turkish cryptocurrency investors at the time of this study. Thus, the findings of this study are limited to Turkish cryptocurrency investors. The results may change if the same analysis is applied in another country where different cryptocurrency exchanges are available. We believe our study opens a new path for future research. Our results provide helpful information to widen the research and apply it in different countries to see if the results would change with different investor profiles. In the future, cryptocurrency exchange selection can be made by adding new criteria or by using a different country sample. Researchers can operate the proposed framework to make other investment decisions. Further, the developed framework can be applied in various areas, such as energy, engineering, health, business, and agriculture.

Appendix 1

Fuzzy sets

Zadeh (1965) generated fuzzy sets for the purpose of solving practical real-life problems under uncertain environments. A fuzzy set (Ã) is a set whose elements hold a degree of membership function $\mu_{\tilde{A}}(x)$, where each (X) element is a real number. The membership function $\mu_{\tilde{A}}(x)$ represents the degree of the membership for every element in the set. A triangular fuzzy number (TFN) is $(\widetilde{A})=(l, m, u)$ a fuzzy set defined on the set of real numbers where l, m, and u represent the lower, modal, upper value of the membership function, respectively. The membership function of $(\widetilde{A})$ is formulated as Eq. (1).

$$\mu_{\tilde{A}}(x) = \begin{cases} 0, & x < l \\ \frac{x-l}{m-l}, & l \leq x < m \\ \frac{u-x}{u-m}, & m \leq x \leq u \\ 0, & x > u \end{cases} \tag{1}$$

For the evaluation of selected criteria, participating experts use linguistic terms to fill in the questionnaire, and later on, corresponding TFNs are performed in the analysis. Table 8 demonstrates the linguistic terms and corresponding TFNs.

Supposing $\tilde{A}_1\ (l_1, m_1, u_1)$ and $\tilde{A}_2\ (l_2, m_2, u_2)$ are two TFNs, calculation steps between the two are defined as follows.

Table 8 Linguistic evaluation scale for criteria (Ecer and Pamucar 2020)

Linguistic term	Value
Equally importance (EI)	(1, 1, 1)
Weakly important (WI)	(0.67, 1, 1.5)
Fairly important (FI)	(1.5, 2, 2.5)
Very important (VI)	(2.5, 3, 3.5)
Absolutely important (AI)	(3.5, 4, 4.5)

Addition:

$$\tilde{A}_1 + \tilde{A}_2 = (l_1 + l_2, m_1 + m_2, u_1 + u_2) \tag{2}$$

Subtraction:

$$\tilde{A}_1 - \tilde{A}_2 = (l_1 - u_2, m_1 - m_2, u_1 - l_2) \tag{3}$$

Multiplication:

$$\tilde{A}_1 x \tilde{A}_2 = (l_1 x l_2, m_1 x m_2, u_1 x u_2) \tag{4}$$

$$k x \tilde{A}_1 = (k x l_1, k x m_1, k x u_1), (k > 0) \tag{5}$$

Division:

$$\frac{\tilde{A}_1}{k} = \left(\frac{l_1}{k}, \frac{m_1}{k}, \frac{u_1}{k}\right), (k > 0) \tag{6}$$

The graded mean integration representation (GMIR) $R\left(\tilde{A}_i\right)$ is calculated as:

$$R\left(\tilde{A}_i\right) = \frac{l_i + 4m_i + u_i}{6} \tag{7}$$

FBWM'H

The BWM technique was developed by Rezaei (2015). Recently, Guo and Zhao (2017) adopted the method to the uncertain environment as FBWM. FBWM can be tracked to solve real-life problems where uncertainty exist. Decision makers are asked to rank different criteria according to importance from a set of criteria using a linguistic scale. Later, the best and worst criteria are defined. A decision-maker first compares pairwise the best criterion with the others. Then, s/he compares the others pairwise with the worst criterion. Expert preferences are transformed into a nonlinear optimization problem, and thus the criterion weights are obtained. FBWM has several steps as below (Guo and Zhao 2017; Tanrıverdi et al. 2022).

Step 1: Determination of a set of criteria that effect the decision-making process of investors while choosing a cryptocurrency exchange.
Step 2: Distinguishing the *best* and the *worst* criteria by decision makers (experts). In this step, we ask each expert to rank the criteria from best to worst according to their personal opinion. At the end of this process, each expert selects a best C_B and a worst C_W item.
Step 3: At this step, we ask decision makers (experts) to make pairwise comparisons of best C_B and the worst C_W criteria with other criteria. Decision makers define the significance of C_B over the other criteria as well as over the other criteria over the C_W

using the linguistic terms. Then, we will have two vectors, namely called Best to Others (BO), and Others to Worst vectors (OW). Let $\widetilde{A}_{\mathrm{B}}$ be the best to others and $\widetilde{A}_{\mathrm{W}}$ be the others to worst vectors where;

$$\widetilde{A}_{\mathrm{B}} = (\widetilde{a}_{B_1}, \widetilde{a}_{B_2}, \widetilde{a}_{B_3}, \ldots \widetilde{a}_{B_n})$$

$$\widetilde{A}_{\mathrm{W}} = (\widetilde{a}_{1W}, \widetilde{a}_{2W}, \widetilde{a}_{3W}, \ldots \widetilde{a}_{nW})$$

Step 4: This step involves identifying the fuzzy weight for each decision-making criterion related to cryptocurrency exchange selection. By solving Eq. (8), we obtain the fuzzy weights for each decision criterion ($\widetilde{w}_1^*, \widetilde{w}_2^*, \widetilde{w}_3^*, \widetilde{w}_4^*, \ldots\ldots \widetilde{w}_n^*$).

$$min\widetilde{\xi}^*$$
$$\text{s.t.} \begin{cases} \left| \frac{(l_B^w, m_B^w, u_B^w)}{\left(l_j^w, m_j^w, u_j^w\right)} - \left(l_{Bj}, m_{Bj}, u_{Bj}\right) \right| \le (k^*, k^*, k^*) \\ \left| \frac{\left(l_j^w, m_j^w, u_j^w\right)}{(l_W^w, m_W^w, u_W^w)} - \left(l_{jw}, m_{jW}, u_{jw}\right) \right| \le (k^*, k^*, k^*) \\ \sum_{j=1}^{n} R\left(\widetilde{w}_j\right) = 1 \\ l_j^w \le m_j^w \le u_j^w \\ l_j^w \ge 0 \\ j = 1, 2, \cdots, \mathrm{n} \end{cases} \tag{8}$$

Step 5: In the last step, first, the Heronian function (Eq. 9) is operated to aggregate assessments estimated by each expert. Last, the triangular fuzzy weights of the criteria are transformed into a crisp coefficient through Eq. (7).

$$\widetilde{\varrho}_{ij} = \left(\varrho_{ij}^l, \varrho_{ij}^m, \varrho_{ij}^u\right) = \begin{cases} \varrho_i^l = \left(\frac{2}{k^2+k} \sum_{i=1}^{n} \sum_{j=1}^{n} \varrho_i^{l_p} \varrho_j^{l_q}\right)^{\frac{1}{p+q}} \\ \varrho_i^m = \left(\frac{2}{k^2+k} \sum_{i=1}^{n} \sum_{j=1}^{n} \varrho_i^{m_p} \varrho_j^{m_q}\right)^{\frac{1}{p+q}} \\ \varrho_i^u = \left(\frac{2}{k^2+k} \sum_{i=1}^{n} \sum_{j=1}^{n} \varrho_i^{u_p} \varrho_j^{u_q}\right)^{\frac{1}{p+q}} \end{cases} \tag{9}$$

where k shows the number of experts, whereas $p, q \ge 0$ are positive integers.

FMARCOS'H

FMARCOS is an ordinary fuzzy extension of MARCOS and developed by Stankovic et al. (2020). We use the improved FMARCOS (FMARCOS'H) framework in the second phase of our analysis to assess alternative exchanges by following these steps below.

Step 1. Creating a primary matrix. The linguistic scale used in this study for the evaluation of the alternatives regarding decision-making criteria by the experts (Table 9) (Stankovic et al. 2020).
Step 2. We determine the fuzzy anti ideal $\widetilde{A}(AI)$ and fuzzy ideal $\widetilde{A}(ID)$ solutions.

Table 9 Linguistic evaluation scale for alternatives (Stankovic et al. 2020)

Linguistic term	Value
Extremely poor (EP)	(1, 1, 1)
Very poor (VP)	(1, 1, 3)
Poor (P)	(1, 3, 3)
Medium poor (MP)	(3, 3, 5)
Medium (M)	(3, 5, 5)
Medium good (MG)	(5, 5, 7)
Good (G)	(5, 7, 7)
Very good (VG)	(7, 7, 9)
Extremely good (EG)	(7, 9, 9)

Fuzzy ideal $\widetilde{A}(ID)$ is the best performing alternative, whereas the fuzzy anti-ideal $\widetilde{A}(AI)$ is the worst performing one. Depending what kind of criteria (cost or benefit) $\widetilde{A}(ID)$ and $\widetilde{A}(AI)$ calculated by applying Eqs. (10)–(11).

$$\widetilde{A}(AI) = \underset{i}{min}\widetilde{x}_{ij} \text{ if } j \in Benefit \text{ and } \underset{i}{max}\widetilde{x}_{ij} \text{ if } j \in Cost \tag{10}$$

$$\widetilde{A}(ID) = \underset{i}{max}\widetilde{x}_{ij} \text{ if } j \in Benefit \text{ and } \underset{i}{min}\widetilde{x}_{ij} \text{ if } j \in Cost \tag{11}$$

B and C represent the maximization-group and minimization-group criteria, respectively.

Step 3. We form a normalized fuzzy matrix $\widetilde{N} = \left[\widetilde{n}_{ij}\right]_{m\times n}$.

$$\widetilde{n}_{ij} = \left(n_{ij}^{l}, n_{ij}^{m}, n_{ij}^{u}\right) = \left(\frac{x_{id}^{l}}{x_{ij}^{u}}, \frac{x_{id}^{l}}{x_{ij}^{m}}, \frac{x_{id}^{l}}{x_{ij}^{l}}\right) \text{ if } j \in C \tag{12}$$

$$\widetilde{n}_{ij} = \left(n_{ij}^{l}, n_{ij}^{m}, n_{ij}^{u}\right) = \left(\frac{x_{ij}^{l}}{x_{id}^{u}}, \frac{x_{ij}^{m}}{x_{id}^{u}}, \frac{x_{ij}^{u}}{x_{id}^{u}}\right) \text{ if } j \in B \tag{13}$$

where $x_{ij}^{l}, x_{ij}^{m}, x_{ij}^{u}$ and $x_{id'}^{l}, x_{id'}^{m}, x_{id}^{u}$ represent the components of the $\widetilde{X}$ matrix.

Step 4. Calculation of the weighted fuzzy matrix $\widetilde{V} = \left[\widetilde{v}_{ij}\right]_{m\times n}$. Matrix $\widetilde{V}$ is calculated by multiplication of matrix $\widetilde{N}$ with the fuzzy weight coefficients of the criterion $\widetilde{w}_j$ (14).

$$\widetilde{v}_{ij} = \left(v_{ij}^{l}, v_{ij}^{m}, v_{ij}^{u}\right) = \widetilde{n}_{ij} \otimes \widetilde{w}_j = \left(n_{ij}^{l} \times w_j^{l}, n_{ij}^{m} \times w_j^{m}, n_{ij}^{u} \times w_j^{u}\right) \tag{14}$$

Step 5. The aggregated matrix $(\widetilde{A}_i)$ is calculated through Heronian function (Eq. 9):

Step 6. Computation of the utility degree of each alternative $\widetilde{K}_i$ through application of Eqs. (15)–(16).

$$\widetilde{K}_i^- = \frac{\widetilde{A}_i}{\widetilde{A}_{ai}} = \left(\frac{a_i^l}{a_{ai}^u}, \frac{a_i^m}{a_{ai}^m}, \frac{a_i^u}{a_{ai}^l}\right) \tag{15}$$

$$\widetilde{K}_i^+ = \frac{\widetilde{A}_i}{\widetilde{A}_{id}} = \left(\frac{a_i^l}{a_{id}^u}, \frac{a_i^m}{a_{id}^m}, \frac{a_i^u}{a_{id}^l}\right) \tag{16}$$

Step 7. Fuzzy matrix $\widetilde{T}_i$ is calculated by Eq. (17).

$$\widetilde{T}_i = \widetilde{t}_i = \left(t_i^l, t_i^m, t_i^u\right) = \widetilde{K}_i^- \oplus \widetilde{K}_i^+ = \left(k_i^{-l} + k_i^{+l}, k_i^{-m} + k_i^{+m}, k_i^{-u} + k_i^{+u}\right) \tag{17}$$

After the calculation of fuzzy $\widetilde{T}_i$ matrix, we determine a new fuzzy number $\widetilde{D}$ using Eq. (18).

$$\widetilde{D} = \left(d^l, d^m, d^u\right) = \max_i \widetilde{t}_{ij} \tag{18}$$

Now, by defuzzifying $\widetilde{D}$ using Eq. (7), we obtain crisp values of attributes (df_{crisp}).

Step 8. After finding df_{crisp}, the next step is the determination the utility function of the ideal and anti-ideal solutions by applying Eqs. (19)–(20).

$$f\left(\widetilde{K}_i^+\right) = \frac{\widetilde{K}_i^-}{df_{\text{crisp}}} = \left(\frac{k_i^{-l}}{df_{\text{crisp}}}, \frac{k_i^{-m}}{df_{\text{crisp}}}, \frac{k_i^{-u}}{df_{\text{crisp}}}\right) \tag{19}$$

$$f\left(\widetilde{K}_i^-\right) = \frac{\widetilde{K}_i^+}{df_{\text{crisp}}} = \left(\frac{k_i^{+l}}{df_{\text{crisp}}}, \frac{k_i^{+m}}{df_{\text{crisp}}}, \frac{k_i^{+u}}{df_{\text{crisp}}}\right) \tag{20}$$

Afterward, defuzzification of $\widetilde{K}_i^-, \widetilde{K}_i^+, f\left(\widetilde{K}_i^+\right), f\left(\widetilde{K}_i^-\right)$ is necessary.

Step 9. Determining the utility function of all the alternatives by applying Eq. (21).

$$f(K_i) = \frac{K_i^+ + K_i^-}{1 + \frac{1 - f(K_i^+)}{f(K_i^+)} + \frac{1 - f(K_i^-)}{f(K_i^-)}} \tag{21}$$

Based on the values calculated using the equation above, we are able to rank the alternatives.

Appendix 2

To achieve the fuzzy values of weights of criteria, a fuzzy model can be construct for the first expert, as shown below.

$$\text{Expert1}(\text{C1} - \text{C7}) \rightarrow \min k$$

$$s.t.$$

$$
\begin{cases}
\left|\frac{w_2^l}{w_1^u} - 0.67\right| \le k.u_2; \left|\frac{w_2^m}{w_1^m} - 1\right| \le k.m_2; \left|\frac{w_2^l}{w_1^u} - 1.5\right| \le k.l_1; \\
\left|\frac{w_2^l}{w_3^u} - 3.5\right| \le k.u_3; \left|\frac{w_2^m}{w_3^m} - 4\right| \le k.m_3; \left|\frac{w_2^l}{w_3^u} - 4.5\right| \le k.l_3; \\
\left|\frac{w_2^l}{w_4^u} - 0.67\right| \le k.u_4; \left|\frac{w_2^m}{w_4^m} - 1\right| \le k.m_4; \left|\frac{w_2^l}{w_4^u} - 1.5\right| \le k.l_4; \\
\left|\frac{w_2^l}{w_5^u} - 1.5\right| \le k.u_5; \left|\frac{w_2^m}{w_5^m} - 2\right| \le k.m_5; \left|\frac{w_2^l}{w_5^u} - 2.5\right| \le k.l_5; \\
\left|\frac{w_2^l}{w_6^u} - 1.5\right| \le k.u_5; \left|\frac{w_2^m}{w_6^m} - 2\right| \le k.m_5; \left|\frac{w_2^l}{w_6^u} - 2.5\right| \le k.l_6; \\
\left|\frac{w_2^l}{w_7^u} - 2.5\right| \le k.u_5; \left|\frac{w_2^m}{w_7^m} - 3\right| \le k.m_5; \left|\frac{w_2^l}{w_7^u} - 3.5\right| \le k.l_7; \\
\left|\frac{w_1^l}{w_3^u} - 2.5\right| \le k.u_5; \left|\frac{w_1^m}{w_3^m} - 3\right| \le k.m_5; \left|\frac{w_1^l}{w_3^u} - 3.5\right| \le k.l_3; \\
\left|\frac{w_4^l}{w_3^u} - 2.5\right| \le k.u_3; \left|\frac{w_4^m}{w_3^m} - 3\right| \le k.m_3; \left|\frac{w_4^l}{w_3^u} - 3.5\right| \le k.l_3; \\
\left|\frac{w_5^l}{w_3^u} - 1.5\right| \le k.u_3; \left|\frac{w_5^m}{w_3^m} - 2\right| \le k.m_3; \left|\frac{w_5^l}{w_3^u} - 2.5\right| \le k.l_3; \\
\left|\frac{w_6^l}{w_3^u} - 1.5\right| \le k.u_3; \left|\frac{w_6^m}{w_3^m} - 2\right| \le k.m_3; \left|\frac{w_6^l}{w_3^u} - 2.5\right| \le k.l_3; \\
\left|\frac{w_7^l}{w_3^u} - 0.67\right| \le k.u_3; \left|\frac{w_7^m}{w_3^m} - 1\right| \le k.m_3; \left|\frac{w_7^l}{w_3^u} - 1.5\right| \le k.l_3; \\
(w_1^l + 4.w_1^m + w_1^u)/6 + (w_2^l + 4.w_2^m + w_2^u)/6 + \\
(w_3^l + 4.w_3^m + w_3^u)/6 + (w_4^l + 4.w_4^m + w_4^u)/6 + \\
(w_5^l + 4.w_5^m + w_5^u)/6 + (w_6^l + 4.w_6^m + w_6^u)/6 + \\
(w_7^l + 4.w_7^m + w_7^u)/6; \\
k \ge 0; \\
w_j^l \le w_j^m \le w_j^u; \forall j = 1, 2, \ldots, 7 \\
w_j^l, w_j^m, w_j^u \ge 0; \forall j = 1, 2, \ldots, 7
\end{cases}
$$

The fuzzy weights of criteria are calculated by Lingo, as presented in Table 3. Final weight with the Heronian function is obtained for C1 as follows.

$$
C_1^{p=q=1} = \begin{pmatrix}
\frac{2}{6*7} * \left(0.166^1.0.166^1 + 0.166^1.0.236^1 + 0.166^1.0.206^1 + 0.166^1.0.265^1 + 0.166^1.0.162^1 + 0.166^1.0.220^1 + \ldots\right) = 0.203 \\
\frac{2}{6*7} * \left(0.173^1.0.173^1 + 0.173^1.0.280^1 + 0.173^1.0.249^1 + 0.173^1.0.265^1 + 0.173^1.0.223^1 + 0.173^1.0.230^1 + \ldots\right) = 0.229 \\
\frac{2}{6*7} * \left(0.230^1.0.230^1 + 0.230^1.0.280^1 + 0.230^1.0.283^1 + 0.230^1.0.281^1 + 0.230^1.0.223^1 + 0.230^1.0.265^1 + \ldots\right) = 0.253
\end{pmatrix}
$$

$$= (0.203, 0.229, 0.253)$$

Appendix 3

Since C1 is a benefit-type criterion, the fuzzy normalized value of it can be calculated as follows.

$$\widetilde{n}_{C1} = \frac{6.667}{8.667} = 0.769$$

To find the fuzzy weighted-normalized value of C1, $\widetilde{n}_{C1}$ and C1's weight is multiplied.

$$\widetilde{\nu}_{C1} = 0.769 \cdot 0.229 = 0.176$$

In order to obtain the aggregated matrix ($\widetilde{A}_i$), the Heronian function (Eq. 9) is applied.

$$A_1^{p=q=1} = \begin{pmatrix} \frac{2}{6*7} * \left(0.176^1.0.176^1 + 0.176^1.0.140^1 + 0.176^1.0.045^1 \right. \\ \left. +0.176^1.0.093^1 + 0.176^1.0.075^1 + 0.176^1.0.0095^1 + 0.176^1.0.0029^1 + \ldots \right) = 0.105 \\ \frac{2}{6*7} * \left(0.202^1.0.202^1 + 0.202^1.0.166^1 + 0.202^1.0.051^1 + 0.202^1.0.116^1 \right. \\ \left. +0.202^1.0.089^1 + 0.202^1.0.120^1 + 0.202^1.0.033^1 + \ldots \right) = 0.125 \\ \frac{2}{6*7} * \left(0.229^1.0.229^1 + 0.229^1.0.180^1 + 0.229^1.0.064^1 \right. \\ \left. +0.229^1.0.120^1 + 0.229^1.0.096^1 + 0.229^1.0.125^1 + 0.229^1.0.038^1 + \ldots \right) = 0.129 \end{pmatrix}$$

$$= (0.105, 0.125, 0.129)$$

We compute the utility degree of each alternative $\widetilde{K}_{A1}$ as follows.

$$\widetilde{K}_{A1}^{-} = \left(\frac{0.105}{0.068}, \frac{0.125}{0.056}, \frac{0.129}{0.041}\right) = (1.550, 2.206, 3.141)$$

$$\widetilde{K}_{A1}^{+} == \left(\frac{0.105}{0.151}, \frac{0.125}{0.139}, \frac{0.129}{0.113}\right) = (0.692, 0.896, 1.140)$$

Afterward, fuzzy matrix $\widetilde{T}_i$ is calculated and maximum value of $\widetilde{T}_i$ is decided as $df_{crisp} = 3.362$ after calculations based on Eqs. (17)–(18). The utility function of the ideal and anti-ideal solutions of A1 is calculated as follows.

$$f\left(\widetilde{K}_{A1}^{+}\right) = \left(\frac{1.550}{3.362}, \frac{2.206}{3.362}, \frac{3.141}{3.362}\right) = (0.461, 0.654, 0.934)$$

$$f\left(\widetilde{K}_{A1}^{-}\right) = \left(\frac{0.692}{3.362}, \frac{0.896}{3.362}, \frac{1.140}{3.362}\right) = (0.206, 0.266, 0.339)$$

After defuzzification of $f\left(\widetilde{K}_{A1}^{+}\right)$ and $f\left(\widetilde{K}_{A1}^{-}\right)$, we can get $f(K_1)$ value of A1.

$$f(K_{A1}) = \frac{2.252 + 0.902}{1 + \frac{1-0.670}{0.670} + \frac{1-0.268}{0.268}} = 0.748$$

Abbreviations

ADA	Cardano
BWM	Best–worst method
ETH	Ethereum
FBWM	Fuzzy best–worst method
FBWM'H	FBWM with Heronian
FMARCOS	Fuzzy measurement of alternatives and ranking according to compromise solution
FMARCOS'H	FMARCOS with Heronian
GMIR	Graded mean integration representation
MARCOS	Measurement of alternatives and ranking according to compromise solution
MCDM	Multi-criteria decision-making
USDT	Tether

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