Annals of Operations Research
https://doi.org/10.1007/s10479-023-05421-3

ORIGINAL RESEARCH

Bitcoin network-based anonymity and privacy model for metaverse implementation in Industry 5.0 using linear Diophantine fuzzy sets

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Accepted: 24 May 2023

Abstract
Metaverse is a new technology expected to generate economic growth in Industry 5.0. Numerous studies have shown that current bitcoin networks offer remarkable prospects for future developments involving metaverse with anonymity and privacy. Hence, modelling effective Industry 5.0 platforms for the bitcoin network is crucial for the future metaverse environment. This modelling process can be classified as multiple-attribute decision-making given three issues: the existence of multiple anonymity and privacy attributes, the uncertainty related to the relative importance of these attributes and the variability of data. The present study endeavours to combine the fuzzy weighted with zero inconsistency method and Diophantine linear fuzzy sets with multiobjective optimisation based on ratio analysis plus the multiplicative form (MULTIMOORA) to determine the ideal approach for metaverse implementation in Industry 5.0. The decision matrix for the study is built by intersecting 22 bitcoin networks to support Industry 5.0's metaverse environment with 24 anonymity and privacy evaluation attributes. The proposed method is further developed to ascertain the importance level of the anonymity and privacy evaluation attributes. These data are used in MULTIMOORA. A sensitivity analysis, correlation coefficient test and comparative analysis are performed to assess the robustness of the proposed method.

Keywords Multiple attribute decision-making · Diophantine linear fuzzy sets · Industry 5.0 · Metaverse · Bitcoin networks · anonymity privacy

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Published online: 17 June 2023

1 Introduction

Industry 5.0, which is considered the next phase of industrial evolution, aims to blend the innovation of human professionals with effective, intelligent, precise machines to offer manufacturing solutions that are superior to those of Industry 4.0 in terms of resource efficiency and user preference. Three factors, namely, quality of life, inclusivity and sustainability, are becoming increasingly crucial and eliciting much attention in Industry 5.0 (Verma et al., 2022). From a security perspective, Industry 5.0 can benefit substantially from blockchain technology. A critical issue in Industry 5.0 is the centralisation of control over a substantial number of heterogeneously linked devices (Mourtzis et al., 2022). Blockchain technology can be used to establish decentralised and independent administration and educational sites by providing widespread trust (Saniuk et al., 2022; Viriyasitavat & Hoonsopon, 2019). The unchangeable ledger provided by blockchain technology allows record maintenance and secure peer-to-peer communication. In Industry 5.0 applications, this unchangeable ledger promotes operational accountability and transparency for crucial occurrences (Deepa et al. 2021).

The utilisation of smart contracts in Future Industry 5.0 can facilitate security measures via authentication and automated service-oriented operations. Additionally, a segmented and distributed strategy using blockchain can be applied to increase the protection of data and transactions (Lin et al., 2018; Lin et al., 2017). Blockchain can also be used to facilitate data collection and receipt (Mittal et al., 2019). It may be used to digitise the identities of individuals and companies in Industry 5.0 to effectively manage clients. Blockchain technology is essential when industrial actions are undertaken through a public network, including network access and participant authentication (Lin et al., 2018). Digital identities in blockchain can be employed to govern assets, belongings, items and services. Additionally, original work can be archived and saved using blockchain technology, which can also be used to register IP rights (Verma et al., 2022). Blockchain and smart contracts can assist in the automation of contractual procedures by automating the steps of agreements between various parties. Moreover, machine-level connectivity and data exchange are now possible through blockchain-supported cloud manufacturing, which is built on this technology (Andoni et al., 2019). Therefore, procedure data should be safeguarded against hostile attacks that could compromise the security and privacy of sensitive data. Moreover, to accommodate customised requirements, communication nodes need to uphold client data. A fundamental approach to resolve privacy concerns is to employ equitable information practices and client norms when accessing data with permission (Lee et al., 2011).

Artificial intelligence models may not be able to personalise confidentiality strategies effectively due to the limited data interchange needed because explicit data fields are concealed. Achieving balance between the trade-offs of personalisation and privacy is imperative (Alanazi et al., 2015; Hussain et al., 2016). However, privacy and security solutions fail due to the lack of consideration for the peculiar behaviour of sensor nodes. Confidence in data exchange and control is crucial in Industry 5.0 when diverse and decentralised networks collaborate. Blockchain is a possible solution for constructing accessible ledgers where industrial operations data can be easily tracked and managed. In a peer-to-peer network, documenting transactions and tracking assets are simplified by the shared, distributed and immutable ledger known as blockchain (Verma et al., 2022). It creates dependable review tools that aid in compliance and auditing (Singh et al., 2022). The utilisation of blockchain technology in peer-to-peer networks simplifies the process of documenting transactions and tracking assets due to the shared, distributed, and immutable nature of the ledger (Verma et al., 2022).

The development of such reliable review instruments facilitates compliance and auditing (Singh et al., 2022). Blockchain is a digital ledger that maintains a continuously growing list of records called blocks, which are linked and secured using cryptography. The blocks are arranged in chronological order, ensuring the integrity and immutability of the data. The block header within the blockchain system obtains a hash value that is linked to the hash value of the preceding block.

Subsequently, once the data are introduced to the chain, they cannot be changed. The block's hash is altered when any of the transactions within it is updated (Verma et al., 2022). Technology advancements associated with Industry 5.0 are expected to generate new economic growth (Viriyasitavat & Hoonsopon, 2019). Industry 5.0 technologies include metaverse. By 2050, metaverse technology will have reached the level of complete autonomy (Duggal et al., 2022).

The term 'metaverse' indicates a continuously populated multiuser environment that merges the real world with digitally created elements (Mystakidis, 2022). Despite augmented reality (AR) and virtual reality (VR) becoming widespread in different industries, mixed reality and VR are amongst the most crucial components of the metaverse because they effectively give individuals a 3D comprehensive virtual environment (Kobzan et al., 2018). Therefore, to build a 3D Internet area for improved user engagement that resembles the actual world, the metaverse uses AR and VR, along with the concepts of blockchain and social media. It combines various characteristics, including AR, VR, live video, animation and interactive user interfaces. Businesses can benefit greatly from using this 3D Internet area to create and experiment. Businesses can test their goods and services in the metaverse and receive quick and accurate real-time feedback. The metaverse has ramifications that are beneficial to businesses. Users can enjoy the high level of interaction and complete experience of using VR headsets, haptic gloves, AR and extended reality, and this technology is swiftly developing to support the creation of the metaverse. Organisations are beginning to assess metaverse capabilities and how their present business strategies may use these capabilities (Dwivedi et al., 2022).

The opportunity is huge for enterprises to change their corporate strategies and abilities to operate in the metaverse, with dramatic effects on marketing, tourism, leisure, hospitality, citizen-government involvement, health, education and social networks. Future users of the metaverse will have many options available to them, many of which may be beyond their current awareness due to the effortless transition between the real and virtual worlds and experiences and interactions (Dick, 2021). The ability of individuals and organisations to build their own virtual worlds is something platform providers are working to improve, but several obstacles from sociotechnical and governance viewpoints must be overcome. Substantial issues of concern about ethics, data security, legislation, safety and the possible negative psychological effects on vulnerable individuals of society have been uncovered through studies (Lee et al., 2021). From the perspective of security, the metaverse presents a series of obstacles. These obstacles originate from the metaverse's novelty, complexity and multisensory nature, which may have negative effects on users and victims of security abuses. The foundational elements of the metaverse economy are crypto-assets, such as cryptocurrencies (e.g., bitcoin) and nonfungible tokens (NFTs). NFTs enable the verification of these assets and even identities whilst representing the proprietorship of digital in-game items, virtual avatars, residential properties and other assets. The same function that money performs in the present economy is also performed by cryptocurrencies in the metaverse (Dwivedi et al., 2022).

To date, no research has expanded the fuzzy weighted with zero inconsistency (FWZIC) method within the context of Diophantine linear fuzzy sets (LDFSs). Furthermore, LDFS-FWZIC and multiobjective optimisation based on ratio analysis plus the multiplicative form (MULTIMOORA) techniques have not been employed together in a case study. Consequently, we are inspired to propose novel LDFS-FWZIC and MULTIMOORA methods for modelling bitcoin networks to support Industry 5.0's metaverse environment and determine the best one that benefits the Industry 5.0 metaverse with bitcoin network developers. The weight of evaluation attributes is estimated by LDFS-FWZIC. The MULTIMOORA method uses the obtained weights to model bitcoin networks to support Industry 5.0's metaverse environment. The study's novelty and contributions can be summarised as follows:

1. This study constructed a decision matrix (DM) for modelling bitcoin networks to support Industry 5.0's metaverse environment-based anonymity and privacy evaluation attributes.
2. This study extended the FWZIC method to the context of the LDFS environment, and the resulting approach is named LDFS-FWZIC.
3. This study proposed a decision modelling approach for bitcoin networks to support Industry 5.0's metaverse environment by constructing a DM and integrating LDFS-FWZIC and MULTIMOORA methods.

The remaining portions of this study are structured as follows. Related studies on bitcoin networks to support Industry 5.0's metaverse environment and the current multicriteria decision-making (MCDM) methods are presented in Sect. 2. The study methodology is thoroughly described in Sect. 3 after a review of the procedures and materials. The results from DM, LDFS-FWZIC and MULTIMOORA are provided in Sect. 4. The efficiency and superiority of the suggested methods are verified in Sect. 5 by conducting sensitivity and comparative analyses. Section 6 discusses the managerial implications, and Sect. 7 provides the conclusion.

2 Related work

This section consists of two subsections. The first one (Sect. 2.1) presents the problem and gap in modelling bitcoin networks to support Industry 5.0's metaverse environment. The second section (Sect. 2.2) discusses the limitations and strengths of current MCDM methods and the recommended solutions.

2.1 Problem and research gap

In bitcoin networks, the sender's and recipient's addresses, the amount sent and the transaction's time are stored in the blockchain (Dupont & Squicciarini, 2015; Koshy et al., 2014; Lischke & Fabian, 2016; Meiklejohn et al., 2013). Anonymity and privacy in bitcoin networks are considered highlight points, given that many academics have shown that bitcoin networks to support Industry 5.0's metaverse environment (hereafter simplified as "bitcoin networks") provide exciting new opportunities for future studies.

During the first 10 years of the bitcoin network's existence, Ajay Kumar et al. (Kumar et al., 2020) conducted a study with the goal of examining the local topology and geometry of the network. For this purpose, they constructed a bitcoin user graph by processing data from bitcoin transactions. They used the 'Analyses Network by Calculating Network Metrics, Gives Cost Information of Performed Study' development attributes in their study. Ansah et al. (Kwansah Ansah et al., 2019) emphasised the importance of preserving user identity and transactional activity in bitcoin cryptocurrency transactions in their study and used 'Privacy or Anonymity Improvement Measures, Uses Adversary, Uses Threat Model' development attributes. Lv et al. (2020) constructed a system for visually analysing bitcoin transactions by employing a graph database and utilised true multiple database sources to examine the entity information of bitcoin exchanges in the sequence to accomplish deanonymization. They used the development attributes in 'Performs Actual Deanonymization, Performs Flow Analysis, Training Machine Learning Models, Performs Weight Analysis, Build Visual Analysis System for Bitcoin Transactions, Uses Real-world Data, Investigates a Case of Real-world, Uses Metrics to Measure the Success of a Clustering Strategy, Predictions, Gives Cost Information of Performed Study'. Additionally, they implemented a supervised learning mechanism in their system to determine the validity of unidentified bitcoin transactions. By using publicly available data from online social networks, blockchain and onion websites, Jawaheri et al. (2020) examined the viability of deanonymizing Tor hidden service users who utilise bitcoin as a payment method. They used the development attributes in 'Performs Actual Deanonymization, Performs Flow Analysis, Analyses Network Which Uses Hidden Services, Tools for Downloading Blockchain Data, Analysis Including Twitter Data, Investigates a Case of Real-World, Performs Methods for Expanding the Set of Bitcoin Addresses, Privacy or Anonymity Improvement Measures, Uses Adversary, Gives Cost Information of Performed Study'. Biryukov et al. (2014) proposed a practical technique for deanonymizing bitcoin users that allows users' pseudonyms to be connected to the IP addresses from which transactions are made. Their methods are effective when users are protected by network address translations (NATs) or firewalls maintained by their ISPs, which is both the most typical and difficult circumstance. They attempted to link a user's transactions behind a NAT and the differentiation of connections and transactions between various users behind the same NAT; they achieved this task by using the development attributes in 'BBC, ANUHS, P/AIM, UA, GCIOPS'.

The analysis of studies provided above revealed that various bitcoin network alternatives are directly affected by anonymity and privacy development attributes. Bitcoin networks analysing practice to support Industry 5.0's metaverse environment necessitates the combination of anonymity and privacy development attributes. To date, no study has combined all anonymity and privacy development attributes in existing bitcoin network alternatives. Furthermore, these attributes have not been regarded as evaluation criteria in previous studies. Thus, the modelling of bitcoin networks to select the ideal one is critical and difficult. The task of supporting Industry 5.0's metaverse environment is complicated by the various combinations of anonymous and privacy evaluation attributes present in bitcoin networks. Given these distinctions, existing bitcoin networks should not be compared using a single platform. In the future, this will also be the case when studying and evaluating the application of the metaverse environment in the context of Industry 5.0, so this is considered a research gap.

To support Industry 5.0's metaverse environment through the modelling of bitcoin networks, the three key concerns that have been identified must be addressed to bridge the existing research gap; these three are multiple anonymity and privacy evaluation attributes (Bonab et al., 2023; Khan et al., 2023; Qahtan et al., 2023a, b, c, d, e), uncertainty regarding the anonymity and privacy attributes' importance level (Bakır et al., 2021; Jagtap & Karande, 2023; Tešić et al., 2023) and data variation (Alnoor et al., 2022; Karamaşa et al., 2021; Qahtan, Alsattar et al., 2022). Some development attributes (e.g. BBC, URWD, PFA and ANBCNM) have been used by previous studies on bitcoin networks. Hence, multiple attributes should be considered when modelling these networks to support Industry 5.0's metaverse environment. Furthermore, prior studies have integrated these developmental attributes in diverse ways, and unanimous agreement about the importance of these attributes has not been attained, leading to the fluctuating importance of the mentioned attributes. Moreover, data variety emerges when certain bitcoin networks exhibit superior performance compared with others, and these networks can be represented as the optimal network based on specific attributes. Conversely, alternative networks may be favoured over the aforementioned ones based on differing attributes. Consequently, the modelling of bitcoin networks to support Industry 5.0's metaverse environment leads to a complex multiple-attribute decision-making (MADM) problem due to the aforementioned concerns. The present issue serves as a motivation for this study, which aims to devise an MADM solution for constructing an optimal bitcoin network that can facilitate the metaverse environment of Industry 5.0 and address the existing research gap. According to Alamleh et al., (2022a, b), decision-making involves a cognitive process where an individual, group or organisation chooses a particular option from a range of options with the aim of attaining a specific objective or solving a challenge. Therefore, it can aim to identify the optimal bitcoin network to support Industry 5.0's metaverse environment based on specific attributes. Then, it can be applied in the future direction of the metaverse environment in the context of Industry 5.0.

2.2 MCDM methods and recommended solution

The two major contexts in which existing MADM methods have been developed are mathematical and human approaches (Jumaah et al., 2018; Napi et al., 2019; Yas et al., 2018; Zaidan et al., 2020), which are covered in this section. The modelling of alternatives based on numerous attributes has been addressed in various studies in the fields of medicine (Alamleh et al., 2022a, b), agriculture, transportation, community (Albahri et al., 2022a, 2022b; Qahtan et al., 2023a) and supplier modelling in companies (Stević et al., 2017; Stojić et al., 2018). These methods include weighted aggregated sum product assessment (WASPAS), multiobjective optimisation on the basis of a ratio analysis (MOORA), multiobjective optimisation by simple ratio analysis (MOOSRA) and MULTIMOORA. Recently, Arian Hafezalkotob et al. (2019) stated that the MULTIMOORA method is the optimal theoretical approach for addressing different MADM issues. MULTIMOORA, introduced in 2010 by Brauers and Zavadskas, is a good method for modelling alternatives. The result of this method is a model, which is a summary of the results of triple modelling methods: (a) ratio system, (b) reference point approach and (c) full multiplicative form. The final modelling of the alternatives can be achieved by aggregating the determined subordinate models. Four different types of modelling aggregation tools are utilised for the development of MULTIMOORA: (a) dominance-based method, (b) mathematical operators, (c) MADM techniques and (d) programming approaches (Arian Hafezalkotob et al., 2019).

Modelling aggregation tools have some drawbacks (Dong et al., 2019). For example, dominance theory based on dominance, transition and equality was developed and used to aggregate the three models into one because it is not yet automated; therefore, identifying the models of the alternatives can be regarded as complicated (Arian Hafezalkotob & Hafezalkotob, 2016). As circular reasoning occurs, it appears to ignore the relative importance of the alternatives and relies only on ordinal values, resulting in identical models in some cases (Baležentis & Baležentis, 2014). Whilst the improved Borda rule does not necessitate manual comparison or particular conditions (Wu et al., 2018), utility values and subordinate models are used to determine the final models (Wang et al., 2018). According to the description above, modelling bitcoin networks to support Industry 5.0's metaverse environment by using the MULTIMOORA approach is effective in resolving the MADM problem. However, MULTIMOORA is limited by a primary drawback, which is the inability to provide weights for the assessment of attributes in the order of importance. Consequently, an external method is required to assign weights to the attributes.

AHP, ANP and BWM methods, which successfully weigh criteria with a high percentage of success, have been established as strategies for giving weights to evaluation attributes when using human approaches. For example, the multiobjective decision-making problem for AR goggles was addressed and resolved using the MULTIMOORA method under a neutrosophic environment in the work of Aydin (2018). Ashkan Hafezalkotob et al. (2018) used the target-based MULTIMOORA method to evaluate olive harvesting machines. Kabak et al. (2018) evaluated the status of bike-share stations in Karsiyaka, Izmir, to locate future station sites by using MULTIMOORA combined with AHP. Supplier selection in a company manufacturing polyvinyl chloride carpentry was performed in the study of Stojić et al. (2018) by using MULTIMOORA combined with AHP and WASPAS under a rough environment. In the work of Wu et al. (2018), multiexpert MCDM problems were solved with linguistic evaluations by using MULTIMOORA. The multiobjective decision-making problem for laptop modelling was addressed and solved by MULTIMOORA and MOOSRA methods in the study of Aytaç Adalı & Tuş Işık (2017). Meanwhile, Stević et al. (2017) performed supplier modelling in a construction company by using MULTIMOORA combined with AHP. The completion of unfinished residential buildings to achieve appropriate construction project objectives was assessed using MULTIMOORA combined with AHP, ARAS and MOORA methods in the work of Turskis et al. (2016). J. Wang et al. (2021) modelled appropriate and complete meta-evaluation criteria by using MULTIMOORA combined with IVIF-BWM. Omrani et al. (2020) measured and modelled semihuman development index scores for provinces of Iran by using MULTIMOORA combined with BWM. Ijadi Maghsoodi et al. (2020b) solved the phase change material modelling problem by combining BWM with the interval-valued target-based combined compromise solution method and MULTIMOORA. Jafarnejad et al. (2020) defined the best tariff policy by the government and policy makers influencing the price of biofuels, and the profit of biorefineries was determined using MULTIMOORA combined with BWM. Meanwhile, in the work of Arian Hafezalkotob et al. (2020), the modelling problem of a hybrid vehicle engine was solved using interval MULTIMOORA. Cheng et al. (2020) analysed appropriate solutions after identifying the most critical risk factors during a surgical procedure by using FMEA and MULTIMOORA methods under a single-valued trapezoidal neutrosophic environment combined with BWM. Yang et al. (2020) proposed a method and applied it to train selection during the Spring Festival travel rush by using group MULTIMOORA combined with BWM/NWHFEs. In the study of Ijadi Maghsoodi et al. (2020a), the personnel modelling problem in mega-structured organisations was solved using MULTIMOORA combined with BWM. However, the inconsistent weighing methods for these approaches continue to be a concern (Albahri et al., 2022a, b; Alnoor et al., 2022).

Recently, the weight coefficients of attributes with zero inconsistency have been computed using the FWZIC method. With the assistance of experts, the FWZIC method determines the importance of the attributes in the decision-making process (Al Sereidi et al., 2022). The first version of the method, however, was highly confusing and used triangular fuzzy numbers (Ibrahim et al., 2023). At present, experts encounter difficulty in expressing a conclusive inclination towards pertinent options that are grounded on a range of attributes, particularly when depending on unreliable, inaccurate, incomplete information (Alsattar et al., 2022). As a result, FWZIC has been developed various fuzzy sets (Mahmoud et al., 2022; Qahtan et al., 2022b).

Unreliable, inaccurate, incomplete information remains a real issue despite previous efforts. Therefore, to overcome any expert doubt that can occur during the production of positive and negative opinion matrices, an appropriate FS environment must be used.

In various real-world domains, intuitionistic fuzzy sets (IFSs), q-rung orthopair fuzzy sets (q-ROFSs) and Pythagorean fuzzy sets (PFSs) are used and have many applications; at the same time, they suffer from issues related to the grades of membership and nonmembership. Therefore, the concept of LDFS, which gives decision makers unlimited flexibility in selecting scores, was introduced (Riaz & Hashmi, 2019). This tool has proven to be highly effective in expressing the decision maker's evaluation (DM) in MCDM; therefore, it provides a convenient method for decision experts (DEs) to deal with vague and uncertain information in a comprehensive manner (Iampan et al., 2021). Many studies have applied the idea of LDFS. For instance, Hashmi et al. (2021) presented a robust hybrid model of spherical LDFS (soft and rough sets) that is more productive and applicable than any other model due to the effectiveness of the proposed reference parameters. In the study of Riaz et al. (2020), the concepts of linear Diophantine fuzzy soft–rough sets (LDFSRSs) and soft–rough linear Diophantine fuzzy sets (SRLDFSs) were proposed as new hybrid models of soft sets, rough sets and LDFS. Hashmi et al. (2021) introduced the notion of fuzzy linear Diophantine spherical groups (SLDFSs) with the inclusion of the reference or control parameters. The informative ambiguity and imprecision of FWZIC can be overcome using this LDFS.

3 Methods and materials

The methodology section comprises three subsections, as illustrated in Fig. 1. Section 3.1 outlines the construction of the DM of bitcoin networks intended to support Industry 5.0's metaverse environment. Sect. 3.2 explains the LDFS-FWZIC method for obtaining the weights of assessment attributes. The MULTIMOORA method is employed in Sect. 3.3 to model bitcoin networks for facilitating Industry 5.0's metaverse environment and ascertains the optimal network by merging the estimated weights and the derived DM.

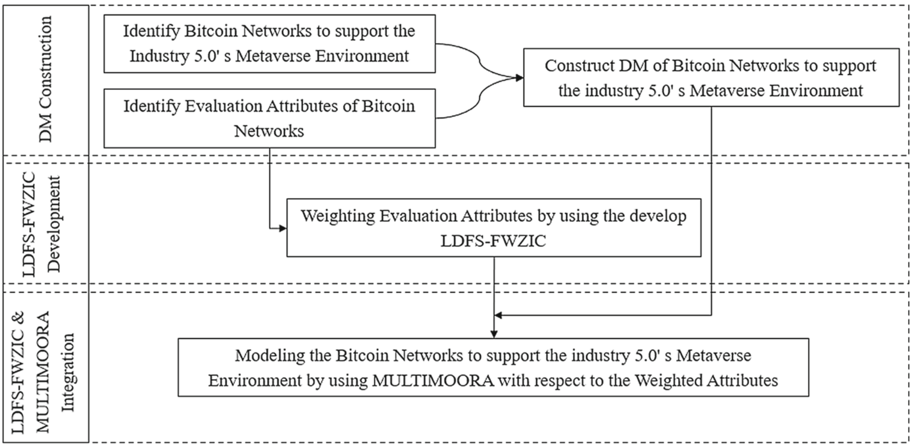

Fig. 1 Representation of the proposed methodology.

3.1 Construction of bitcoin networks' DM

The DM of bitcoin networks to support Industry 5.0's metaverse environment is formed as follows:

- The attributes that influence the evaluation of bitcoin networks are investigated. In accordance with Merve Can Kus Khalilov and Albert Levi (Kus Khalilov & Levi, 2018) and other research analyses, the main evaluation attributes of bitcoin networks are considered the major category in the analysis. Twenty-four anonymity and privacy characteristic properties are used as development attributes in bitcoin network studies. (1) Built Bitcoin Client (BBC): A specially created bitcoin client is utilised for the study. This property holds true for studies that use the network and prefer a customised client to meet their demands. (2) Performs Actual Deanonymization (PAD): Deanonymization is achieved in the experiments by transacting and employing off-network information technologies. (3) Performs Flow Analysis (PFA): Blockchain data analysis allows for the examination of a user's bitcoin inflows and outflows during a certain period or for a specific number of transactions and the tracing of bitcoin flows between transactions and specific addresses. This type of study employs transaction and user networks. (4) Analysing Networks by Calculating Network Metrics (ANBCNM): For the network metrics, the calculated edge number, density and average path length of the transaction and user networks are used to assess the bitcoin network. (5) Analyses Networks Using Hidden Services (ANUHS) (Biryukov & Pustogarov, 2015; Koshy et al., 2014): In bitcoin networks, this case is addressed when customers employ anonymity services (hidden services), such as TOR, I2P and TRR. (6) Training Machine Learning Models (TMLM) (Lv et al., 2020; Nerurkar et al., 2021): The models are trained based on the characteristics of the graph data to predict the validity of unidentified bitcoin transactions. Unusual transactions in bitcoin networks and other applications are detected by evaluating the monitored blockchain network behaviour and traffic by using the machine learning method. (7) Time series analysis (PTSA) (Nerurkar et al., 2021): This metric is used to forecast the network's future prospects. (8) Performs Weight Analysis (PWA) (Lv et al., 2020): The amount of bitcoin transmitted from the input bitcoin address to each recipient bitcoin address is defined as a percentage to simplify the deanonymization work. Furthermore, the complexity of the deanonymization process is lowered by employing the weight analytic method to acquire data on associated users requiring focus. (9) Tools for Downloading Blockchain Data (TFDBD): Blockchain data are obtained using specific tools, such as APIs built on top of Bitcoin Core to extend the Bitcoin Core and give additional indexing for powerful address queries. Examples are Extra Examples Scraper, Scrapy and Bitcoin Core Client S/W. (10) Build Visual Analysis System for Bitcoin Transactions (BVASFBT) (Lv et al., 2020; Reid & Harrigan, 2013; Spagnuolo et al., 2014): The impact of deanonymization is achieved by utilising real-world data sources and creating a visual analysis system for bitcoin transactions based on a graph database to assess the entity data of transactions in the network. The path between two addresses can be simply calculated using graph visualisation. (11) Uses Analytical Tools (UAT) (Spagnuolo et al., 2014): BitIodine, for example, is a modular framework that parses the blockchain, clusters the addresses that are likely to belong to the same person or group of users, classifies and labels such users and visualises complicated data retrieved from the bitcoin network. BitIodine automatically identifies users with information about their identity and actions that are gathered from publicly available data sources. Manual inquiry is also supported by BitIodine, which finds and reverses paths between addresses or users. (12) Analysis Including Twitter Data (AITD) (Jawaheri et al., 2020; Reid & Harrigan, 2013): Mean crawled online social networks, particularly Twitter, can be used for public bitcoin addresses. (13) Uses Real-world Data (URWD) (Kus Khalilov & Levi, 2018; Lv et al., 2020): Actual data are used in the experiments. (14) Analyses Legacy Wallets (ALW) (Nick, 2015): Wallets that employ a bitcoin version prior to 0.12 are considered old. Reuse of addresses can be avoided by refraining from fresh-changing pubkeys, which users must explicitly request. (15) Investigates a Real-world Case (IRWC) (Jawaheri et al., 2020; Kus Khalilov & Levi, 2018; Lv et al., 2020): By evaluating blockchain data and employing off-network information, a real-world theft or ransomware case can be investigated. In other words, a real case can be traced and described to show the impact of linking, further demonstrating how bitcoin addresses can be used to deanonymize individuals retrospectively. (16) Perform Methods for Expanding the Set of Bitcoin Addresses (PMFETSOBA) (Jawaheri et al., 2020): The purpose of Wallet-Closure Analysis, similar to that of Perform Wallet-Closure Analysis, is to increase the number of bitcoin addresses under a user's control to establish several distinct mappings across addresses and identities. In this manner, many ties between the user and hidden services can be identified by increasing the number of bitcoin addresses per user. Additionally, the Union-Locate Graph Algorithm can be used to find groups of addresses that are likely to belong to the same person. (17) Investigates Inactive Addresses/Bitcoins (IIA/B) (Kus Khalilov & Levi, 2018; Meiklejohn et al., 2013; Neudecker & Hartenstein, 2017; Ober et al., 2013): Off-network information and blockchain data are used to examine addresses that are no longer in use and connected bitcoins that are no longer in circulation. This metric can determine the ratio of these addresses to all addresses or the ratio of bitcoins at these addresses to all bitcoins. Examples include saving accounts, dormant bitcoin, sink addresses and change addresses (made by the bitcoin client internally and never reused). (18) Uses Metrics to Measure the Success of a Clustering Strategy (UMTMTSOCS) (Lv et al., 2020; Nick, 2015): A clustering strategy's performance can be measured in different ways. Precision and recall metrics are currently being reconsidered. The number of accurately identified pubkeys as a percentage of the total number of pubkeys found by the technique is known as precision. The number of successfully identified pubkeys as a percentage of the total number of pubkeys in the wallet is called recall. (19) Privacy or Anonymity Improvement Measures (P/AIM) (Androulaki et al., 2013; Biryukov & Pustogarov, 2015; Biryukov et al., 2014; Jawaheri et al., 2020; Kus Khalilov & Levi, 2018; Kwansah Ansah et al., 2019; Nick, 2015; Ortega, 2013; Reid & Harrigan, 2013): It outlines the steps to improve privacy or anonymity. (20) Metrics to Evaluate Privacy or Anonymity (MTEP/A) (Kus Khalilov & Levi, 2018): In bitcoin, metrics that assess privacy or anonymity are supplied. (21) Predictions (Lv et al., 2020; Nerurkar et al., 2021) (P): A future research direction is investigated and recommended, apart from making theoretical predictions and random guessing. (22) Uses Adversary (UA) (Androulaki et al., 2013; Biryukov & Pustogarov, 2015; Biryukov et al., 2014; Fanti & Viswanath, 2017; Jawaheri et al., 2020; Kwansah Ansah et al., 2019; Ober et al., 2013): This metric represents an attacker with access to or the ability to acquire bitcoin addresses of Tor hidden services and their users. It does not require network resources to function, but it may extract publicly accessible data from online social networks, blockchain and onion pages (the adversary is motivated to obtain knowledge about all or a subset of bitcoin users' addresses/transactions). (23) Uses Threat Model (UTM) (Fleder et al., 2015; Kwansah Ansah et al., 2019): It assumes that a dishonest node tries to perform an attack by using malicious bitcoin nodes to link input–output addresses to reveal the genuine identity and transaction behaviour of users in the blockchain. To create bitcoin addresses and transactions, a dishonest node may leverage bitcoin wallet features in an aggressive manner. Notably, a shady node can be part of the bitcoin network. This scenario can lead to a dishonest node making a poor attempt to link a user and an address. (24) Gives Cost Information of Performed Study (GCIOPS) (Biryukov et al., 2014; Koshy et al., 2014; Kumar et al., 2020; Kus Khalilov & Levi, 2018; Lv et al., 2020; Moser et al., 2013; Nerurkar et al., 2021; Neudecker & Hartenstein, 2017; Spagnuolo et al., 2014): The cost of the study or attack is specified in terms of money, storage space or time.

- A list of bitcoin networks to support Industry 5.0's metaverse environment is identified. In this context, 22 networks are introduced and analysed. For instance, in the first bitcoin network BN1 (Reid & Harrigan, 2013), two networks' topological structures are considered by the researchers by using data from bitcoin's public transaction history. The nontrivial topological structure, the complementing viewpoints offered by the two networks and the consequences on the anonymity of the bitcoin system are demonstrated. These structures are used together with other data and methodologies to look into a purported bitcoin theft. In BN2 (Androulaki et al., 2013), the privacy properties of bitcoin are examined when bitcoin is employed as the main form of payment for people's everyday transactions in a university environment. Specifically, the anonymity that bitcoin offers is assessed by (i) examining the real bitcoin system and (ii) using a simulator that accurately represents the use of bitcoin in a university. The 22 networks represent the alternatives in this study.
- By performing a crossover between the pre-identified 22 networks and 24 evaluation attributes, as shown in Table 1, the DM of bitcoin networks is formulated to support Industry 5.0's metaverse environment in future directions.

The resulting DM serves as an input to the proposed MULTIMOORA. Therefore, on the basis of the identified evaluation attributes listed in Table 1, each bitcoin network can be modelled to support Industry 5.0's metaverse environment. Notably, each of the attributes is beneficial. The modelling of bitcoin networks to support Industry 5.0's metaverse environment is challenging, if not impossible, when relying only on human opinion. The process is challenging because of the three main issues, namely, multiple anonymity and privacy evaluation attributes, uncertainty regarding the anonymity and privacy attributes' importance level and data variation, that were previously discussed in Section 2. The LDFS-FWZIC method is used in the next section to weigh the evaluation attributes.

3.2 LDFS–FWZIC method development

An FWZIC method (Mohammed et al., 2022) with LDFS (Riaz & Hashmi, 2019) is developed and expanded in this subsection. The five steps listed below comprise the proposed LDFS-FWZIC method.i. In the evaluation and modelling of bitcoin networks to support Industry 5.0's metaverse environment, a list of evaluation attributes is examined and investigated.ii. At least three field experts are chosen to form a group of structured expert judgments (e.g. bitcoin network developer, cyber security specialist, computer engineer and communication engineer). Then, a questionnaire designed to collect data is endorsed by the selected experts. Additionally, the experts assign the importance of the attributes by using the endorsed questionnaire and five linguistic terms of importance, as demonstrated in Table 2.iii. The expert decision matrix (EDM) is constructed by the intersection of the evaluation attributes of the bitcoin networks with a group of structured expert judgments. The evaluation attributes are intersected with each expert, as shown in Eq. (1), in which the linguistic terms from the earlier step are replaced with a numeric scale (Table 2) for additional analysis.

Table 1 DM of bitcoin networks.

Nets/Attributes	BBC	PAD	PFA	ANBCNM	ANUHS	TMLM	PTSA	PWA	TFDBD	BVASFBT	UAT	AITD	URWD	ALW
BN1	…	…	…	…	…	…	…	…	…	…	…	…	…	…
BN2	…	…	…	…	…	…	…	…	…	…	…	…	…	…
BN3	…	…	…	…	…	…	…	…	…	…	…	…	…	…
….	…	…	…	…	…	…	…	…	…	…	…	…	…	…
BNn	…	…	…	…	…	…	…	…	…	…	…	…	…	…

Nets/Attributes	IRWC	PMFETSOBA	IIA/B	UMTMTSOCS	P/AIM	MTEP/A	P	UA	UTM	GCIOPS
BN1	…	…	…	…	…	…	…	…	…	…
BN2	…	…	…	…	…	…	…	…	…	…
BN3	…	…	…	…	…	…	…	…	…	…
….	…	…	…	…	…	…	…	…	…	…
BNn	…	…	…	…	…	…	…	…	…	…

**BN stands for Bitcoin Network

Table 2 Importance scale for the LDFS-FWZIC method.

Linguistic terms	Numeric scale	LDFS	
		$A_d(\varsigma), S_d(\varsigma)$	(, β)
Not important	1	(0.1, 0.8)	(0.1 ,0.8)
Slightly important	2	(0.25, 0.6)	(0.25, 0.6)
Moderately important	3	(0.5, 0.4)	(0.5, 0.4)
Important	4	(0.75, 0.2)	(0.75, 0.2)
Very important	5	(0.9, 0.05)	(0.9, 0.5)

$$EDM = \begin{array}{c c} & \begin{array}{ccc} EA1 & \ldots & EAn \end{array} \\ \begin{array}{c} E_1 \\ \vdots \\ E_{f5} \end{array} & \begin{bmatrix} EA_{24}/E_5 & \cdots & EA_{1n}/E_{1n} \\ \vdots & \ddots & \vdots \\ EA_{f1}/E_{f1} & \cdots & EA_{fn}/E_{fn} \end{bmatrix} \end{array} \quad (1)$$

iv. LDFS-EDM is created by applying LDFS's membership and reference parameters on EDM. LDFS, which replaces the numeric scale in EDM, is shown in Table 2. LDFS's membership and reference parameters are described in Definition 1.

Definition 1 (Riaz & Hashmi, 2019)**:** Let Q be the nonempty reference set. An LDFS $F on Q$ is an object of the form

$$F_d = \{(\varsigma, (A_d(\varsigma), S_d(\varsigma)), (\alpha, \beta)) : \varsigma \in Q\},$$

where $A_d(\varsigma)$, $S_d(\varsigma)$ and α, *β[0, 1]* are membership, nonmembership and reference parameters, respectively. These grades satisfy the following condition:

$$0 \leq \alpha A_d(\varsigma) + \beta S_d(\varsigma) \leq 1 \forall \varsigma \in Q with 0 \leq \alpha + \beta \leq 1.$$

These reference parameters can aid in the definition or classification of a system. They expand the space of grades in LDFS and remove constraints on them. The part of hesitation can be assessed as follows:

$$E\pi_d = 1 - (\alpha A_d(\varsigma) + \beta S_d(\varsigma), \quad (2)$$

where E is the reference parameter related to the degree of indeterminacy. Therefore, $M = (A_d, S_d), (\alpha, \beta)$ is called a linear Diophantine fuzzy number (LDFN) with $0 \leq \alpha A_d(\varsigma) + \beta S_d(\varsigma) \leq 1 and 0 \leq \alpha + \beta \leq 1$.v. The weight values of each evaluation attribute used to evaluate bitcoin networks are generated using the LDFS-EDM obtained in the previous phase. By utilising the LDFN operator (Riaz & Hashmi, 2019) described in Eq. (2), the LDFS-FNs for each evaluated attribute amongst the five experts inside LDFS-EDM are aggregated as

$$DPFA(\gamma) = \frac{1}{n}(\gamma_1 \oplus \gamma_2 \oplus \cdots \oplus \gamma_n) = ([1 - \prod_{j=1}^{n}(1 - A_d(\varsigma)_{\gamma j})^{\frac{1}{n}}], \prod_{j=1}^{n} S_d(\varsigma)_{\gamma j}^{\frac{1}{n}}, [1 - \prod_{j=1}^{n}(1 - \alpha_{\gamma j})^{\frac{1}{n}}], \prod_{j=1}^{n} \beta_{\gamma j}^{\frac{1}{n}} \quad (3)$$

$$N = ((A_d(\varsigma),\ S_d(\varsigma)),\ (\alpha(\varsigma),\ \beta(\varsigma))) = (< (A_d(\varsigma),\ S_d(\varsigma) >, < \alpha(\varsigma),\ \beta(\varsigma) >,$$

$$where\ A_d(\varsigma),\ S_d(\varsigma), \alpha(\varsigma),\ \beta(\varsigma) \epsilon [0, 1],\ 0\ \leq\ \alpha(\varsigma)A_d(\varsigma) + \beta(\varsigma)S_d(\varsigma)\ \leq 1$$

- Defuzzification is employed to obtain the final weight, with Eq. (4) being used to defuzzify the weight values in LDFS to their crisp values by using the scoring function of LDFS.

$$P_{Md} = P(M_d) = \frac{1}{2}[A_d - S_d] + (\alpha - \beta)] \tag{4}$$

- The summation of attribute weights should be equal to one. If this requirement is not satisfied, then the following formula is used to rescale the weights:

$$w_j = s(\aleph)/\sum_{j=1}^{J} s(\aleph). \tag{5}$$

Algorithm 1 Illustration of the Pseudocode of the LDFS–FWZIC Method

Algorithm 1: Weighting of Bitcoin Evaluation Attributes Using LDFS-FWZIC

Step 1: Define the Evaluation Attributes of Bitcoin Network:
identify EA [i]

➢ EA is the set of the specified evaluation attributes of bitcoin networks to support the Industry 5.0 metaverse environment.

Step 2: Structured Expert Judgment:
Define EX [i]

➢ EX is the set of potential nominated expert panels.

Define EF, Imp

➢ The evaluation form (EF) for the evaluation attributes, as well as the degree of importance scale (Imp), are defined and built in this step.

m ← length (EX)
For i in {1..m}
if EX(i) is true then EX(i) ← EF(i)
endif
endfor

➢ The experts who decided to participate will be given the attribute evaluation form.

Step 3: Building the Expert Decision Matrix (EDM):
Initialize EDM [i, j] ← E ⊎ D
J ← length (EA)
m ← length (EX)

➢ EDM is created by the crossover established between selected expert panels with the bitcoin network evaluation attributes.

For j in {1..J}
For i in {1..m}
$\mathrm{EDM}[i, j] \leftarrow \mathrm{Imp}(\mathrm{EX}_{ij}/\mathrm{EA}_{ij})$
endfor
endfor

➢ In EDM, the selected expert's importance score for each evaluation attribute is allocated.

Step 4: Application of LDFS Membership Function:
For j in {1..J}
For i in {1..m}
LDFS EDM[i, j] ← EDM[i, j]
endfor
endfor

➢ By using fuzzy number, convert EDM's linguistic term into LDFS EDM, as shown in Table 5.

Step 5: Compute the weight for each Evaluation Attribute:
Step 5.1: Apply LDFS Aggregation Equation

➢ By using Eq. (3), apply the aggregation equation to aggregate LDFS-FNs for each evaluation attribute amongst the five experts inside LDFS-EDM.

$$DPFA(\gamma) = \frac{1}{n}(\gamma_1 \oplus \gamma_2 \oplus \ldots \oplus \gamma_n) = \left(\left[1 - \prod_{j=1}^{n}\left(1 - A_d(\varsigma)_{\gamma j}\right)^{\frac{1}{n}}\right], \prod_{j=1}^{n} S_d(\varsigma)_{\gamma j}^{\frac{1}{n}}, \left[1 - \prod_{j=1}^{n}(1 - \alpha_{\gamma j})^{\frac{1}{n}}\right], \prod_{j=1}^{n} \beta_{\gamma j}^{\frac{1}{n}}\right.$$

Step 5.3: Find the Score Value

➢ Defuzzication is conducted to find the score value for each evaluation attribute by using Eq. (4).

For j in {1..J}
$$\mathrm{P}_{\mathrm{Md}} = \mathrm{P}(\mathrm{M_d}) = \frac{1}{2}[\mathrm{A_d} - \mathrm{S_d}] + (\alpha - \beta)]$$
Endfor

➢ The final weight for each evaluation attribute is computed with Eq. (5).

Step 5.4: Find the Final Weight
For j in {1..J}
$$\mathrm{w}[j] \leftarrow \mathrm{s}[j]/\sum_{j=1}^{J} \mathrm{s}[j]$$
endfor
Endfor
Endfor

3.3 MULTIMOORA method

The MULTIMOORA method (Arian Hafezalkotob et al., 2019) is employed to model the bitcoin networks to support Industry 5.0's metaverse environment and determine the ideal environment for future analyses of bitcoin networks. MULTIMOORA used two inputs: the DM of bitcoin networks (Section 3.1) and the determined weights of the evaluation attributes (Section 3.2). The following is a summary of MULTIMOORA's modelling steps:i. In this step, the normalised DM should be constructed because alternative ratings on the problem's many evaluation attributes may have different dimensions; thus, they should be normalised before being included in an MADM model. Consequently, multiple scales or units are used to convey the values assigned to the various evaluation attributes; in that form, they are incomparable. Different attribute dimensions are converted to nondimensional attributes in this step, thus enabling comparisons across evaluation attributes. Therefore, on the basis of the vector normalisation ratio, we can build the normalised DM, which is represented as follows:

$$\left[x_{ij}\right]_{mn}, \left[w_j\right]_{1*n},$$

$$where\ i = 1, \ldots, m j = 1, ..., n, \quad D_1\ D_j\ ...D_n$$

$$X = \begin{bmatrix} x_{11} & x_{1j} & \ldots & x_{1n} \\ x_{i1} & x_{ij} & \ldots & x_{in} \\ \vdots & \vdots & \vdots & \vdots \\ x_{m1} & x_{mj} & \ldots & x_{mn} \end{bmatrix} \begin{matrix} A_1 \\ A_i \\ A_m \end{matrix},$$

where (x_{ij}) represents the ratings of (m) alternatives of the problem with respect to (n) evaluation attributes.

W= $[w_1 ... w_1\ \ldots\ w_1]$

$$\left[x_{ij}^*\right]_{mn}, wherei = 1, ..., mj = 1, ..., n$$

$$x_{ij}^* = x_{ij}/\sqrt{\sum_{i=1}^{m}(x_{ij})^2} \tag{6}$$

ii. In this step, we should compute the subordinate utilities, namely, the utilities of the 'ratio system, reference point approach and full multiplicative form', as follows:

$\{y_i\}_{mx1} i = 1, \ldots, m$ for RS,
$\{z_i\}_{mx1} i \ldots\ldots, m$ for RPA,
$\{u_i\}_{mx1} \cdots = 1, ..., m$ for FMF.

The weighted normalised ratings are added for the evaluation attributes to calculate the utility of the ratio system as follows:

$$y_i = \sum_{j=1}^{g} w_j x_{ij}^* - \sum_{j=g+1}^{n} w_j x_{ij}^*, \tag{7}$$

where the number of available evaluation attributes is g and the number of unavailable evaluation attributes is $(n–g)$.

The Tchebycheff Min–Max Metric is used in the reference point approach. The Tchebycheff Min–Max Metric is derived from the general theory of the Murkowski metric, which is the source of various decision analytic methodologies, such as goal programming (Arian Hafezalkotob et al., 2019). The utility is obtained by initially defining the maximum objective reference point (MORP) vector as follows:

$$r_j = \left\{max_i x_{ij}^*, \ j \leq g; min_i x_{ij}^*, \ j > g\right\}. \tag{8}$$

The distance between each member of the MORP vector's weighted value and the weighted alternative rating is calculated as follows:

$$d_{ij} = \left[w_j r_j - w_j x_{\mathrm{ij}}^*\right]. \tag{9}$$

The utility of RPA is calculated by maximising the distance given in Eq. (9) in the following manner:

$$z_i = max_j d_{ij}. \tag{10}$$

Hence, we can compute the utility of the full multiplicative form as follows:

$$u_i = \pi_{j=1}^{g} (x_{\mathrm{ij}}^*)^{wj} / \pi_{j=g+1}^{n} (x_{\mathrm{ij}}^*)^{wj}. \tag{11}$$

iii. In this step, the subordinate models are generated (the models of the ratio system, reference point approach and full multiplicative form, i.e. $\mathrm{R_{RS}}$, $\mathrm{R_{RPA}}$ and $\mathrm{R_{FMF}}$.

The ideal alternative based on the ratio system has the maximum utility $\mathrm{y_i}$, and it is modelled in descending order as follows:

$$R_{RS} = \left\{A_{i|max_i y_i} > .... > A_{i|min_i y_i}\right\}. \tag{12}$$

The ideal alternative based on the reference point approach has the lowest utility zi, and the approach is modelled in ascending order as follows:

$$R_{RAP} = \{A_{i|min_i z_i} > .... > A_{i|max_i z_i}\}. \tag{13}$$

The ideal alternative based on FMF has the highest maximum utility $\mathrm{u_i}$, and its modelling is generated in descending order as follows:

$$R_{FMF} = \{A_{i|max_i u_i} > .... > A_{i|min_i u_i}\}. \tag{14}$$

iv. Generate the final modelling of alternatives by employing modelling aggregation tools. In this step, the model position method is applied. This modelling aggregation tool, also known as the reciprocal model method, considers each alternative's position in accordance with each subordinate modelling technique. To determine the final modelling, the model position method uses the score MPM (Ai) for each alternative. The score is as follows:

$$MPM(A_i) = 1/(1/r(y_i) + 1/r(z_i) + \ 1/r(u_i)), \tag{15}$$

where $r(y_i)$, $r(z_i)$ and $r(u_i)$ are the modelling of RS, MPA and FMF, respectively. The ideal alternative based on the model position method has the lowest value of $MPM(A_i)$.

Algorithm 2 Pseudocode of the MULTIMOORA Method

Algorithm 2: Modelling the Bitcoin Network Alternatives Using MULTIMOORA

Step1: Formulated and Normalized Decision Matrix:	
Identify EA [i]	➢ EA is the set of the identified evaluation attributes of bitcoin networks to support the Industry 5.0 metaverse environment.
Identify BN[i]	➢ BN is the set of the identified bitcoin network alternatives.
J ← length (D) m ← length (BN) For j in {1..J} For i in {1..m} if BN(i) is true then	
$x_{ij}^{*} = x_{ij} / \sqrt{\sum_{i=1}^{m} (x_{ij})^{2}}$	➢ The normalised decision matrix is calculated with Eq. (6).

Endif
Endfor
Endfor	

Step 2: Compute the Subordinate Utilities: RS, RPA, FMF	
Input: w[i]	➢ The weights of evaluation attributes are determined through LDFS-FWZIC by referring to Algorithm 1.
J ← length (EA) m ← length (BN) For j in {1..J} For i in {1..m}	
$y_i = \sum_{j=1}^{g} w_j x_{ij}^{*} - \sum_{j=g+1}^{n} w_j x_{ij}^{*}$ $r_j = \{ \max_i x_{ij}^{*}, \quad j \le g; \ \min_i x_{ij}^{*}, \quad j > g \}$ $d_{ij} = [w_j r_j - w_j x_{ij}^{*}]$ $z_i = \max_j d_{ij}$ $u_i = \pi_{j=1}^{g} (x_{ij}^{*})^{wj} / \pi_{j=g+1}^{n} (x_{ij}^{*})^{wj}$	➢ RS is calculated with Eq. (7). ➢ Define and calculate MORP before calculating RS by Eqs. (8) and (9). ➢ RPA and FMF are calculated with Eqs. (10) and (11), respectively.
Endfor Endfor	
Step 3: Generate the Subordinate Modelling : RS, RPA, and FMF	
For j in {1..J} For i in {1..m}	
$R_{RS} = \{ A_{i \mid \max_i y_i} > \ldots . > A_{i \mid \min_i y_i} \}$ $R_{RAP} = \{ A_{i \mid \min_i z_i} > \ldots . > A_{i \mid \max_i z_i} \}$ $R_{FMF} = \{ A_{i \mid \max_i u_i} > \ldots . > A_{i \mid \min_i u_i} \}$	➢ Generate the modelling of RS, RPA and FMF with Eqs. (12), (13) and (14), respectively.
Endfor Endfor	
Step 4: Generate of the Final Modelling	
For j in {1..J} $\mathrm{MPM}\ (A_i) = 1/(1/r(y_i) + 1/r(z_i) + 1/r(u_i))$	➢ The final models are generated by applying the model position method, and it is done with Eq. (15).
Step 5: Modelling the Alternatives According to the Value of the Model Position Method, and the Best Alternative Has the Lowest MPM (A i)	

4 Results and discussion

In Sect. 4.1, the results of the constructed DM of the bitcoin networks to support Industry 5.0's metaverse environment and the procedure of evaluation are presented and discussed, and in Sect. 4.2, the results of LDFS-FWZIC evaluation attribute weighting are examined. In Sect. 4.3, the modelling results of the bitcoin networks derived by the MULTIMOORA method are presented.

4.1 Results of bitcoin networks' DM and procedure of evaluation

The constructed DM of bitcoin networks' results for supporting Industry 5.0's metaverse environment are presented in this section. On the basis of the single main category of evaluation attributes, including 24 evaluation attributes, 22 networks are identified and evaluated. Table 3 shows the intersection of each network with the evaluation attributes.

Ten development attributes and 19 alternatives, which are bitcoin networks (BN), were addressed by Kus Khalilov and Levi (2018) who covered studies up to 2018. Then, a number of studies from 2018 and beyond were examined. Fourteen additional attributes and five new bitcoin networks were added, increasing the total number of evaluation attributes and alternatives to 24 and 22, respectively. As a result and in accordance with Table 3, the assessment is based on whether the attributes are present in each network. A value of 0 indicates that the attribute is not present in the network, and a value of 1 indicates that it is present. The results of the LDFS-FWZIC method's weighting of the evaluation attributes are discussed in the section that follows.

4.2 Results of weighting the evaluation attributes

This section presents the results of LDFS-FWZIC. The complete absence of inconsistencies in the weighted attributes offered by LDFS-FWZIC is a critical advantage of this method. A questionnaire and five linguistic terms are employed to elicit the preferences of five experts for each attribute and determine their relative importance. Table 4 presents the final EDM of the predefined attributes.

The language measures of relevance within EDM are substituted for further analysis with numerical scales (Table 2). Then, by replacing the numeric scales with LDFS (Table 2), LDFS-EDM is created. Eq. (1) and Definition 1 show that LDFS uses each attribute's LDFS-EDM to construct LDFS-EDM. Table 9 in Appendix A presents the overall computation outcomes. The scores and weights for each attribute are determined based on Eqs. (4) and (5), as presented in Table 5.

The final weighting results of the bitcoin network to support Industry 5.0's meta-verse environment are presented in Table 5. The table also displays the level of importance of the 24 anonymity and privacy evaluation attributes, as determined by the proposed LDFS-FWZIC. The evaluation attributes are discussed in descending order of final weights starting from the highest to the lowest. The aforementioned results present a list of values for various attributes, namely, PFA, URWD, P/AIM, GCIOPS, PTSA, P, IRWC, UAT, MTEP/A, PAD, PWA, UA, IIA/B, ANUHS, UMTMTSOCS, BBC, TMLM, PMFETSOBA, UTM, ALW, BVASFBT, ANBCNM, TFDBD and AITD. The weight value of PFA is 0.0556, and URWD, P/AIM and GCIOPS have values of 0.0519, 0.0519 and 0.0502, respectively. PTSA, P, IRWC, UAT, MTEP/A and PAD have values of 0.0499, 0.0488, 0.0482, 0.0451, 0.0448 and 0.0437, respectively. PWA has a value of 0.0431, UA has a value of 0.0419, IIA/B has a value of

Table 3 DM of bitcoin networks to support Industry 5.0's metaverse environment.

Nets/Attributes	BBC	PAD	PFA	ANBCNM	ANUHS	TMLM	PTSA	PWA	TFDBD	BVASFBT	UAT	AITD	URWD	ALW
BN1 (Reid & Harrigan, 2013)	0	1	1	1	0	0	0	0	0	1	0	1	0	0
BN2 (Androulaki et al., 2013)	0	0	0	0	0	0	0	0	0	0	0	0	1	0
BN3 (Ober et al., 2013)	0	0	0	0	0	0	0	0	0	0	0	0	0	0
BN4 (Ortega, 2013)	0	0	0	0	0	0	0	0	0	0	0	0	0	0
BN5 (Baumann et al., 2014)	0	1	0	1	0	0	0	0	0	0	0	0	0	0
BN6 (Meiklejohn et al., 2013)	0	1	1	0	0	0	0	0	0	0	0	0	0	0
BN7 (Spagnuolo et al., 2014)	0	1	1	0	0	0	0	0	1	1	1	0	0	0
BN8 (Nick, 2015)	0	0	0	0	0	0	0	0	0	0	0	0	1	1
BN9 (Zhao & Guan, 2015)	0	0	1	1	0	0	0	0	0	0	0	0	0	0
BN10 (Fleder et al., 2015)	0	1	1	0	0	0	0	0	1	0	0	0	0	0
BN11 (Moser et al., 2013)	0	0	1	0	0	0	0	0	1	0	0	0	0	0
BN12 (Koshy et al., 2014)	1	0	0	0	0	0	0	0	0	0	0	0	0	0
BN13 (Biryukov et al., 2014)	1	0	0	0	1	0	0	0	0	0	0	0	0	0

Table 3 (continued)

Nets/Attributes	BBC	PAD	PFA	ANBCNM	ANUHS	TMLM	PTSA	PWA	TFDBD	BVASFBT	UAT	AITD	URWD	ALW
BN14 (Biryukov & Pustogarov, 2015)	1	0	0	0	1	0	0	0	0	0	0	0	0	0
BN15 (Fanti & Viswanath, 2017)	0	0	0	1	0	0	0	0	0	0	0	0	1	0
BN16 (Neudecker & Hartenstein, 2017)	0	0	0	0	0	0	0	0	0	0	0	0	0	0
BN17 (Feld et al., 2014)	0	0	0	0	0	0	0	0	1	0	0	0	0	0
BN18 (Jawaheri et al., 2020)	0	1	1	0	1	0	0	0	1	0	0	1	0	0
BN19 (Nerurkar et al., 2021)	0	0	0	1	0	1	1	0	0	0	0	0	0	0
BN20 (Lv et al., 2020)	0	1	1	0	0	1	0	1	0	1	0	0	1	0
BN21 (Kwansah Ansah et al., 2019)	0	0	0	0	0	0	0	0	0	0	0	0	0	0
BN22 (Kumar et al., 2020)	0	0	0	1	0	0	0	0	0	0	0	0	0	0

Nets/Attributes	IRWC	PMFETSOBA	IIA/B	UMTMTSOCS	P/AIM	MTEP/A	P	UA	UTM	GCIOPS
BN1 (Reid & Harrigan, 2013)	1	0	0	0	1	0	0	0	0	0
BN2 (Androulaki et al., 2013)	0	0	0	0	1	1	0	1	0	0
BN3 (Ober et al., 2013)	0	0	1	0	0	1	0	1	0	0
BN4 (Ortega, 2013)	0	0	0	0	1	0	0	0	0	0
BN5	0	0	0	0	0	0	0	0	0	0

Table 3 (continued)

Nets/Attributes	IRWC	PMFETSOBA	IIA/B	UMTMTSOCS	P/AIM	MTEP/A	P	UA	UTM	GCIOPS
BN6 (Meiklejohn et al., 2013)	1	0	1	0	0	0	0	0	0	0
BN7 (Spagnuolo et al., 2014)	1	0	0	0	0	0	0	0	0	1
BN8 (Nick, 2015)	0	0	0	1	1	0	0	0	0	0
BN9	1	0	0	0	0	0	0	0	0	0
BN10 (Fleder et al., 2015)	1	0	0	0	0	0	0	0	1	0
BN11 (Moser et al., 2013)	0	0	0	0	0	1	0	0	0	1
BN12 (Koshy et al., 2014)	0	0	0	0	0	0	0	0	0	1
BN13 (Biryukov et al., 2014)	0	0	0	0	1	0	0	1	0	1
BN14 (Biryukov & Pustogarov, 2015)	0	0	0	0	1	0	0	1	0	0
BN15 (Fanti & Viswanath, 2017)	0	0	0	0	0	0	1	1	0	0
BN16 (Neudecker & Hartenstein, 2017)	0	0	1	0	0	0	0	0	0	1
BN17	0	0	0	0	0	1	0	0	0	0
BN18 (Jawaheri et al., 2020)	1	1	0	0	1	0	0	1	0	1
BN19 (Nerurkar et al., 2021)	0	0	0	0	0	0	1	0	0	1
BN20 (Lv et al., 2020)	1	0	0	1	0	0	1	0	0	1
BN21 (Kwansah Ansah et al., 2019)	0	0	0	0	1	0	0	1	1	0
BN22 (Kumar et al., 2020)	0	0	0	0	0	0	0	0	0	1

Table 4 EDM Based on the Preferences of Five Experts.

Experts/Attributes	Exp1	Exp2	Exp3	Exp4	Exp5
BBC	I	I	MI	I	MI
PAD	MI	VI	VI	I	MI
PFA	VI	VI	VI	VI	VI
ANBCNM	I	I	SI	MI	MI
ANUHS	MI	VI	I	MI	I
TMLM	MI	I	VI	SI	VI
PTSA	I	VI	VI	I	I
PWA	MI	I	I	I	I
TFDBD	MI	M I	SI	I	M I
BVASFBT	I	I	NI	MI	I
UAT	VI	I	MI	I	I
AITD	MI	SI	SI	SI	SI
URWD	I	VI	VI	VI	I
ALW	MI	I	I	N I	VI
IRWC	VI	I	I	I	I
PMFETSOBA	MI	VI	VI	SI	I
IIA/B	SI	VI	VI	M I	VI
UMTMTSOCS	I	M I	M I	I	I
P/AIM	I	VI	VI	VI	I
MTEP/A	VI	I	I	M I	I
P	MI	VI	VI	VI	I
UA	VI	M I	I	MI	I
UTM	I	MI	I	M I	I
GCIOPS	I	I	VI	VI	I

0.0419, ANUHS has a value of 0.0414, UMTMTSOCS has a value of 0.0402, BBC has a weight value of 0.0401, TMLM has a value of 0.0399, PMFETSOBA has a value of 0.0399, UTM has a value of 0.0398, ALW has a value of 0.0360, BVASFBT has a value of 0.03448, ANBCNM has a value of 0.0331, TFDBD has a value of 0.0297 and AITD has a value of 0.0081.

4.3 Bitcoin network modelling results

In this study, the MULTIMOORA method and the weights obtained by the LDFS-FWZIC method are used to model 22 bitcoin networks to support Industry 5.0's metaverse environment. This section reveals the results of using the MULTIMOORA method to determine the final modelling of the networks in Step 3. The results are shown in Table 6.

Table 6 presents the results of the computed subordinate utilities, which are indicated as the utility of the ratio system, reference point approach and full multiplicative form, as mentioned in the third section of the MULTIMOORA discussion. It also shows the results of the produced subordinate modelling and the modelling of R_{RS}, R_{RAP} and R_{FMF} (ratio

Table 5 Results of modelling and weighting the evaluation attributes.

Attributes		Def. of $\tilde{w}$	Final weight	Attributes		Def. of $\tilde{w}$	Final weight
EA1	BBC	0.1975	0.0401	EA13	URWD	0.2560	0.0519
EA2	PAD	0.2156	0.0437	EA14	ALW	0.1772	0.0360
EA3	PFA	0.2741	0.0556	EA15	IRWC	0.2377	0.0482
EA4	ANBCNM	0.1630	0.0331	EA16	PMFETSOBA	0.1965	0.0399
EA5	ANUHS	0.2041	0.0414	EA17	IIA/B	0.2065	0.0419
EA6	TMLM	0.1968	0.0399	EA18	UMTMTSOCS	0.1981	0.0402
EA7	PTSA	0.2459	0.0499	EA19	P/AIM	0.2560	0.0519
EA8	PWA	0.2122	0.0431	EA20	MTEP/A	0.2208	0.0448
EA9	TFDBD	0.1464	0.0297	EA21	P	0.2403	0.0488
EA10	BVASFBT	0.1699	0.0345	EA22	UA	0.2067	0.0419
EA11	UAT	0.2226	0.0452	EA23	UTM	0.1963	0.0398
EA12	AITD	0.0399	0.0081	EA24	GCIOPS	0.2476	0.0502

Table 6 Bitcoin network results based on MULTIMOORA.

Bitcoin networks	R_{RS}		R_{RAP}		R_{FMF}		Aggregation	
	Score	Model	Score	Model	Score	Model	Score	Model
BN1	0.1120	5	0.0499	2	0.0010	4	1.0526	5
BN2	0.0827	10	0.0499	2	0.0005	8	1.3793	9
BN3	0.0625	14	0.0499	2	0.0003	16	1.5775	14
BN4	0.0185	22	0.0499	2	0.0002	22	1.6923	22
BN5	0.0301	21	0.0499	2	0.0002	20	1.6733	21
BN6	0.0787	12	0.0499	2	0.0005	9	1.4400	11
BN7	0.1496	3	0.0499	2	0.0013	3	0.8571	4
BN8	0.1088	6	0.0499	2	0.0005	10	1.3043	8
BN9	0.0515	16	0.0499	2	0.0003	14	1.5775	14
BN10	0.0960	8	0.0499	2	0.0006	7	1.3023	7
BN11	0.0722	13	0.0499	2	0.0004	11	1.4974	13
BN12	0.0400	18	0.0499	2	0.0002	18	1.6364	18
BN13	0.0981	7	0.0499	2	0.0007	6	1.2353	6
BN14	0.0813	11	0.0499	2	0.0004	13	1.4974	12
BN15	0.0836	9	0.0499	2	0.0004	12	1.4400	10
BN16	0.0410	17	0.0499	2	0.0002	17	1.6190	17
BN17	0.0358	19	0.0499	2	0.0002	21	1.6660	20
BN18	0.1883	2	0.0499	2	0.0031	2	0.6667	2
BN19	0.1366	4	0.0452	1	0.0007	5	0.6897	3
BN20	0.2450	1	0.0499	2	0.0049	1	0.4000	1
BN21	0.0625	15	0.0499	2	0.0003	15	1.5789	16
BN22	0.0303	20	0.0499	2	0.0002	19	1.6594	19

system, reference point approach and full multiplicative form). The final modelling of bitcoin networks to support Industry 5.0's metaverse environment is determined using modelling aggregation tools, namely, the model position method MPM, and the results are listed in Table 6. Consequently, the best alternative based on the model position method has the lowest MPM (A i). Furthermore, BN20 has the lowest MPM of 1, followed by BN18, which has an MPM of 2. BN19 has an MPM of 3, BN7 has an MPM of 4, BN1 has an MPM of 5, BN13 has an MPM of 6, BN10 has an MPM of 7, BN8 has an MPM of 8, BN2 has an MPM of 9, BN15 has an MPM of 10, BN6 has an MPM of 11, BN14 has an MPM of 12, BN11 has an MPM of 13, BN9 and BN3 have an MPM of 14, BN21 has an MPM of 16, BN16 has an MPM of 17, BN12 has an MPM of 18, BN22 has an MPM of 19, BN17 has an MPM of 20, BN5 has an MPM of 21 and BN4 has an MPM of 22.

5 Evaluation and validation

By conducting a sensitivity analysis, this section validates the proposed method (Sect. 5.1). Then, by using 14 comparative points, the proposed method is compared with benchmark ones (Sect. 5.2).

5.1 Sensitivity analysis

A sensitivity analysis is conducted to determine how the major evaluation attribute influences the effectiveness of the proposed methods. The attribute with the greatest weight value is referred to as the 'most essential attribute'. Many researchers, such as Mahmoud et al. (2022) and Qahtan et al. (2022b), recommended using a sensitivity analysis to show the weight ratio by adopting Eq. (16).

$$w_c = (1 - w_s) \times \left(w_c^o / W_c^0\right) = w_c^o - \Delta x \alpha_c, \tag{16}$$

wherew_s indicates the most important evaluation attribute,w_c^o indicates the original weight values determined by the LDF-FWZIC method,

W_c^0 indicates the original weight summing for the shifting weight values of the evaluation attributes,

Δx indicates the range of modifications made to the weights of the privacy and anonymity evaluation attributes, which are the limit values of the most important evaluation attributes.

The α_c values of each evaluation attribute can be calculated using Eq. (17), and the limit values of Δx can be deduced using Eq. (18). After determining the Δx limits, the new weight values of the evaluation attributes are derived with Eq. (16). In consideration of the new weights of the evaluation attributes, the bitcoin network models are computed.

$$\alpha_c = w_c^o / W_c^0 \tag{17}$$

$$-w_s \leq \Delta x \leq 1 - w_s \tag{18}$$

PFA (EA3 = 0.0556) is the most essential evaluation attribute amongst the 24 anonymity and privacy evaluation attributes in the networks. On this basis, the relative weights of each evaluation attribute are calculated using Eq. (16), yielding nine scenarios for changing the weights of the evaluation attributes in the bitcoin network's main category. As shown in Table 7, the elasticity coefficient (α_c) is calculated for each of the evaluation attributes. The PFA evaluation attributes in the bitcoin network have limit values of $-0.0556 \leq \Delta x \leq 0.9444$.

Table 7 New weight values for each evaluation attribute of the nine scenarios for bitcoin networks.

Evaluation attributes	Original weights	S1	S2	S3	S4	S5	S6	S7	S8	S9	α_c
EA1	0.0401	0.0424	0.0371	0.0318	0.0265	0.0212	0.0159	0.0106	0.0053	0.0000	0.0424
EA2	0.0437	0.0463	0.0405	0.0347	0.0290	0.0232	0.0174	0.0116	0.0058	0.0000	0.0463
EA3	0.0556	0.0000	0.1250	0.2500	0.3750	0.5000	0.6250	0.7500	0.8750	0.9998	0.0589
EA4	0.0331	0.0350	0.0307	0.0263	0.0219	0.0175	0.0131	0.0088	0.0044	0.0000	0.0350
EA5	0.0414	0.0439	0.0384	0.0329	0.0274	0.0219	0.0164	0.0110	0.0055	0.0000	0.0439
EA6	0.0399	0.0423	0.0370	0.0317	0.0264	0.0211	0.0159	0.0106	0.0053	0.0000	0.0423
EA7	0.0499	0.0528	0.0462	0.0396	0.0330	0.0264	0.0198	0.0132	0.0066	0.0000	0.0528
EA8	0.0431	0.0456	0.0399	0.0342	0.0285	0.0228	0.0171	0.0114	0.0057	0.0000	0.0456
EA9	0.0297	0.0315	0.0275	0.0236	0.0197	0.0157	0.0118	0.0079	0.0039	0.0000	0.0315
EA10	0.0345	0.0365	0.0319	0.0274	0.0228	0.0183	0.0137	0.0091	0.0046	0.0000	0.0365
EA11	0.0452	0.0478	0.0419	0.0359	0.0299	0.0239	0.0179	0.0120	0.0060	0.0000	0.0478
EA12	0.0081	0.0086	0.0075	0.0064	0.0054	0.0043	0.0032	0.0021	0.0011	0.0000	0.0086
EA13	0.0519	0.0550	0.0481	0.0413	0.0344	0.0275	0.0206	0.0138	0.0069	0.0000	0.0550
EA14	0.0360	0.0381	0.0333	0.0286	0.0238	0.0190	0.0143	0.0095	0.0048	0.0000	0.0381
EA15	0.0482	0.0511	0.0447	0.0383	0.0319	0.0255	0.0192	0.0128	0.0064	0.0000	0.0511
EA16	0.0399	0.0422	0.0369	0.0317	0.0264	0.0211	0.0158	0.0106	0.0053	0.0000	0.0422
EA17	0.0419	0.0444	0.0388	0.0333	0.0277	0.0222	0.0166	0.0111	0.0055	0.0000	0.0444
EA18	0.0402	0.0426	0.0372	0.0319	0.0266	0.0213	0.0160	0.0106	0.0053	0.0000	0.0426
EA19	0.0519	0.0550	0.0481	0.0413	0.0344	0.0275	0.0206	0.0138	0.0069	0.0000	0.0550
EA20	0.0448	0.0475	0.0415	0.0356	0.0297	0.0237	0.0178	0.0119	0.0059	0.0000	0.0475
EA21	0.0488	0.0516	0.0452	0.0387	0.0323	0.0258	0.0194	0.0129	0.0065	0.0000	0.0516
EA22	0.0419	0.0444	0.0389	0.0333	0.0278	0.0222	0.0167	0.0111	0.0056	0.0000	0.0444
EA23	0.0398	0.0422	0.0369	0.0316	0.0264	0.0211	0.0158	0.0105	0.0053	0.0000	0.0422
EA24	0.0502	0.0532	0.0465	0.0399	0.0332	0.0266	0.0199	0.0133	0.0066	0.0000	0.0532

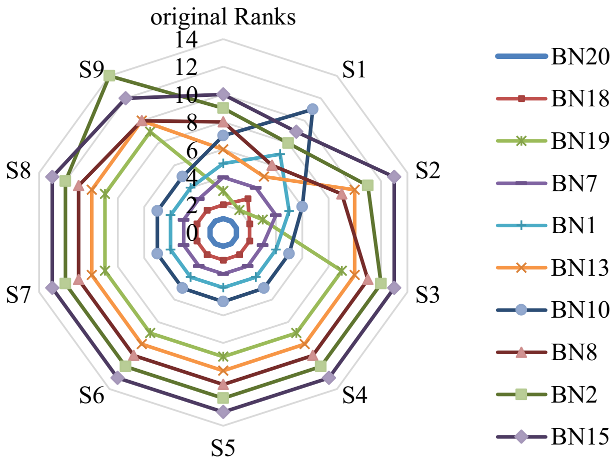

Fig. 2 Sensitivity analysis of modelling the top 10 bitcoin network alternatives in nine scenarios

Subsequently, on the basis of the limits of x, various attribute weight sets (S1, S2..., S9) for sensitivity analysis are calculated. Table 7 lists the new weight sets used for the sensitivity analysis. Each set of weights must have a total attribute weight that is equal to one ($wc=1$).

The sensitivity of the modelled bitcoin network to support Industry 5.0's metaverse environment is assessed using the weight values generated. In each of the nine scenarios, the goal is to see how changing the weights affects the final models. The impacts of adjusting the evaluation attribute weight in the model of bitcoin networks for all values are shown in Fig. 2. In some cases, the importance level of the anonymity and privacy evaluation attributes has a considerable impact on the individual model of bitcoin networks. The proposed integration method FWZIC with MULTIMOORA demonstrates its power in the majority of the nine scenarios. The models of the 22 networks in the bitcoin network category to support Industry 5.0's metaverse environment are compared across all values. Fig. 2 presents the models of the top 10 BNs, and the overall models of the 22 BNs are given in Table 10 in Appendix A.

The modelling of the first alternative BN1 is changed from its modelling in LDFS-FWZIC; it moves to the seventh model in S1 and keeps the same modelling result (Model=5) as LDFS-FWZIC in S2, but it moves to the fourth model in S3, S4, S5, S6, S7, S8 and S9 across all α values. For all α values and scenarios, BN2 drops to the eighth model in S1 but rises to eleventh and fourteenth in S2 and S9, respectively; then, it moves to twelfth in the remaining scenarios. BN3 drops to the thirteenth model in S1 and rises to the fifteenth model in S2, S3, S4, S5, S6, S7, S8 and S9 across all α values. For all α values, BN4 maintains the same model, which is the 22nd, in all nine scenarios. Except for S9 where it drops to the 22nd model across all α values, BN5 maintains the same model in the remaining scenarios. For all α values, BN6 moves to the fourteenth and seventh models in S1 and S2, respectively, and to the sixth model in seven scenarios. BN7 moves to the third model in seven scenarios and maintains the same model in S1 and S2 across all α values. In S1, S2 and S9, BN8 moves to the sixth, ninth and tenth models, respectively, but in six scenarios, it moves to the eleventh model across all α values. In S1 and S2, BN9 moves to the nineteenth and twelfth models, respectively, but in seven scenarios, it moves to the eighth model across all α values. In seven scenarios, BN10 moves to the fifth model across all α values, but it moves to the eleventh and sixth models in S1 and S2, respectively. In seven scenarios, BN11 moves to the seventh model across all α values, but it moves to the fifteenth and eighth models in S1 and S2, respectively. In S1 and S9, BN12 moves to the seventeenth and nineteenth models, respectively, but maintains its model in seven scenarios across all α values. In S1, BN13 moves to the fifth model, but it moves to the tenth model in eight scenarios across all α values. BN14 moves to the tenth and twelfth models in S1 and S9, respectively, but it moves to the fourteenth model in seven scenarios across all α values. BN15 moves to the ninth and twelfth models in S1 and S9, respectively, but it moves to the thirteenth model in seven scenarios across all α values. BN16 moves to the sixteenth and eighteenth models across all α values in S1 and S9, respectively, but it remains at the same model in seven scenarios. BN17 keeps the same model across all α values in eight scenarios, and it moves to the seventeenth model in S9. In eight scenarios, BN18 keeps the same model across all α values, and it moves to the third model in S1. In S2, BN19 maintains the same model as the third model but moves to the second model in S1 and the ninth in the remaining scenarios across all α values. BN20 keeps the same model across all α values in all scenarios. BN21 keeps the same model in S9, but in S1, it moves to the twelfth model; in seven scenarios, it moves to the fifteenth model across all values. Finally, BN22 maintains the same model across all α values in the seven scenarios, but it moves to eighteenth and twenty-first in S1 and S9, respectively.

Spearman's model correlation coefficient (rho), weighted Spearman's model correlation coefficient (rw) and model similarity coefficient (WS) are utilised to measure the degree and direction (positive or negative) of the correlation between the original and new models. To support Industry 5.0's metaverse environment in the nine scenarios, Fig. 3 shows the rho, rw and WS values of bitcoin networks.

According to Fig. 3, in nine scenarios (S1–S9), a high and positive correlation exists between the original and new models, with rho varying from 0.8 to 0.9 and rw and WS values being equal to 0.9 in all nine scenarios. A high and positive correlation is indicated by the mean values of rho, rw and WS, which are 0.9, 0.9 and 1, respectively.

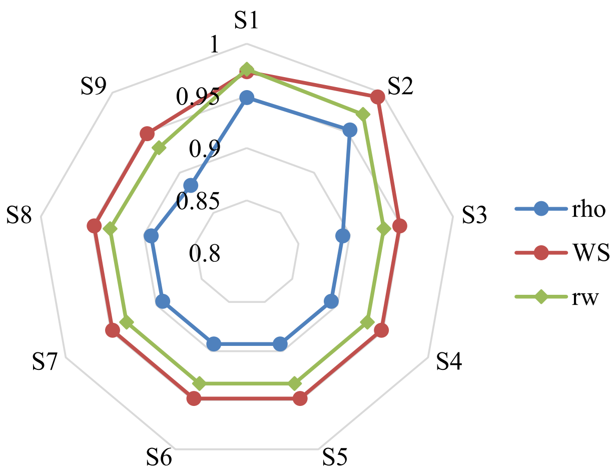

Fig. 3 Correlation of modelling amongst the nine scenarios for bitcoin network alternatives

5.2 Comparative analysis

The proposed method is compared with the current MADM method, which is S-FWZIC combined with GRA-TOPSIS (Qahtan et al., 2022). Fourteen theory- and application-based comparison points are considered in the comparison. The MADM issues related to evaluating and modelling bitcoin networks to support Industry 5.0's metaverse environment are considered in the application-based comparison. The weighting and modelling methods used in this study and the study of Qahtan et al. (2022) are compared in the theory-based comparison. The comparison points are summarised in Table 8.

The application-based comparison utilises three comparison points, and the theory-based comparison uses 11 comparison points, as shown in Table 8. In the application-based comparison, the three comparison points are satisfactorily addressed in the study of Qahtan et al. (2022) and this study (100%). Meanwhile, the work of Qahtan et al. (2022) meets all seven of the comparison weighing method points, which equals 100%, and so does this study. Additionally, the study of Qahtan et al. (2022) only achieves two of the four points required by the modelling method or 50%, whereas this study achieves three (75%) of the four required points. Overall, the study of Qahtan et al. (2022) satisfies 12 of the 14 comparison points (85.7%) but falls short on two (14.3%) of them. Meanwhile, this study achieves 13 out of 14 points (92%) and falls short on only one (8%) of them. These results indicate that a suitable method for comparing bitcoin networks can be devised, and the best network can be chosen based on the most critical comparison points.

6 Managerial implications

The following is a summary of the study's many beneficial managerial implications. Firstly, this study helps industrial managers and developers of bitcoin networks choose the best analytic method for bitcoin networks to support Industry 5.0's metaverse environment. Industrial managers and developers of bitcoin networks may use the study's findings to enhance the growth of their companies. Additionally, by building on this study, the proposed bitcoin network analysis standards may be developed in a way that will be compatible with Industry 5.0 metaverse's future environment. Secondly, this study can help with the comprehension of bitcoin networks and the mitigation of the negative impacts of deanonymization attempts. Additionally, by establishing the optimum analysis for bitcoin networks to support Industry 5.0's metaverse environment that facilitates a portion of full digital autonomy in the future, this study may be pertinent for stakeholders and all other economic and institutional actors. Thirdly, through the integration of various analytical facets, this study endeavours to assist stakeholders and investors in formulating and communicating a precise and practical solution. The study's results may serve as a convincing argument for policymakers to maintain their efforts in supporting the establishment of analytical standards for bitcoin networks that can facilitate the realisation of Industry 5.0's metaverse environment.

7 Conclusion

To model bitcoin networks to support Industry 5.0's metaverse environment on the basis of 24 evaluation attributes, this work extended the FWZIC method with LDFS and integrated it with the MULTIMOORA method. IFSs, q-ROFSs and PFSs are less effective and flexible

Table 8 Comparison points between the two studies

Comparison points			This study	Qahtan, Sharif et al., (2022)
Application-based comparison		The case study considered a variety of attributes	√	√
		The importance level of the case study's attributes was taken into consideration	√	√
		The issue with the data variation in the case study was solved	√	√
Theory-based comparison	Weighting method	The weighting method's inconsistency issue was solved	√	√
		The weighting method's dependency problem amongst attributes was solved	√	√
		Pairwise comparisons were unnecessary for the weighting method	√	√
		Uncomplicated collection of the opinions of the experts	√	√
		The weighing method's problems with unreliable, imprecise and incomplete information were solved	√	√
		The weighting method and applied FS produced a range of grades	√	√
		Other FS extensions were made more universal by the weighting method-applied FS	√	√
	Modelling method	The modelling method's informational ambiguity was solved	√	X
		The averaged solution's modelling method reduced the likelihood of expert bias against the alternative	√	√

Table 8 (continued)

Comparison points		This study	Qahtan, Sharif et al., (2022)
	By normalizing the data, the modelling method significantly decreased the likelihood of deviating from the optimal solution	√	√
	The modelling method necessitated the need for an additional method for attribute weighing because of its inability to offer weights to assess attributes in order of importance	X	X
Total score		92%	85.70%
Accumulative difference		8%	14.30%

in how they handle uncertainty compared with LDFS (Riaz & Hashmi, 2019). LDFS can give the decision maker (DM) limitless flexibility in modelling scores in contrast to many common FSs. The construction of DM was the first step in the methodology, followed by the establishment of LDFS-FWZIC and MULTIMOORA methods. The LDFS-FWZIC method was developed to estimate the weight of the evaluation attributes. The MULTIMOORA method for modelling bitcoin networks used the derived weight values and the constructed DM as input.

The LDFS-FWZIC method's findings showed that BBC is the attribute that matters the most when evaluating bitcoin networks to support Industry 5.0's metaverse environment, and Analysis Including Twitter Data is the least important attribute. The MULTIMOORA method identified BN20 as the best bitcoin network, followed by BN18, BN19 and BN4 (the worst bitcoin network). The proposed method was also proven to be sensitive to changes in the relative importance of the evaluation attributes, and a moderately positive correlation was observed for the BN20 and BN4 values. Comparative analysis revealed that this study covered 14 comparative points, whereas a prior study only covered 10.

The limitations of this study must also be highlighted. In terms of addressing the issues of unreliable, inaccurate, and incomplete information, this study concentrated on developing LDFS-FWZIC. Furthermore, in solving the ambiguity problem, this study extended MULTIMOORA with LDFS. The appointed experts received the same treatment without being given preference on the basis of their level of experience. Prioritising experts, however, can produce reasonable outcomes. The EDM in this study was constructed using five linguistic importance measurements. However, seven or 10 important linguistic measurements may be investigated to develop an EDM. For the purpose of defuzzing and aggregating the LDFNs in LDFS-EDM, this study used a single aggregation operator and scoring function. However, another aggregation operator and score function may also be adopted. Through the use of LDFS, this study extended FWZIC. The interval-valued Fermatean fuzzy rough set, for example, can be combined with the FWZIC method as an extension. Moreover, blockchain is essential in Industry 5.0 for safeguarding assets and data flows in many industrial operations and sections. From a security perspective, the ability of blockchain to serve Industry 5.0 depends on the internal specifications of the main structure, frameworks and schemes that blockchain ledgers support. Presently, the blockchain network (as with bitcoin and several other blockchain-based cryptocurrencies) records and verifies all transactions. Consequently, the blockchain network's ledger grows considerably, which increases the time required to traverse each block in the chain. Each block has a predetermined size that can only accommodate a certain amount of transactional data. In accordance with the consensus process used to validate the currently formed block, the blockchain differs in the size of the block and the time of adding (e.g. approximately every 10 minutes in bitcoin) (Shabgahi et al., 2022). For instance, only seven to eight transactions may be processed per second (bitcoin can process approximately 4.6 transactions per second) (Shabgahi et al., 2022) by various public blockchain ledgers. By contrast, in real-time industrial applications, millions of transactions occur, making blockchain deployment challenging and posing a scaling problem (Verma et al., 2022).

In bitcoin networks, scalability is an issue when utilising a blockchain over a network. The reason is that every node in the system, which could number in thousands, is required to exchange, store and validate all transactions. Individuals experience the effects of bitcoin's capacity restrictions in the form of increased transaction costs and latency. Individuals must pay high transaction fees in response to the rising demand for transactions and to ensure that their transaction is beneficial for miners, which consequently increases the likelihood that it will be included in a block. A transaction's appearance in the blockchain takes long to process due to network congestion and transaction queueing (Shabgahi et al., 2022). On the Industry 5.0 side, creating sidechain ledgers that can migrate transactional data between chains on the basis of application use cases can effectively resolve the problem. Enabling sharding in blockchain, which creates small blockchain ledgers under the jurisdiction of a sharded authority, is another strategy. Only one action needs to be taken to ensure a fair consensus principle on sharded blockchain and to arrange transactions fairly in the main chain and prevent selected applicants from receiving higher priority than others (Verma et al., 2022). From the bitcoin network side, the scalability issue has many potential solutions. Solutions for Layers 0, 1 and 2 comprise the majority of the suggestions. Solutions at Layer 0 aim to improve infrastructure, such as the network connecting the nodes. By altering the consensus method and protocols, Layer 1 solutions attempt to improve the inadequacies of the blockchain. Off-chain solutions, which is another term for Layer 2 solutions, suggest ways to depart from the blockchain (Shabgahi et al., 2022). On this basis, Industry 5.0 and bitcoin networks are likely to face the issue of scalability of payment or transaction exchange channels. Consequently, the infrastructure of the upcoming metaverse that supports bitcoin and other cryptocurrencies under the Industry 5.0 concept needs to be studied, and the solutions used to address this issue should be analysed for evaluation purposes.

Appendix A

See Tables 9 and 10.

Table 9 Results of Scoring and Weighting for Evaluation Attributes.

Experts EA		Exp1	Exp2	Exp3	Exp4	Exp5	$\tilde{W}$
	$A_d(\varsigma)$	0.0469	0.0420	0.0301	0.0505	0.0292	0.6698
EA1	$S_d(\varsigma)$	0.2000	0.2000	0.4000	0.2000	0.4000	0.0000
		0.0469	0.0420	0.0301	0.0505	0.0292	0.6698
	β	0.2000	0.2000	0.4000	0.2000	0.4000	0.0000
	$A_d(\varsigma)$	0.0313	0.0504	0.0542	0.0505	0.0292	0.7031
EA2	$S_d(\varsigma)$	0.4000	0.0500	0.0500	0.2000	0.4000	0.0000
		0.0313	0.0504	0.0542	0.0505	0.0292	0.7031
	β	0.4000	0.0500	0.0500	0.2000	0.4000	0.0000
	$A_d(\varsigma)$	0.0563	0.0504	0.0542	0.0606	0.0526	0.7985
EA3	$S_d(\varsigma)$	0.0500	0.0500	0.0500	0.0500	0.0500	0.0000
		0.0563	0.0504	0.0542	0.0606	0.0526	0.7985
	β	0.0500	0.0500	0.0500	0.0500	0.0500	0.0000
	$A_d(\varsigma)$	0.0469	0.0420	0.0151	0.0337	0.0292	0.5986
EA4	$S_d(\varsigma)$	0.2000	0.2000	0.6000	0.4000	0.4000	0.0000
		0.0469	0.0420	0.0151	0.0337	0.0292	0.5986
	β	0.2000	0.2000	0.6000	0.4000	0.4000	0.0000
	$A_d(\varsigma)$	0.0313	0.0504	0.0452	0.0337	0.0439	0.6812
EA5	$S_d(\varsigma)$	0.4000	0.0500	0.2000	0.4000	0.2000	0.0000
		0.0313	0.0504	0.0452	0.0337	0.0439	0.6812
	β	0.4000	0.0500	0.2000	0.4000	0.2000	0.0000
	$A_d(\varsigma)$	0.0313	0.0420	0.0542	0.0168	0.0526	0.6660
EA6	$S_d(\varsigma)$	0.4000	0.2000	0.0500	0.6000	0.0500	0.0000
		0.0313	0.0420	0.0542	0.0168	0.0526	0.6660
	β	0.4000	0.2000	0.0500	0.6000	0.0500	0.0000
	$A_d(\varsigma)$	0.0469	0.0504	0.0542	0.0505	0.0439	0.7561
EA7	$S_d(\varsigma)$	0.2000	0.0500	0.0500	0.2000	0.2000	0.0000
		0.0469	0.0504	0.0542	0.0505	0.0439	0.7561
	β	0.2000	0.0500	0.0500	0.2000	0.2000	0.0000
	$A_d(\varsigma)$	0.0313	0.0420	0.0452	0.0505	0.0439	0.6977
EA8	$S_d(\varsigma)$	0.4000	0.2000	0.2000	0.2000	0.2000	0.0000
		0.0313	0.0420	0.0452	0.0505	0.0439	0.6977
	β	0.4000	0.2000	0.2000	0.2000	0.2000	0.0000
	$A_d(\varsigma)$	0.0313	0.0280	0.0151	0.0505	0.0292	0.5668

Table 9 (continued)

Experts EA		Exp1	Exp2	Exp3	Exp4	Exp5	$\tilde{W}$
EA9	$S_d(\varsigma)$	0.4000	0.4000	0.6000	0.2000	0.4000	0.0000
		0.0313	0.0280	0.0151	0.0505	0.0292	0.5668
	β	0.4000	0.4000	0.6000	0.2000	0.4000	0.0000
	$A_d(\varsigma)$	0.0469	0.0420	0.0060	0.0337	0.0439	0.6119
EA10	$S_d(\varsigma)$	0.2000	0.2000	0.8000	0.4000	0.2000	0.0000
		0.0469	0.0420	0.0060	0.0337	0.0439	0.6119
	β	0.2000	0.2000	0.8000	0.4000	0.2000	0.0000
	$A_d(\varsigma)$	0.0563	0.0420	0.0301	0.0505	0.0439	0.7163
EA11	$S_d(\varsigma)$	0.0500	0.2000	0.4000	0.2000	0.2000	0.0000
		0.0563	0.0420	0.0301	0.0505	0.0439	0.7163
	β	0.0500	0.2000	0.4000	0.2000	0.2000	0.0000
	$A_d(\varsigma)$	0.0313	0.0140	0.0151	0.0168	0.0146	0.3820
EA12	$S_d(\varsigma)$	0.4000	0.6000	0.6000	0.6000	0.6000	0.0000
		0.0313	0.0140	0.0151	0.0168	0.0146	0.3820
	β	0.4000	0.6000	0.6000	0.6000	0.6000	0.0000
	$A_d(\varsigma)$	0.0469	0.0504	0.0542	0.0606	0.0439	0.7720
EA13	$S_d(\varsigma)$	0.2000	0.5000	0.5000	0.5000	0.2000	0.0000
		0.0469	0.0504	0.0542	0.0606	0.0439	0.7720
	β	0.2000	0.5000	0.5000	0.5000	0.2000	0.0000
	$A_d(\varsigma)$	0.0313	0.0420	0.0452	0.0067	0.0526	0.6243
EA14	$S_d(\varsigma)$	0.4000	0.2000	0.2000	0.8000	0.0500	0.0000
		0.0313	0.0420	0.0452	0.0067	0.0526	0.6243
	β	0.4000	0.2000	0.2000	0.8000	0.0500	0.0000
	$A_d(\varsigma)$	0.0563	0.0420	0.0452	0.0505	0.0439	0.7428
EA15	$S_d(\varsigma)$	0.0500	0.2000	0.2000	0.2000	0.2000	0.0000
		0.0563	0.0420	0.0452	0.0505	0.0439	0.7428
	β	0.0500	0.2000	0.2000	0.2000	0.2000	0.0000
	$A_d(\varsigma)$	0.0313	0.0504	0.0542	0.0168	0.0439	0.6653
EA16	$S_d(\varsigma)$	0.4000	0.0500	0.0500	0.6000	0.2000	0.0000
		0.0313	0.0504	0.0542	0.0168	0.0439	0.6653
	β	0.4000	0.0500	0.0500	0.6000	0.2000	0.0000
	$A_d(\varsigma)$	0.0156	0.0504	0.0542	0.0337	0.0526	0.6856
EA17	$S_d(\varsigma)$	0.6000	0.0500	0.0500	0.4000	0.0500	0.0000
		0.0156	0.0504	0.0542	0.0337	0.0526	0.6856
	β	0.6000	0.0500	0.0500	0.4000	0.0500	0.0000
	$A_d(\varsigma)$	0.0469	0.0280	0.0301	0.0505	0.0439	0.6710

Table 9 (continued)

Experts EA		Exp1	Exp2	Exp3	Exp4	Exp5	W̃
EA18	$S_d(\varsigma)$	0.2000	0.4000	0.4000	0.2000	0.2000	0.0000
		0.0469	0.0280	0.0301	0.0505	0.0439	0.6710
	β	0.2000	0.4000	0.4000	0.2000	0.2000	0.0000
	$A_d(\varsigma)$	0.0469	0.0504	0.0542	0.0606	0.0439	0.7720
EA19	$S_d(\varsigma)$	0.2000	0.0500	0.0500	0.0500	0.2000	0.0000
		0.0469	0.0504	0.0542	0.0606	0.0439	0.7720
	β	0.2000	0.0500	0.0500	0.0500	0.2000	0.0000
	$A_d(\varsigma)$	0.0563	0.0420	0.0452	0.0337	0.0439	0.7131
EA20	$S_d(\varsigma)$	0.0500	0.2000	0.2000	0.4000	0.2000	0.0000
		0.0563	0.0420	0.0452	0.0337	0.0439	0.7131
	β	0.0500	0.2000	0.2000	0.4000	0.2000	0.0000
	$A_d(\varsigma)$	0.0313	0.0504	0.0542	0.0606	0.0439	0.7470
EA21	$S_d(\varsigma)$	0.4000	0.0500	0.0500	0.0500	0.2000	0.0000
		0.0313	0.0504	0.0542	0.0606	0.0439	0.7470
	β	0.4000	0.0500	0.0500	0.0500	0.2000	0.0000
	$A_d(\varsigma)$	0.0563	0.0280	0.0452	0.0337	0.0439	0.6864
EA22	$S_d(\varsigma)$	0.0500	0.4000	0.2000	0.4000	0.2000	0.0000
		0.0563	0.0280	0.0452	0.0337	0.0439	0.6864
	β	0.0500	0.4000	0.2000	0.4000	0.2000	0.0000
	$A_d(\varsigma)$	0.0469	0.0280	0.0452	0.0337	0.0439	0.6674
EA23	$S_d(\varsigma)$	0.2000	0.4000	0.2000	0.4000	0.2000	0.0000
		0.0469	0.0280	0.0452	0.0337	0.0439	0.6674
	β	0.2000	0.4000	0.2000	0.4000	0.2000	0.0000
	$A_d(\varsigma)$	0.0469	0.0420	0.0542	0.0606	0.0439	0.7588
EA24	$S_d(\varsigma)$	0.2000	0.2000	0.0500	0.0500	0.2000	0.0000
		0.0469	0.0420	0.0542	0.0606	0.0439	0.7588
	β	0.2000	0.2000	0.0500	0.0500	0.2000	0.0000

Table 10 Sensitivity Analysis of Modelling the 22 Bitcoin Network Alternatives in Nine Scenarios

Bitcoin networks	Original modelling	S1	S2	S3	S4	S5	S6	S7	S8	S9
BN1	5	7	5	4	4	4	4	4	4	4
BN2	9	8	11	12	12	12	12	12	12	14
BN3	14	13	15	15	15	15	15	15	15	15
BN4	22	22	22	22	22	22	22	22	22	22
BN5	21	21	21	21	21	21	21	21	21	20
BN6	11	14	7	6	6	6	6	6	6	6
BN7	4	4	4	3	3	3	3	3	3	3
BN8	8	6	9	11	11	11	11	11	11	10
BN9	14	19	12	8	8	8	8	8	8	8
BN10	7	11	6	5	5	5	5	5	5	5
BN11	13	15	8	7	7	7	7	7	7	7
BN12	18	17	18	18	18	18	18	18	18	19
BN13	6	5	10	10	10	10	10	10	10	10
BN14	12	10	14	14	14	14	14	14	14	12
BN15	10	9	13	13	13	13	13	13	13	12
BN16	17	16	17	17	17	17	17	17	17	18
BN17	20	20	20	20	20	20	20	20	20	17
BN18	2	3	2	2	2	2	2	2	2	2
BN19	3	2	3	9	9	9	9	9	9	9
BN20	1	1	1	1	1	1	1	1	1	1
BN21	16	12	15	15	15	15	15	15	15	16
BN22	19	18	19	19	19	19	19	19	19	21

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