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Research article

A novel approach based on similarity measure for the multiple attribute group decision-making problem in selecting a sustainable cryptocurrency

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ABSTRACT

Environmental impact and sustainability challenges in the cryptocurrencies has become increasingly examined in the literature. However, studies of the multiple attribute group decision making (MAGDM) method for major selection of cryptocurrencies in advancing sustainability are still at an early stage. In particular, research on the fuzzy-MAGDM method in the evaluation of sustainability in cryptocurrencies is scarce. This paper adds contributions by developing a novel MAGDM approach to evaluate the sustainability development of major cryptocurrencies. It proposes a similarity measure for interval-valued Pythagorean fuzzy numbers (IVPFNs) based on whitenisation weight function and membership function in grey systems theory for IVPFNs. It further developed a novel generalised interval-valued Pythagorean fuzzy weighted grey similarity (GIPFWGS) measure approach to provide a more rigorous evaluation in complex decision marking problem with embedding ideal solution and membership degree. It also conducts a sustainability evaluation model of major cryptocurrencies as a numerical application and performs a robustness assessment with different variations of the expert's weight to test how different values of parameter θ can affect the ranking results of alternatives. The results suggest that Stellar is the most sustainable cryptocurrency, while Bitcoin with its intensive energy consumption, high mining cost and high computing power provides the least effective support for its sustainable development. A comparative analysis with the average value method and Euclidean distance method was performed to validate the reliability of the proposed decision-making model and provides evidence that the GIPFWGS has better fault tolerance.

1. Introduction

With the growing popularity of the digital economy and the rise of blockchain technology (in the financial markets as elsewhere), the emergence of cryptocurrencies can be considered to be a major linchpin of future FinTech innovations. They have also attracted great interest because of their potential to reshape the competitive landscape of the financial market [1]. Amid greater adoption, this disruptive technology embraces potential efficient cross-border transactions and, coupled with their global reach due to decentralised control of peer-to-peer exchanges, they will also have a significant impact on energy and commodities trading [2–4]. However, concerns have been raised about the sustainable development challenges posed by cryptocurrencies in the context of energy intensity

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and financial stability. Inadequate operational frameworks and regulatory perimeters across ledgers in major jurisdictions heighten risks across the integrity of financial markets. This has drawn increasing attention from financial regulators, such as the IMF and FATF. Therefore, there is a clear need to quantify sustainability evaluation methods on cryptocurrencies to catch up with the dazzling growth of the cryptocurrency market.

Multiple attribute group decision making (MAGDM) is an important branch of the general class of operations research and is used to arrive at an optimum decision from a set of decision alternatives in the presence of multiple conflicting criteria through a group of decision makers (experts). MAGDM is widely used in areas such as management decision, strategic planning, portfolio selection, and sustainable development [5–8]. It allows real-life complex decision problems to be addressed under imprecision and vagueness, where the available information is not always provided or may be manipulated. To deal with the MAGDM problem, the attribute value can be expressed in a fuzzy environment by linguistic variables, fuzzy numbers, interval numbers, intuitionistic fuzzy numbers, and so on. Zadeh [9] introduced the concept of fuzzy set theory, in which the uncertainty of an element is mapped to the degree of membership valued within the unit interval [0,1]. Atanassov [10] further developed an intuitionistic fuzzy set that incorporates membership degree with non-membership degree and hesitancy degree. The intuitionistic fuzzy set specifies a dual degree of membership, whereby the sum of membership and non-membership degree for each set in the universe of discourse should be less than or equal to one. Yager [11] proposed the Pythagorean fuzzy set (PFS), which challenged the restrictive constraint imposed in intuitionistic fuzzy set (IFS) but may not be applicable to a complex problem in practical applications where the sum of membership and non-membership degrees are greater than one. The prominent characteristic of PFS is that it satisfies a larger admissible condition that the sum of squares of membership and non-membership degree is less than or equal to one, while the sum of the two degrees can be greater than one. It therefore elaborates greater vagueness and uncertainty involved in decision-making. Then, Yager [12] used q-rung Orthopair Fuzzy Sets in multiple attribute dynamic decision, which enables the experts to express their assessments with more choice. Following this research, Jana et al. [13] introduced a dynamic multiple attribute decision making approach with complex q-rung Orthopair fuzzy information.

Garg [14] presented a novel interval-valued Pythagorean fuzzy accuracy function. Meanwhile, Liang et al. [15] proposed the maximising deviation method based on the interval-valued Pythagorean fuzzy weighted arithmetic aggregating operator. In a study of an application to regional energy efficiency, Tao [16] discussed the ORESTE method based on MAGDM with PFS, and further utilised entropy and cross-entropy measures of PFS to solve the MAGDM problem within the interval-valued Pythagorean fuzzy environment. Among others, the interval-valued Pythagorean fuzzy set (IVPFS) for MAGDM provides a qualitative way to deal with vagueness and uncertainty. The IVPFS uses a step wise algorithm to rate, based on the distance measures of interval-valued Pythagorean fuzzy numbers (IVPFNs), each alternative solution and then select the best alternative from a set of alternatives. This approach allows for a more accurate description of MAGDM problems by reflecting optimised criteria and preferences of criteria based on the human perception of decision makers. To extract more fuzzy information and reduce the influence of extreme opinions from experts, Pythagorean fuzzy power Dombi operators has been proposed in which Dombi operations are combined with the power averaging operator [17].

Deng's [18] grey theory is another prominent decision-making approach to capture uncertainty. It classifies systems with completely-known information as white systems, systems with completely-unknown information as black systems, and systems with partially-known and partially-unknown information are classified as grey systems. It handles limited information by extracting and generating useful information from partially-known information, ultimately turns the grey number into a generative number and obtains a generating function with strong regularity, thereby accelerating the understanding of the grey systems [19]. The practical applications of grey systems theory have also provided new approaches for studying problems in corporate behaviour, transportation [20] and urban systems [21].

The MAGDM method has been introduced as the selection process and regarded as the best solution for dealing with sustainability conflicts at both micro- and macro-levels of analysis [22]. Although an increasing number of initiatives have discussed sustainability in the blockchain technology and cryptocurrencies from different perspectives, research on the use of the fuzzy-MAGDM method to evaluate sustainability in the blockchain is still in an early stage. Jin et al. [23] presented a decision-making model based on the Pythagorean fuzzy linguistic entropy and similarity measure to address a sustainable blockchain product assessment problem. Erol et al. [24] proposed an integrated fuzzy-MAGDM evaluation model to scrutinise the applicability of blockchain for the critical functions of sustainable supply chains. Paul et al. [25] proposed a novel Pythagorean fuzzy Jensen-Shannon Song divergence measure to evaluate the degree of divergence between two Pythagorean fuzzy sets in decision-making problems related to sustainable carbon-dioxide storage assessment, where there is a high degree of uncertainty and vagueness. Mishra et al. [26] proposed a novel similarity measure for the interval-valued Pythagorean fuzzy-complex proportional assessment method, which is aimed at evaluating the effectiveness of waste-to-energy sustainability technologies.

However, to our best knowledge, research on fuzzy-MAGDM method to the evaluation of sustainability in cryptocurrencies is still scarce. To make up for these gaps in the literature, this study proposes a novel fuzzy-MAGDM to make three contributions to the literature. First, it presents a novel similarity measure for IVPFNs based on whitenisation weight function in grey systems theory for IVPFNs to solve MAGDM problems, which improves on conveniently presenting information of uncertain and inconsistent data by providing a more rigorous evaluation in complex decision marking problem with embedding ideal solution and membership degree. Second, it incorporates the generalised interval-valued Pythagorean fuzzy vector grey similarity (GIPFVGS) measure and generalised interval-valued Pythagorean fuzzy ordered weighted averaging (GIPFOWA) aggregation operator, which is a simple and effective Pythagorean fuzzy group decision method. The generalised interval-valued Pythagorean fuzzy weighted grey similarity (GIPFWGS) measure is then developed, which enhances the fault tolerance and robustness of the assessment. Third, it develops an evaluation model of major cryptocurrencies as a numerical application and demonstrates the ability of the algorithm of the proposed method to address the optimal expert's weights and select the most sustainable cryptocurrency based on the optimised preference value. Considering the frequent major risk events that have occurred in the cryptocurrency market in recent years, an accurate evaluation of cryptocurrencies' sustainability is crucial for studies of the stability of the financial market and to protect the investors' interests.

Table 1 gives a list of the abbreviations that have been used in this paper. The rest of this paper proceeds as follows. Section 2 briefly describes the basic concept of IVPFS, IVPFN, grey theory and law of operation. Section 3 introduces a novel grey similarity measure for IVPFNs and GIPFWGS measure. Section 4 explores the application of GIPFWGS based on the GIPFOWA aggregation operator. In Section 5, the proposed method is applied with the numerical example of substantiality evaluation of cryptocurrencies. A comparative analysis has been done in section 6. Finally, the conclusion and limitations of the study are presented in Section 7.

2. Preliminaries

Definition 1 [27]: Intuitionistic fuzzy number (IFN).

Let X be a universe of discourse. A is defined as an IFS in X given by

$$A = \{ < x, \alpha_A(x), \beta_A(x) > | 0 \le \alpha_A(x) + \beta_A(x) \le 1, x \in X \}$$

where $\alpha_A : X \to [0,1], x \to \alpha_A(x)$ denotes the degree of membership and $\beta_A : X \to [0,1], x \to \beta_A(x)$ denotes the degree of non-membership of element x belonging to the IFS A, respectively.

Definition 2 [28]: Pythagorean fuzzy number (PFN).

Let X be a universe of discourse. A is defined as a PFS in X given by

$$A = \{ < x, \alpha_A(x), \beta_A(x) > | x \in X \}$$

where $\alpha_A : X \to [0,1]$ denote the degree of membership and $\beta_A : X \to [0,1]$ denotes the degree of non-membership of element x belonging to the PFS A, respectively, and $\forall x \in X$, it holds that

$$0 \le {\alpha_A}^2(x) + {\beta_A}^2(x) \le 1 \ \alpha_A(x), \beta_A(x) \in [0,1]$$

where $\gamma_A(x) = \sqrt{1 - {\alpha_A}^2(x) - {\beta_A}^2(x)}$ is the degree of indeterminacy of element x belonging to the PFS A.

Definition 3 [29]: Interval-valued Pythagorean fuzzy number (IVPFN).

Let X be a universe of discourse. A is defined as an IVPFS in X given by

$$A = \{ < x, [\alpha_A^-(x), \alpha_A^+(x)], [\beta_A^-(x), \beta_A^+(x)] > | x \in X \}$$

where $[\alpha_A^-(x), \alpha_A^+(x)] \subseteq [0,1]$ denotes the degree of membership and $[\beta_A^-(x), \beta_A^+(x)] \subseteq [0,1]$ denotes the degree of non-membership of element x belonging to the IVPFS A, respectively, with the condition $0 \le (\alpha_A^+(x))^2 + (\beta_A^+(x))^2 \le 1$ and $\alpha_A^-(x) \ge 0, \beta_A^-(x) \ge 0$, $\forall x \in X$. $\gamma_A(x) = [\gamma_A^-(x), \gamma_A^+(x)] = [\sqrt{1 - {\alpha_A^+}^2(x) - {\beta_A^+}^2(x)}, \sqrt{1 - {\alpha_A^-}^2(x) - {\beta_A^-}^2(x)}]$ is the degree of indeterminacy of element x belonging to the PFS A.

Algorithm of IVPFN [30]:

Let $\mu = ([\alpha_A^-, \alpha_A^+], [\beta_A^-, \beta_A^+])$ be the IVPFN, given two IVPFNs $\mu_1 = ([\alpha_1^-, \alpha_1^+], [\beta_1^-, \beta_1^+])$ and $\mu_2 = ([\alpha_2^-, \alpha_2^+], [\beta_2^-, \beta_2^+])$, the operational laws of IVPFNs [17] are defined as follows:

Table 1
Abbreviation table.

Abbreviation	Full Name
MAGDM	multiple attribute group decision making
IFS	intuitionistic fuzzy set
IFN	intuitionistic fuzzy number
PFS	Pythagorean fuzzy set
PFN	Pythagorean fuzzy number
IVPFS	interval-valued Pythagorean fuzzy set
IVPFN	interval-valued Pythagorean fuzzy number
GOWA	generalised ordered weighted averaging
IVPFV	interval-valued Pythagorean fuzzy vector
IPFNGS	interval-valued Pythagorean fuzzy number grey similarity
GIPFVGS	generalised interval-valued Pythagorean fuzzy vector grey similarity
GIPFWGS	generalised interval-valued Pythagorean fuzzy weighted grey similarity
IPFM	interval-valued Pythagorean fuzzy matrix
GIPFOWA	generalised interval-valued Pythagorean fuzzy ordered weighted averaging
IPFWGGS	interval-valued Pythagorean fuzzy weighted geometric grey similarity
IPFWAGS	interval-valued Pythagorean fuzzy weighted averaging grey similarity
IPFWQGS	interval-valued Pythagorean fuzzy weighted quadratic grey similarity

$$\mu_1 \oplus \mu_2 = \left(\left[\sqrt{(\alpha_1^-)^2 + (\alpha_2^-)^2 - (\alpha_1^-)^2(\alpha_2^-)^2}, \sqrt{(\alpha_1^+)^2 + (\alpha_2^+)^2 - (\alpha_1^+)^2(\alpha_2^+)^2}\right], [\beta_1^-\beta_2^-, \beta_1^+\beta_2^+]\right)$$

$$\mu_1 \otimes \mu_2 = \left([\alpha_1^-\alpha_2^-, \alpha_1^+\alpha_2^+], \left[\sqrt{(\beta_1^-)^2 + (\beta_2^-)^2 - (\beta_1^-)^2(\beta_2^-)^2}, \sqrt{(\beta_1^+)^2 + (\beta_2^+)^2 - (\beta_1^+)^2(\beta_2^+)^2}\right]\right)$$

$$\lambda\mu_1 = \left(\left[\sqrt{1-\left(1-(\alpha_1^-)^2\right)^\lambda}, \sqrt{1-\left(1-(\alpha_1^+)^2\right)^\lambda}\right], \left[(\beta_1^-)^\lambda, (\beta_1^+)^\lambda\right]\right), \lambda > 0$$

$$\mu_1^\lambda = \left(\left[(\alpha_1^-)^\lambda, (\alpha_1^+)^\lambda\right], \left[\sqrt{1-\left(1-(\beta_1^-)^2\right)^\lambda}, \sqrt{1-\left(1-(\beta_1^+)^2\right)^\lambda}\right]\right), \lambda > 0$$

The IVPFN satisfies the following operational law:

let $\mu_i = ([\alpha_i^-, \alpha_i^+], [\beta_i^-, \beta_i^+]), (i = 1, 2)$ be IVPFN, then $\begin{cases} \mu_1 \oplus \mu_2 = \mu_2 \oplus \mu_1 \\ \mu_1 \otimes \mu_2 = \mu_2 \otimes \mu_1 \\ \lambda(\mu_1 \oplus \mu_2) = \lambda\mu_1 \oplus \lambda\mu_2 \\ (\mu_1 \otimes \mu_2)^\lambda = \mu_1{}^\lambda \otimes \mu_2{}^\lambda \end{cases}$.

To get the detailed sustainability assessment ranking of each cryptocurrency, the score function and accuracy function are introduced in this research.

Definition 4 [31]: The score function and accuracy function of IVPFNs.

Let $\mu = ([\alpha^-, \alpha^+], [\beta^-, \beta^+])$ be IVPFN, the score function of μ is defined in formula (1) and (2):

$$G(\mu) = 1 + \frac{(\alpha^-)^2 + (\alpha^+)^2}{2} - \frac{(\beta^-)^2 + (\beta^+)^2}{2} \tag{1}$$

$$F(\mu) = \frac{(\alpha^-)^2 + (\alpha^+)^2}{2} + \frac{(\beta^-)^2 + (\beta^+)^2}{2} \tag{2}$$

The two functions provide comparison laws for two different IVPFNs μ_1 and μ_2. The order relation is given by:

(1) *If* $G(\mu_1) < G(\mu_2)$, *then* $\mu_1 < \mu_2$

(2) *If* $G(\mu_1) > G(\mu_2)$, *then* $\mu_1 > \mu_2$

(3) *If* $G(\mu_1) = G(\mu_2)$, *then* $\begin{cases} \text{if } F(\mu_1) < F(\mu_2), \text{then } \mu_1 < \mu_2 \\ \text{if } F(\mu_1) > F(\mu_2), \text{then } \mu_1 > \mu_2 \\ \text{if } F(\mu_1) = F(\mu_2), \text{then } \mu_1 = \mu_2 \end{cases}$

Definition 5. [32]: Whitenisation weight function

Whitenisation weight functions are applied to determine the clustering indices to the grey similarity. Let $r_{j,l}$ be the dimensionless number of l^{th} grey at the j^{th} index, where $(l = 1, 2, ..., q)$, and $f_{j,l}$ be the whitenisation weight function.

The whitenisation weight function of lower bound measure is described in formula (3) as a piecewise function:

$$f_{j,l} = \begin{cases} 1 & x \in [0, r_{j,l-1}] \\ \dfrac{r_{j,l} - x}{r_{j,l} - r_{j,l-1}} & x \in (r_{j,l-1}, r_{j,l}] \\ 0 & x \in (r_{j,l}, \infty) \end{cases} \tag{3}$$

The whitenisation weight function of moderate measure is described in formula (4) as a piecewise function:

$$f_{j,l} = \begin{cases} \dfrac{x - r_{j,l-1}}{r_{j,l} - r_{j,l-1}} & x \in [r_{j,l-1}, r_{j,l}] \\ \dfrac{r_{j,l+1} - x}{r_{j,l+1} - r_{j,l}} & x \in (r_{j,l}, r_{j,l+1}] \\ 0 & others \end{cases} \tag{4}$$

The whitenisation weight function of upper bound measure is described in formula (5) as a piecewise function:

$$f_{j,l} = \begin{cases} 0 & x \in (0, r_{j,l-1}) \\ \dfrac{x - r_{j,l-1}}{r_{j,l} - r_{j,l-1}} & x \in [r_{j,l-1}, r_{j,l}) \\ 1 & x \in [r_{j,l}, \infty) \end{cases} \tag{5}$$

Definition 6: Following Yager [33], this paper applies the generalised ordered weighted averaging (GOWA) operator that generalises a wide range of mean operators, which enhances its adaptability in a fuzzy environment.

Let GOWA operator of dimension n be a mapping $GOWA : R^n \rightarrow R$ that has an associated weighting vector ω satisfying $\sum_{j=1}^{n} \omega_j = 1$,

$\omega_j \in [0,1]$ in formula (6):

$$GOWA(a_1, a_2, ..., a_n) = \left(\sum_{j=1}^{n} \omega_j b_j^{\theta}\right)^{\frac{1}{\theta}} \tag{6}$$

where b_j is the j^{th} largest of numerical values $a_1, a_2, ..., a_n$, θ is the parameter such that $\theta \neq 0$.

3. Interval-valued pythagorean fuzzy grey similarity measure

In this section, this paper introduces the interval-valued Pythagorean fuzzy vector and the steps to do a grey similarity measure of it.

Definition 7: Interval-valued Pythagorean fuzzy vector (IVPFV).

Let $\mu = (\mu_1, \mu_2, ..., \mu_n)$ be an IVPFS, where $\mu_{ij} = ([\alpha_\mu^-(x_{ij}), \alpha_\mu^+(x_{ij})], [\beta_\mu^-(x_{ij}), \beta_\mu^+(x_{ij})])$ is the IVPFN. $\mu_j (j = 1, 2, ..., n)$ is defined as IVPFV, and $\mu_j = (\mu_{1j}, \mu_{2j}, ..., \mu_{mj})^T$ is the associated vector of μ .

Definition 8: Generalised interval-valued Pythagorean fuzzy vector grey similarity measure (GIPFVGS).

Let $\mu = (\mu_1, \mu_2, ..., \mu_n)$ and $\nu = (\nu_1, \nu_2, ..., \nu_n)$ be two IVPFSs, where $\mu_j = (\mu_{1j}, \mu_{2j}, ..., \mu_{mj})^T$ is the IVPFV of μ and $\nu_j = (\nu_{1j}, \nu_{2j}, ..., \nu_{mj})^T$ is the IVPFV of ν. Under the principle of grey clustering, we define the interval-valued Pythagorean fuzzy number grey similarity measure (IPFNGS) between two IVPFNs $\mu_{ij} = ([\alpha_\mu^-(x_{ij}), \alpha_\mu^+(x_{ij})], [\beta_\mu^-(x_{ij}), \beta_\mu^+(x_{ij})])$ and $\nu_{ij} = ([\alpha_\nu^-(x_{ij}), \alpha_\nu^+(x_{ij})], [\beta_\nu^-(x_{ij}), \beta_\nu^+(x_{ij})])$ in the following manner:

The lower bound grey similarity measure is described in formula (7) as a piecewise function:

$$H(\mu_{ij}, \nu_{ij}) = \begin{cases} 1 & 0 < G(\mu_{ij}) \leq G(\nu_{ij}) \\ 2 - \dfrac{G(\mu_{ij})}{G(\nu_{ij})} & G(\nu_{ij}) < G(\mu_{ij}) < 2G(\nu_{ij}) \\ 0 & others \end{cases} \tag{7}$$

The moderate grey similarity measure is described in formula (8) as a piecewise function:

$$H(\mu_{ij}, \nu_{ij}) = \begin{cases} \dfrac{G(\mu_{ij})}{G(\nu_{ij})} & 0 < G(\mu_{ij}) \leq G(\nu_{ij}) \\ 2 - \dfrac{G(\mu_{ij})}{G(\nu_{ij})} & G(\nu_{ij}) < G(\mu_{ij}) < 2G(\nu_{ij}) \\ 0 & others \end{cases} \tag{8}$$

The upper bound grey similarity measure is described in formula (9) as a piecewise function:

$$H(\mu_{ij}, \nu_{ij}) = \begin{cases} \dfrac{G(\mu_{ij})}{G(\nu_{ij})} & 0 < G(\mu_{ij}) \leq G(\nu_{ij}) \\ 1 & G(\mu_{ij}) > G(\nu_{ij}) \\ 0 & others \end{cases} \tag{9}$$

The GIPFVGS between μ_{ij} and ν_{ij} is therefore defined in formula (10):

$$H(\mu_i, \nu_i) = \sum_{j=1}^{n} p_j H(\mu_{ij}, \nu_{ij}) \tag{10}$$

where $p = (p_1, p_2, \cdots, p_n)$ is the weight vector assigned for the attributes with $p_j \in [0,1]$, $\sum_{j=1}^{n} p_j = 1$.

Here, the concept of membership degree is introduced to improve the fault tolerance of the evaluation. When one expert's evaluation is higher than the ideal solution, the upper bound similarity measure takes the membership degree (similarity) as 1 to correct the resulting bias.

3.1. Theorem 1

Properties of GIPFVGS.

(1) $\text{Non} - \text{negative}: \text{let}\ \mu_i = (\mu_{i1}, \mu_{i2}, ..., \mu_{in})$ and $\nu_i = (\nu_{i1}, \nu_{i2}, ..., \nu_{in})$ be two sets of IVPFVs, then in formula (11):

$$0 \leq H(\mu_i, \nu_i) \leq 1 \tag{11}$$

Since $H(\mu_i, \nu_i) = \sum_{j=1}^{n} p_j H(\mu_{ij}, \nu_{ij})$, and $0 \leq H(\mu_{ij}, \nu_{ij}) \leq 1$, hence $0 \leq H(\mu_i, \nu_i) \leq 1$. $p = (p_1, p_2, \cdots, p_n)$ is the corresponding weight of each component, where $p_j \in [0, 1]$, and $\sum_{j=1}^{n} p_j = 1$.

(2) Monotonicity: let $\mu_i = (\mu_{i1}, \mu_{i2}, ..., \mu_{in})$, $\varphi_i = (\varphi_{i1}, \varphi_{i2}, ..., \varphi_{in})$ and $\nu_i = (\nu_{i1}, \nu_{i2}, ..., \nu_{in})$ be three sets of IVPFVs, if $H(\mu_{ij}, \nu_{ij}) \le H(\varphi_{ij}, \nu_{ij})$ for all j, then in formula (12):

$$H(\mu_i, \nu_i) \le H(\varphi_i, \nu_i) \tag{12}$$

Since $H(\mu_i, \nu_i) = \sum_{j=1}^{n} p_j H(\mu_{ij}, \nu_{ij})$, $H(\varphi_i, \nu_i) = \sum_{j=1}^{n} p_j H(\varphi_{ij}, \nu_{ij})$, and $H(\mu_{ij}, \nu_{ij}) \le H(\varphi_{ij}, \nu_{ij})$ for all j, hence there is $H(\mu_i, \nu_i) \le H(\varphi_i, \nu_i)$.

(3) Boundedness: let $\mu_i = (\mu_{i1}, \mu_{i2}, ..., \mu_{in})$ and $\nu_i = (\nu_{i1}, \nu_{i2}, ..., \nu_{in})$ be two sets of IVPFVs, then in formula (13):

$$c_{\min} \le H(\mu_i, \nu_i) \le c_{\max} \tag{13}$$

where $c_{\max} = \max_j H(\mu_{ij}, \nu_{ij})$ and $c_{\min} = \min_j H(\mu_{ij}, \nu_{ij})$.

Since $H(\mu_i, \nu_i) = \sum_{j=1}^{n} p_j H(\mu_{ij}, \nu_{ij})$, and $\min_j H(\mu_{ij}, \nu_{ij}) \le \sum_{j=1}^{n} p_j H(\mu_{ij}, \nu_{ij}) \le \max_j H(\mu_{ij}, \nu_{ij})$, where $c_{\min} \le \sum_{j=1}^{n} p_j H(\mu_{ij}, \nu_{ij}) \le c_{\max}$. Hence $c_{\min} \le H(\mu_i, \nu_i) \le c_{\max}$.

Definition 9: Interval-valued Pythagorean fuzzy matrix (IPFM).

Set $\mu = (\mu_1, \mu_2, ..., \mu_n)$ as an IVPFS, in which the $\mu_j = (\mu_{1j}, \mu_{2j}, ..., \mu_{mj})^T$ is the column element of μ; meanwhile, set $\mu_{ij} = ([\alpha_\mu^-(x_{ij}), \alpha_\mu^+(x_{ij})], [\beta_\mu^-(x_{ij}), \beta_\mu^+(x_{ij})])$ as an interval-valued Pythagorean fuzzy number (IVPFN). Then, define μ as an IPFM.

Definition 10: The GIPFWGS measure.

Let a GIPFWGS measure of dimension n be a mapping $GIPFWGS : \Omega \times \Omega \to R$ that has an associated weighting satisfying $\sum_{k=1}^{t} \omega_k = 1$, $\omega_k \in [0, 1]$ in formula (14):

$$GIPFWGS(\mu_i, \nu_i) = \left(\sum_{k=1}^{t} \omega_k (H(\mu_i, \nu_i))^\theta \right)^{\frac{1}{\theta}} \tag{14}$$

where $H(\mu_i, \nu_i)$ is an GIPFVGS of μ_i and ν_i. θ is the parameter such that $\theta \ne 0$.

3.1.1. Theorem 2

Properties of the GIPFWGS measure.

(1) Non-negative: let $\mu = (\mu_1, \mu_2, ..., \mu_m)^T$ and $\nu = (\nu_1, \nu_2, ..., \nu_m)^T$ be two sets of IPFMs, then in formula (15):

$$0 \le GIPFWGS(\mu_i, \nu_i) \le 1 \tag{15}$$

Since $GIPFWGCS(\mu_i, \nu_i) = (\sum_{k=1}^{t} \omega_k (H(\mu_i, \nu_i))^\theta)^{\frac{1}{\theta}}$, and $0 \le H(\mu_i, \nu_i) \le 1$. Hence $0 \le GIPFWGS(\mu_i, \nu_i) \le 1$.

(2) Monotonicity: let $\mu = (\mu_1, \mu_2, ..., \mu_m)^T$, $\varphi = (\varphi_1, \varphi_2, ..., \varphi_m)^T$ and $\nu = (\nu_1, \nu_2, ..., \nu_m)^T$ be three sets of IPFMs, if $H(\mu_i, \nu_i) \le H(\varphi_i, \nu_i)$ for all i, then in formula (16):

$$GIPFWGS(\mu_i, \nu_i) \le GIPFWGS(\varphi_i, \nu_i) \tag{16}$$

Since $GIPFWGCS(\mu_i, \nu_i) = (\sum_{k=1}^{t} \omega_k (H(\mu_i, \nu_i))^\theta)^{\frac{1}{\theta}}$, $GIPFWGCS(\varphi_i, \nu_i) = (\sum_{k=1}^{t} \omega_k (H(\varphi_i, \nu_i))^\theta)^{\frac{1}{\theta}}$, and $H(\mu_i, \nu_i) \le H(\varphi_i, \nu_i)$ for all i, Hence

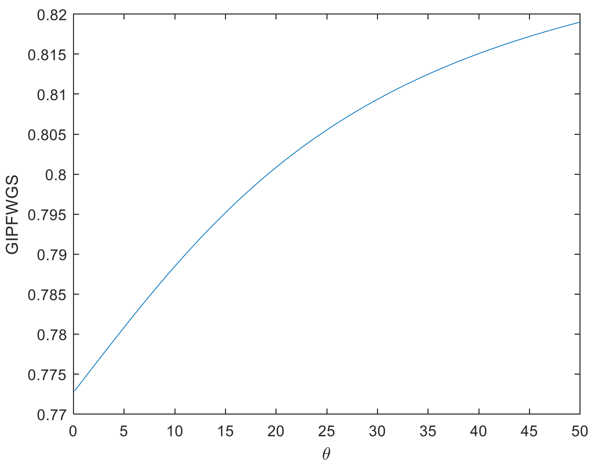

Fig. 1. The changing value of $GIPFWGS(\mu_i, \nu_i)$ with θ (4) Boundedness: let $\mu = (\mu_1, \mu_2, ..., \mu_m)^T$ and $\nu = (\nu_1, \nu_2, ..., \nu_m)^T$ be two sets of IPFMs, then in formula (18).

there is $GIPFWGS(\mu_i, \nu_i) \le GIPFWGS(\varphi_i, \nu_i)$.

3 Monotonicity with respect to θ:

let $\mu = (\mu_1, \mu_2, ..., \mu_m)^T$ and $\nu = (\nu_1, \nu_2, ..., \nu_m)^T$ be two sets of IVPFNs, if $\theta_1 \le \theta_2$, then in formula (17):

$$GIPFWGS_{\theta_1}(\mu_i, \nu_i) \le GIPFWGS_{\theta_2}(\mu_i, \nu_i) \tag{17}$$

Randomly generate three groups of IVPFVs where the length of μ_i and ν_i are equal to 10. Randomly generate weight vector $p = (p_1, p_2, \cdots, p_{10})$ with the length equal to 10. Randomly generate weight vector ω_k with the length equal to 3. The value of $GIPFWGS(\mu_i, \nu_i)$ can be calculated when taking the above variables into equation (14). The value of $GIPFWGS(\mu_i, \nu_i)$ changing with the varying θ is given in Fig. 1. It can be seen that $GIPFWGS(\mu_i, \nu_i)$ is a monotonically increasing function where the value of $GIPFWGS(\mu_i, \nu_i)$ increasing with θ. Hence, when $\theta_1 \le \theta_2$, $GIPFWGS_{\theta_1}(\mu_i, \nu_i) \le GIPFWGS_{\theta_2}(\mu_i, \nu_i)$.

$$c_{\min} \le GIPFWGS(\mu_i, \nu_i) \le c_{\max} \tag{18}$$

where $c_{\max} = \max_i H(\mu_i, \nu_i)$ and $c_{\min} = \min_i H(\mu_i, \nu_i)$.

Since $GIPFWGCS(\mu_i, \nu_i) = \left(\sum_{k=1}^{t} \omega_k (H(\mu_i, \nu_i))^{\theta}\right)^{\frac{1}{\theta}}$ and $\min_i H(\mu_i, \nu_i) \le \left(\sum_{k=1}^{t} \omega_k (H(\mu_i, \nu_i))^{\theta}\right)^{\frac{1}{\theta}} \le \max_i H(\mu_i, \nu_i)$, there is $c_{\min} \le \left(\sum_{k=1}^{t} \omega_k (H(\mu_i, \nu_i))^{\theta}\right)^{\frac{1}{\theta}} \le c_{\max}$. Hence $c_{\min} \le GIPFWGS(\mu_i, \nu_i) \le c_{\max}$.

(5) Idempotency: let $\mu = (\mu_1, \mu_2, ..., \mu_m)^T$ and $\nu = (\nu_1, \nu_2, ..., \nu_m)^T$ be two sets of IPFMs, if any $H(\mu_i, \nu_i) = c_0$ are equal, for all $i = 1, 2, ..., m$, then in formula (19):

$$GIPFWGS(\mu_i, \nu_i) = c_0 \tag{19}$$

$GIPFWGCS(\mu_i, \nu_i) = \left(\sum_{k=1}^{t} \omega_k (H(\mu_i, \nu_i))^{\theta}\right)^{\frac{1}{\theta}} = \left(\sum_{k=1}^{t} \omega_k {c_0}^{\theta}\right)^{\frac{1}{\theta}} = \left({c_0}^{\theta}\right)^{\frac{1}{\theta}} = c_0$ Q.E.D.

4. A novel method for MAGDM based on GIPFWGS

In this section, we discuss the application of the GIPFWGS toward MAGDM problem.

Let $X = \{X_1, X_2, ..., X_m\}$ be a discrete set of m alternatives, $Y = \{Y_1, Y_2, ..., Y_n\}$ be a finite set of n attributes, and $p = \{p_1, p_2, \cdots, p_n\}$ be the weight vector of the attributes, where $p_j \in [0, 1]$ and $\sum_{j=1}^{n} p_j = 1$. Let $Z = \{z_1, z_2, ..., z_t\}$ be a set of t experts (decision makers), and $\omega = \{\omega_1, \omega_2, ..., \omega_t\}$ be the weight vector of experts, where $\omega_k \in [0, 1]$ and $\sum_{k=1}^{t} \omega_k = 1$.

The detailed algorithm of the proposed method is presented as follows:

Input: data U and V, coefficient θ.

Output: s, the rank and $\widehat{\omega}$.

Step 1. Each expert provides an opinion to construct a decision matrix $U^{(k)} = (\mu_{ij}^{(k)})_{m\times n} (k = 1, 2, ..., t)$, where $\mu_{ij}^{(k)}$ is the kth expert's evaluation on alternative X_i with respect to the attribute Y_j.

Step 2. Each expert provides an ideal opinion to construct the ideal vector $V^{(k)} = (\nu_j^{(k)})_{1\times n}$, where $\nu_j^{(k)}$ is the kth expert's ideal solution with respect to the attribute Y_j, which is shown in Table 2,

Step 3. Aggregate the collective GIPFVGS $H(\mu_{ij}, \nu_{ij})$ between expert's opinion $\mu_i^{(k)}$ and ideal solution $\nu^{(k)}$ for each expert in the form of in formula (20),

$$H\left(\mu_i^{(k)}, \nu^{(k)}\right) = \sum_{j=1}^{n} p_j H\left(\mu_{ij}^{(k)}, \nu_j^{(k)}\right) \tag{20}$$

where $\mu_i^{(k)} = (\mu_{i1}^{(k)}, \mu_{i2}^{(k)}, ..., \mu_{in}^{(k)})$, $\nu^{(k)} = (\nu_1^{(k)}, \nu_2^{(k)}, ..., \nu_n^{(k)})$.

Step 4. Utilise the GIPFOWA aggregation operator to aggregate all GIPFVGS into the comprehensive preference value for each alternative X_i, as in formula (21):

$$s_i = \left(\sum_{k=1}^{t} \omega_k \left(H\left(\mu_i^{(k)}, \nu^{(k)}\right)\right)^{\theta}\right)^{\frac{1}{\theta}} \tag{21}$$

Step 5. Rank all alternatives in accordance with the descending order of comprehensive preference value $s_i (i = 1, 2, ..., m)$ and select the best alternative $X_i (i = 1, 2, ..., m)$.

Table 2
Ideal solution of decision matrix $V^{(k)}$.

	Y_1	Y_2	…	Y_j	…	Y_n
$V^{(k)}$	$v_1^{(k)}$	$v_2^{(k)}$	…	$v_j^{(k)}$	…	$v_n^{(k)}$

Step 6. The optimisation problem is to choose the expert's weight vector to maximise the comprehensive preference value, as in formula (22):

$$\max = \sum_{i=1}^{m} s_i$$
$$s.t. \begin{cases} \sum_{k=1}^{t} \omega_k = 1 \\ \omega_k \geq 0, \quad k = 1, 2, \cdots, t \end{cases} \tag{22}$$

The solution can be solved to obtain the optimal experts weight vector $\widehat{\omega} = (\widehat{\omega}_1, \widehat{\omega}_2, \cdots, \widehat{\omega}_t)$.

Step 7. Solve for the optimal expert's weight vector $\widehat{\omega}_\theta$ when choosing different values of θ and revalidate the comprehensive preference value $\widehat{s}_i$ with respect to $\widehat{\omega}_\theta$.

5. Sustainability evaluation of major cryptocurrencies

In this section, we focus on the use of the proposed method with the application of the sustainability evaluation of eight of the most capitalised and liquid cryptocurrencies in the cryptocurrency market (i.e., Bitcoin, Dash, Ethereum, Litecoin, Monero, NEM, Ripple and Stellar lumens). A flowchart of the proposed approach is given in Fig. 2. In total, 10 attributes are considered to evaluate the sustainability of cryptocurrencies. The attributes for sustainability are described as follows.

(1) Underlying technology stability

Issuing cryptocurrencies are usually based on encryption and are supported by technical infrastructure, such as blockchain, to ensure the security of the participants and transactions on distributed ledgers. However, cryptocurrencies differ in terms of transaction speed, clearing and settlement when implementing different cryptographic algorithms and technology application layers. As an investment underlying "crypto-asset", it can be observed that there is fierce competition in the market. The value of a cryptocurrency may sharply fluctuate due to the vulnerability of the technology (e.g., Doge coin was widely known to have technologically been quickly copied/forked from another coin). Hence, technology stability is an important factor for the sustainability of cryptocurrencies.

(2) Transaction anonymity

Decentralisation, anonymity and immutability are the main characteristics of cryptocurrencies and they are highly relevant to their long-term development. In pursuit of secure trading, cryptocurrencies preserve transaction anonymity in a transaction, which presents a privacy enhanced alternative to traditional transaction payment mechanisms. However, cryptocurrencies could have different landscapes in terms of their degree of anonymity (e.g., Bitcoin and Monero) but what sets them apart is the cryptography algorithms that are used when transactions are executed. This heterogeneity results in significant differences in their prospects for development.

(3) Public attention

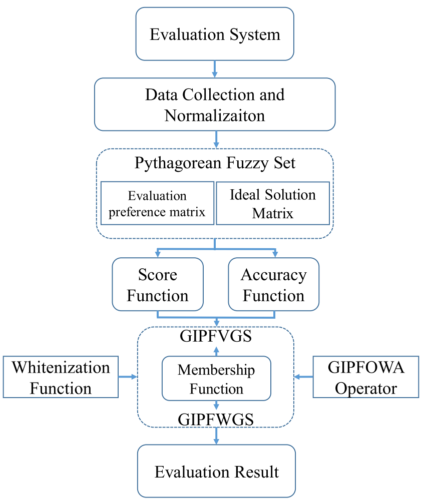

Figure 2. Flowchart of the proposed approach.

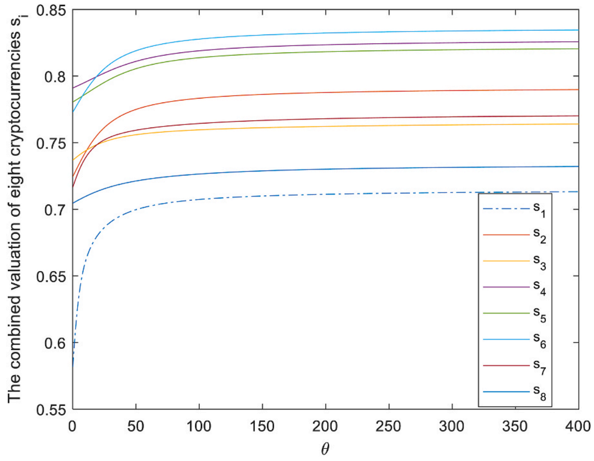

Fig. 3. Variations of comprehensive preference value s_i with changing values of θ In addition, the comprehensive preference value of the eight cryptocurrencies varies when the values of parameter θ are chosen from 0 to 400. As shown in Fig. 3, the comprehensive preference value generally increases as θ increases. As θ approaches 400, the ranking of the eight cryptocurrencies becomes $s_6 > s_4 > s_5 > s_2 > s_7 > s_3 > s_8 > s_1$. In particular, Stellar (X6) is now identified as the most sustainable cryptocurrency (from third to first place), Ripple (X3) decreases from fourth to sixth place, while Bitcoin (X1) remains the most pessimistic cryptocurrency in terms of its sustainability.

Alongside the explosion of interest from media coverage and investor attention, cryptocurrencies have also drawn considerable attention from financial regulators in forming potential policy risks (e.g., China shut down a cryptocurrency mining operation in June 2021 according to the new regulatory policy on cryptocurrencies).

(4) Market liquidity

In general, popular cryptocurrencies with higher market liquidity exhibit a low degree of information asymmetry, while cryptocurrencies with low liquidity levels are more likely to be targeted for illegitimate activities, such as money laundering and terrorist financing, which could have a negative impact on sustainability.

(5) Price stability

Apart from the illicit use, the risk of trading cryptocurrencies is also related to their large price fluctuation. Cryptocurrencies with relatively stable prices are inherently more sustainable than those with higher volatility.

(6) Market trading volume

Market share is as an important indicator of the dominance and popularity of a cryptocurrency. Cryptocurrencies with a high market share are more competitive and have better sustainability prospects.

(7) Regulatory continuity

Regulatory stances toward cryptocurrencies vary by country because they have taken different approaches to regulating the crypto-asset class. With the supervision of cryptocurrency remaining nascent, risk identification and regulation of major cryptocurrencies remain limited and yet effectively developed. The patchwork of regulations may also harm the future of cryptocurrencies.

(8) Energy consumption

The main environmental concerns for cryptocurrencies stem are their energy-intensive activities. The higher energy consumption of cryptocurrencies is clearly not aligned with the government's commitment to environmental sustainability. A sustainable cryptocurrency should inherently have low energy consumption and minimal carbon footprint.

(9) Mining cost

The process of mining cryptocurrencies can be particularly energy-intensive depending on the decentralised consensus mechanisms and consensus validation systems that have been applied among various blockchains. In addition, miners solve complicated mathematical puzzles, which require extensive computational power. Low mining cost can be achieved through low costs of deploying, powering, and cooling mining hardware and facilities, low maintenance demand and highly efficient operation. Therefore, a sustainable cryptocurrency should have low mining cost.

(10) Computing power sustainability

Computing power guarantees the fault tolerance and security of the blockchain systems under different consensus protocols, and is closely related to the sustainable development of cryptocurrencies.

On a scale of 1–10 (1 being the lowest and 10 being the highest), we invited 18 experts to provide evaluation scores of the eight major cryptocurrencies according to their own opinion for the above 10 attributes listed in a questionnaire (as shown in the appendix). The scope of the experts comprises 12 practitioners in financial regulation and institutions and six economists in academic institutions.

The proposed alternative set X= (X1, X2, …, X8) is assigned for: Bitcoin (X_1), Ethereum (X_2), Ripple (X3), Litecoin (X4), Monero (X5), Stellar lumens (X6), Dash (X7), NEM (X8). The associated attributes set Y=(Y_1, Y_2, L, Y_{10}) is assigned for underlying technology stability (Y_1), transaction anonymity (Y_2), public attention level (Y_3), market liquidity (Y_4), price stability (Y_5), market share (Y_6), regulatory continuity (Y_7), energy consumption (Y_8), mining cost (Y_9), and network hash rate (Y_{10}). The expert set Z= (Z_1, Z_2, Z_3) is assigned for: financial regulatory authority experts (Z_1), financial institution practitioners (Z_2), and academic economists (Z_3), where subsets are equally weighted with 33.3%. The weight vector corresponding to the 10 attributes are p = (13.5%, 12.125%, 10.75%, 11.375%, 7.5%, 9%, 10.625%, 8%, 6.875%, 10.25%).

Step 1. According to the expert's opinions, we construct the decision matrix $U^{(k)} = (\mu_{ij}^{(k)})_{8\times10}(k=1,2,3)$ for eight alternatives (cryptocurrencies) $X_i(i=1,2,...,8)$ with respect to 10 attributes $Y_j(j=1,2,...,10)$, provided by all experts Z=(Z_1, Z_2, Z_3), which are shown in Tables 3–5.

Step 2. Set the ideal opinion (group opinion) as the arithmetical mean of all of the individual expert's opinion and construct the ideal opinion decision matrix $V^{(k)} = (\nu_j^{(k)})_{1\times10}$ for all of the attributes from kth group of experts, which are shown in Table 6.

Step 3. Using equation (20), aggregate the collective GIPFVGS $H(\mu_{ij},\nu_{ij})$ between each expert's opinion vector $\mu_i^{(k)}$ and the ideal opinion vector $\nu^{(k)}$, given as

$$H=\begin{pmatrix} 0.6435 & 0.4247 & 0.7152 \\ 0.7243 & 0.6626 & 0.7920 \\ 0.7567 & 0.6901 & 0.7661 \\ 0.8280 & 0.7709 & 0.7753 \\ 0.8228 & 0.7546 & 0.7658 \\ 0.7727 & 0.7135 & 0.8369 \\ 0.7722 & 0.6315 & 0.7537 \\ 0.7128 & 0.6683 & 0.7341 \end{pmatrix}$$

Step 4. When $\theta=2$ and $\omega=(0.333,0.333,0.333)$, using the GIPFOWA aggregation operator shown in Eq. (21), all GIPFVGS are

Table 3
Decision matrix $U^{(1)}$ by expert z_1.

	Y_1	Y_2	Y_3	Y_4
X_1	([0.85,0.95], [0.05,0.15])	([0.7,0.8], [0.2,0.3])	([0.9,0.95], [0.05,0.1])	([0.9,0.93], [0.07,0.1])
X_2	([0.6,0.7], [0.3,0.4])	([0.7,0.8], [0.2,0.3])	([0.3,0.4], [0.6,0.7])	([0.5,0.6], [0.4,0.5])
X_3	([0.55,0.65], [0.35,0.45])	([0.5,0.6], [0.4,0.5])	([0.4,0.5], [0.5,0.6])	([0.45,0.55], [0.45,0.55])
X_4	([0.65,0.75], [0.25,0.35])	([0.7,0.8], [0.2,0.3])	([0.55,0.65], [0.35,0.45])	([0.6,0.7], [0.3,0.4])
X_5	([0.7,0.8], [0.2,0.3])	([0.8,0.9], [0.1,0.2])	([0.5,0.6], [0.4,0.5])	([0.5,0.6], [0.4,0.5])
X_6	([0.6,0.7], [0.3,0.4])	([0.45,0.55], [0.45,0.55])	([0.5,0.6], [0.4,0.5])	([0.5,0.6], [0.4,0.5])
X_7	([0.5,0.6], [0.4,0.5])	([0.6,0.7], [0.3,0.4])	([0.4,0.5], [0.5,0.6])	([0.45,0.55], [0.45,0.55])
X_8	([0.75,0.85], [0.15,0.25])	([0.65,0.75], [0.25,0.35])	([0.8,0.9], [0.1,0.2])	([0.8,0.9], [0.1,0.2])
	Y_5	Y_6	Y_7	Y_8
X_1	([0.6,0.7], [0.3,0.4])	([0.75,0.85], [0.15,0.25])	([0.5,0.6], [0.4,0.5])	([0.9,0.94], [0.06,0.1])
X_2	([0.7,0.8], [0.2,0.3])	([0.3,0.4], [0.6,0.7])	([0.5,0.6], [0.4,0.5])	([0.3,0.4], [0.6,0.7])
X_3	([0.7,0.8], [0.2,0.3])	([0.3,0.4], [0.6,0.7])	([0.5,0.6], [0.4,0.5])	([0.3,0.4], [0.6,0.7])
X_4	([0.7,0.8], [0.2,0.3])	([0.4,0.5], [0.5,0.6])	([0.5,0.6], [0.4,0.5])	([0.4,0.5], [0.5,0.6])
X_5	([0.7,0.8], [0.2,0.3])	([0.4,0.5], [0.5,0.6])	([0.45,0.55], [0.45,0.55])	([0.3,0.4], [0.6,0.7])
X_6	([0.7,0.8], [0.2,0.3])	([0.4,0.5], [0.5,0.6])	([0.5,0.6], [0.4,0.5])	([0.4,0.5], [0.5,0.6])
X_7	([0.6,0.7], [0.3,0.4])	([0.25,0.35], [0.65,0.75])	([0.5,0.6], [0.4,0.5])	([0.25,0.35], [0.65,0.75])
X_8	([0.6,0.7], [0.3,0.4])	([0.6,0.7], [0.3,0.4])	([0.5,0.6], [0.4,0.5])	([0.6,0.7], [0.3,0.4])
	Y_9	Y_{10}		
X_1	([0.9,0.93], [0.07,0.1])	([0.9,0.92], [0.08,0.1])		
X_2	([0.7,0.8], [0.2,0.3])	([0.4,0.5], [0.5,0.6])		
X_3	([0.5,0.6], [0.4,0.5])	([0.4,0.5], [0.5,0.6])		
X_4	([0.6,0.7], [0.3,0.4])	([0.6,0.7], [0.3,0.4])		
X_5	([0.55,0.65], [0.35,0.45])	([0.5,0.6], [0.4,0.5])		
X_6	([0.5,0.6], [0.4,0.5])	([0.4,0.5], [0.5,0.6])		
X_7	([0.5,0.6], [0.4,0.5])	([0.4,0.5], [0.5,0.6])		
X_8	([0.7,0.8], [0.2,0.3])	([0.8,0.9], [0.1,0.2])		

Table 4
Decision matrix $U^{(2)}$ by expert z_2.

	Y_1	Y_2	Y_3	Y_4
X_1	([0.8,0.9], [0.1,0.2])	([0.75,0.85], [0.15,0.25])	([0.9,0.91], [0.09,0.1])	([0.8,0.9], [0.1,0.2])
X_2	([0.4,0.5], [0.5,0.6])	([0.5,0.6], [0.4,0.5])	([0.3,0.4], [0.6,0.7])	([0.3,0.4], [0.6,0.7])
X_3	([0.4,0.5], [0.5,0.6])	([0.6,0.7], [0.3,0.4])	([0.25,0.35], [0.65,0.75])	([0.3,0.4], [0.6,0.7])
X_4	([0.5,0.6], [0.4,0.5])	([0.6,0.7], [0.3,0.4])	([0.4,0.5], [0.5,0.6])	([0.5,0.6], [0.4,0.5])
X_5	([0.5,0.6], [0.4,0.5])	([0.5,0.6], [0.4,0.5])	([0.3,0.4], [0.6,0.7])	([0.4,0.5], [0.5,0.6])
X_6	([0.45,0.55], [0.45,0.55])	([0.5,0.6], [0.4,0.5])	([0.3,0.4], [0.6,0.7])	([0.3,0.4], [0.6,0.7])
X_7	([0.4,0.5], [0.5,0.6])	([0.5,0.6], [0.4,0.5])	([0.3,0.4], [0.6,0.7])	([0.3,0.4], [0.6,0.7])
X_8	([0.7,0.8], [0.2,0.3])	([0.7,0.8], [0.2,0.3])	([0.6,0.7], [0.3,0.4])	([0.6,0.7], [0.3,0.4])
	Y_5	Y_6	Y_7	Y_8
X_1	([0.8,0.9], [0.1,0.2])	([0.75,0.85], [0.15,0.25])	([0.7,0.8], [0.2,0.3])	([0.7,0.8], [0.2,0.3])
X_2	([0.4,0.5], [0.5,0.6])	([0.3,0.4], [0.6,0.7])	([0.4,0.5], [0.5,0.6])	([0.4,0.5], [0.5,0.6])
X_3	([0.6,0.7], [0.3,0.4])	([0.3,0.4], [0.6,0.7])	([0.4,0.5], [0.5,0.6])	([0.4,0.5], [0.5,0.6])
X_4	([0.5,0.6], [0.4,0.5])	([0.4,0.5], [0.5,0.6])	([0.4,0.5], [0.5,0.6])	([0.5,0.6], [0.4,0.5])
X_5	([0.4,0.5], [0.5,0.6])	([0.3,0.4], [0.6,0.7])	([0.45,0.55], [0.45,0.55])	([0.3,0.4], [0.6,0.7])
X_6	([0.5,0.6], [0.4,0.5])	([0.3,0.4], [0.6,0.7])	([0.5,0.6], [0.4,0.5])	([0.4,0.5], [0.5,0.6])
X_7	([0.5,0.6], [0.4,0.5])	([0.2,0.3], [0.7,0.8])	([0.6,0.7], [0.3,0.4])	([0.3,0.4], [0.6,0.7])
X_8	([0.6,0.7], [0.3,0.4])	([0.7,0.8], [0.2,0.3])	([0.5,0.6], [0.4,0.5])	([0.5,0.6], [0.4,0.5])
	Y_9	Y_{10}		
X_1	([0.7,0.8], [0.2,0.3])	([0.85,0.95], [0.05,0.15])		
X_2	([0.6,0.7], [0.3,0.4])	([0.35,0.45], [0.55,0.65])		
X_3	([0.5,0.6], [0.4,0.5])	([0.4,0.5], [0.5,0.6])		
X_4	([0.55,0.65], [0.35,0.45])	([0.55,0.65], [0.35,0.45])		
X_5	([0.4,0.5], [0.5,0.6])	([0.4,0.5], [0.5,0.6])		
X_6	([0.4,0.5], [0.5,0.6])	([0.5,0.6], [0.4,0.5])		
X_7	([0.5,0.6], [0.4,0.5])	([0.3,0.4], [0.6,0.7])		
X_8	([0.5,0.6], [0.4,0.5])	([0.8,0.9], [0.1,0.2])		

Table 5
Decision matrix $U^{(3)}$ by expert z_3.

	Y_1	Y_2	Y_3	Y_4
X_1	([0.8,0.9], [0.1,0.2])	([0.8,0.9], [0.1,0.2])	([0.9,0.91], [0.09,0.1])	([0.7,0.8], [0.2,0.3])
X_2	([0.6,0.7], [0.3,0.4])	([0.8,0.9], [0.1,0.2])	([0.4,0.5], [0.5,0.6])	([0.6,0.7], [0.3,0.4])
X_3	([0.65,0.75], [0.25,0.35])	([0.5,0.6], [0.4,0.5])	([0.4,0.5], [0.5,0.6])	([0.4,0.5], [0.5,0.6])
X_4	([0.75,0.85], [0.15,0.25])	([0.8,0.9], [0.1,0.2])	([0.6,0.7], [0.3,0.4])	([0.65,0.75], [0.25,0.35])
X_5	([0.7,0.8], [0.2,0.3])	([0.8,0.9], [0.1,0.2])	([0.4,0.5], [0.5,0.6])	([0.5,0.6], [0.4,0.5])
X_6	([0.6,0.7], [0.3,0.4])	([0.7,0.8], [0.2,0.3])	([0.6,0.7], [0.3,0.4])	([0.6,0.7], [0.3,0.4])
X_7	([0.5,0.6], [0.4,0.5])	([0.4,0.5], [0.5,0.6])	([0.3,0.4], [0.6,0.7])	([0.5,0.6], [0.4,0.5])
X_8	([0.7,0.8], [0.2,0.3])	([0.65,0.75], [0.25,0.35])	([0.7,0.8], [0.2,0.3])	([0.6,0.7], [0.3,0.4])
	Y_5	Y_6	Y_7	Y_8
X_1	([0.8,0.9], [0.1,0.2])	([0.8,0.9], [0.1,0.2])	([0.6,0.7], [0.3,0.4])	([0.55,0.65], [0.35,0.45])
X_2	([0.7,0.8], [0.2,0.3])	([0.7,0.8], [0.2,0.3])	([0.6,0.7], [0.3,0.4])	([0.5,0.6], [0.4,0.5])
X_3	([0.5,0.6], [0.4,0.5])	([0.6,0.7], [0.3,0.4])	([0.6,0.7], [0.3,0.4])	([0.6,0.7], [0.3,0.4])
X_4	([0.4,0.5], [0.5,0.6])	([0.5,0.6], [0.4,0.5])	([0.6,0.7], [0.3,0.4])	([0.55,0.65], [0.35,0.45])
X_5	([0.5,0.6], [0.4,0.5])	([0.6,0.7], [0.3,0.4])	([0.6,0.7], [0.3,0.4])	([0.6,0.7], [0.3,0.4])
X_6	([0.75,0.85], [0.15,0.25])	([0.7,0.8], [0.2,0.3])	([0.6,0.7], [0.3,0.4])	([0.6,0.7], [0.3,0.4])
X_7	([0.6,0.7], [0.3,0.4])	([0.5,0.6], [0.4,0.5])	([0.55,0.65], [0.35,0.45])	([0.2,0.3], [0.7,0.8])
X_8	([0.7,0.8], [0.2,0.3])	([0.75,0.85], [0.15,0.25])	([0.7,0.8], [0.2,0.3])	([0.7,0.8], [0.2,0.3])
	Y_9	Y_{10}		
X_1	([0.8,0.9], [0.1,0.2])	([0.5,0.6], [0.4,0.5])		
X_2	([0.6,0.7], [0.3,0.4])	([0.6,0.7], [0.3,0.4])		
X_3	([0.3,0.4], [0.6,0.7])	([0.3,0.4], [0.6,0.7])		
X_4	([0.65,0.75], [0.25,0.35])	([0.4,0.5], [0.5,0.6])		
X_5	([0.6,0.7], [0.3,0.4])	([0.3,0.4], [0.6,0.7])		
X_6	([0.4,0.5], [0.5,0.6])	([0.5,0.6], [0.4,0.5])		
X_7	([0.25,0.35], [0.65,0.75])	([0.2,0.3], [0.7,0.8])		
X_8	([0.7,0.8], [0.2,0.3])	([0.6,0.7], [0.3,0.4])		

aggregated to obtain the comprehensive preference value, as follows:

$$s_1 = 0.6072, s_2 = 0.7282, s_3 = 0.7384, s_4 = 0.7918, s_5 = 0.7816, s_6 = 0.7760, s_7 = 0.7219, s_8 = 0.7056$$

Step 5. All comprehensive preferences value $s_i(i = 1, 2, ..., 8)$ are sorted in descending order: $s_4 > s_5 > s_6 > s_3 > s_2 > s_7 > s_8 > s_1$ to observe the ranking order of alternatives: $X_4 > X_5 > X_6 > X_3 > X_2 > X_7 > X_8 > X_1$. Hence, Litecoin ($X_4$) is the most sustainable cryptocurrency (see Table 7).

Step 6. The model chooses the expert's weight to maximise the comprehensive preference value, as follows (see formula (23)):

Table 6
The ideal opinion decision matrix for all experts.

	Y_1	Y_2	Y_3	Y_4
Z_1	([0.9,0.92], [0.08,0.1])	([0.6,0.7], [0.3,0.4])	([0.5,0.7], [0.3,0.5])	([0.6,0.7], [0.3,0.4])
Z_2	([0.85,0.95], [0.05,0.15])	([0.5,0.7], [0.3,0.5])	([0.4,0.5], [0.5,0.6])	([0.4,0.6], [0.4,0.6])
Z_3	([0.85,0.95], [0.05,0.15])	([0.7,0.8], [0.2,0.3])	([0.5,0.7], [0.3,0.5])	([0.5,0.7], [0.3,0.5])
	Y_5	Y_6	Y_7	Y_8
Z_1	([0.6,0.8], [0.2,0.4])	([0.4,0.5], [0.5,0.6])	([0.4,0.5], [0.5,0.6])	([0.2,0.4], [0.6,0.8])
Z_2	([0.5,0.7], [0.3,0.5])	([0.4,0.5], [0.5,0.6])	([0.3,0.4], [0.6,0.7])	([0.25,0.45], [0.55,0.75])
Z_3	([0.6,0.7], [0.3,0.4])	([0.6,0.7], [0.3,0.4])	([0.45,0.55], [0.45,0.55])	([0.35,0.55], [0.45,0.65])
	Y_9	Y_{10}		
Z_1	([0.4,0.5], [0.5,0.6])	([0.65,0.85], [0.15,0.35])		
Z_2	([0.3,0.4], [0.6,0.7])	([0.6,0.8], [0.2,0.4])		
Z_3	([0.3,0.5], [0.5,0.7])	([0.45,0.65], [0.35,0.55])		

Table 7
Sustainability evaluation results for major cryptocurrencies ($\theta = 2$).

Alternatives	Comprehensive Preference value *Si*	Rank
X_1 (Bitcoin)	0.6072	8
X_2 (Ethereum)	0.7282	5
X_3 (Ripple)	0.7384	4
X_4 (Litecoin)	0.7918	1
X_5 (Monero)	0.7816	2
X_6 (Stellar)	0.7760	3
X_7 (Dash)	0.7219	6
X_8 (NEM)	0.7058	7

$$\max = \sum_{i=1}^{8} s_i$$
$$s.t. \begin{cases} \sum_{k=1}^{3} \omega_k = 1 \\ \omega_k \geq 0, \quad k = 1,2,3 \end{cases} \tag{23}$$

The optimal experts weight vector is obtained as $\widehat{\omega} = (\widehat{\omega}_1, \widehat{\omega}_2, \widehat{\omega}_3) = (0,0,1)$.

In the following, we start to perform the robustness test by choosing different values of parameter θ in the GIPFWGS operator. According to **Definition 10**, we can obtain different types of grey similarity measures, for example: the interval-valued Pythagorean fuzzy weighted geometric grey similarity (IPFWGGS) measures, the interval-valued Pythagorean fuzzy weighted averaging grey similarity (IPFWAGS) measures, and the interval-valued Pythagorean fuzzy weighted quadratic grey similarity (IPFWQGS) measures.

(1) When $\theta \rightarrow 0$, the GIPFWGS measure is the IPFWGGS operator given as formula (24):

$$IPFWGGS(\mu,\nu) = \prod_{j=1}^{n} \left(H\left(\mu_j,\nu_j\right)\right)^{\omega_j} \tag{24}$$

(2) When $\theta = 1$, the GIPFWGS operator is the IPFWAGS operator given as formula (25):

$$IPFWAGS(\mu,\nu) = \sum_{j=1}^{n} \omega_j H\left(\mu_j,\nu_j\right) \tag{25}$$

(3) When $\theta = 2$, the GIPFWGS operator is the IPFWQGS operator given as formula (26):

$$IPFWQGS(\mu,\nu) = \left(\sum_{j=1}^{n} \omega_j \left(H\left(\mu_j,\nu_j\right)\right)^2\right)^{\frac{1}{2}} \tag{26}$$

These three different families of GIPFWGS operators are used as approaches to the MAGDM problem of cryptocurrency sustainability evaluation. The results of the comprehensive preference value and the optimal expert's weight are listed in Table 8.

It is clear that Litecoin (X4) has been identified as the best alternative in terms of sustainability evaluation, followed by Monero (X5). Meanwhile, Bitcoin (X1) is the worst alternative, which suggests that the experts are not optimistic about the sustainability prospectus of Bitcoin.

Table 8
Comprehensive preference value based on three different GIPFWGS measures.

	IPFWGGS		IPFWAGS		IPFWQGS	
Alternatives	S_i	Rank	S_i	Rank	S_i	Rank
X_1 (Bitcoin)	0.5805	8	0.5945	8	0.6072	8
X_2 (Ethereum)	0.7244	5	0.7263	5	0.7282	5
X_3 (Ripple)	0.7368	4	0.7376	4	0.7384	4
X_4 (Litecoin)	0.7910	1	0.7914	1	0.7918	1
X_5 (Monero)	0.7805	2	0.7810	2	0.7816	2
X_6 (Stellar)	0.7727	3	0.7744	3	0.776	3
X_7 (Dash)	0.7164	6	0.7192	6	0.7219	6
X_8 (NEM)	0.7045	7	0.7051	7	0.7056	7
Weight	$\widehat{\omega}$ (0, 0, 1)					

Step 7. Solve for the optimal expert's weight vector $\widehat{\omega}_k$ when choosing a different value of θ, and revalidate the comprehensive preference value with respect to $\widehat{\omega}_k$.

Each optimal expert weight is in accordance with the value of θ. When discussing $\theta \in [0, 400]$, Fig. 4 depicts variations of the optimal expert's weight when changing the value of θ. It is observed that as θ approaches to 400, $\widehat{\omega}_1$ (financial regulators) increases from 0 to 0.39, $\widehat{\omega}_3$ (economists in academics) decreases from 1 to 0.61 and $\widehat{\omega}_2$ (financial institutions) remains at 0.

Using Eq. (22), when $\theta \in [0, 400]$, it is shown in Fig. 5 that the rank of optimal comprehensive evaluation value of the eight cryptocurrencies is $s_6 > s_4 > s_5 > s_2 > s_7 > s_3 > s_8 > s_1$, and Stellar (X6) is identified as the most sustainable cryptocurrency.

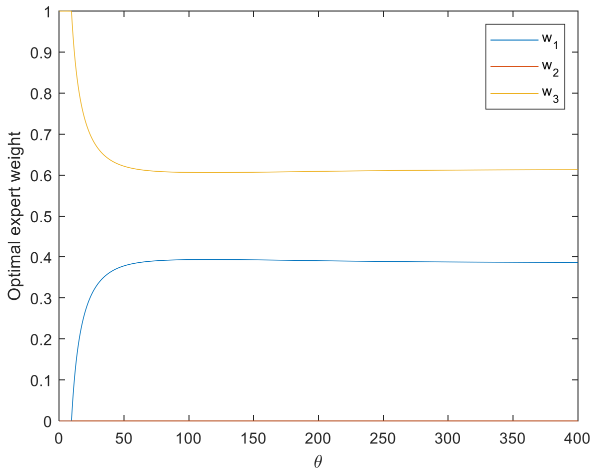

Fig. 4. Variations of the optimal expert's weight with changing values of θ.

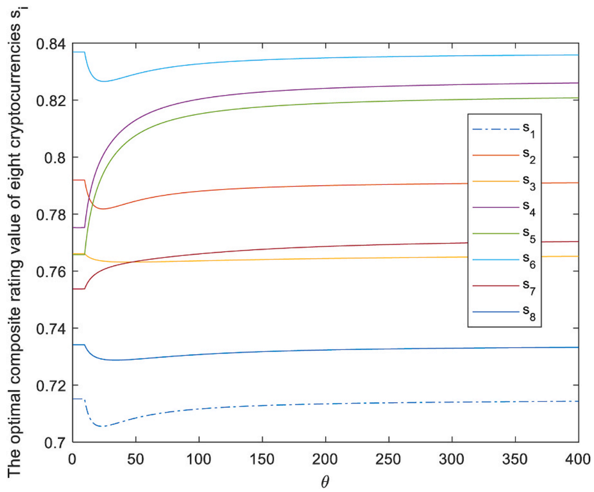

Fig. 5. Variations of $\widehat{s}_i$ with changing values of θ 6. Comparative analysis.

Table 9
Sustainability evaluation results for major cryptocurrencies under average value measure ($\theta = 2$).

Alternatives	Comprehensive Preference value *Si*	Rank
X_1 (Bitcoin)	1.3761	1
X_2 (Ethereum)	1.0539	6
X_3 (Ripple)	0.9976	7
X_4 (Litecoin)	1.1430	3
X_5 (Monero)	1.0956	4
X_6 (Stellar)	1.0829	5
X_7 (Dash)	0.9654	8
X_8 (NEM)	1.2825	2

To authenticate the proposed GIPFWGS measure, this section will describe a comparative analysis that compares our results with the usual average value and Euclidean distance measure. We follow all of the steps that are explained in Section 5 but adopt the above two alternative measures in step 3.

5.1. The average value

The average value method is the averaged value calculation of the score function of the expert's evaluation decision matrix. The comprehensive preference values are obtained as follows:

$s_1 = 1.3761,\ s_2 = 1.0539,\ s_3 = 0.9976,\ s_4 = 1.1430,\ s_5 = 1.0956,\ s_6 = 1.0829,\ s_7 = 0.9654,\ s_8 = 1.2825$

By sorting all comprehensive preference values s_i $(i = 1, 2, ..., 8)$ in descending order: $s_1 > s_8 > s_4 > s_5 > s_6 > s_2 > s_3 > s_7$, we conclude that Bitcoin (X_1) is the most sustainable cryptocurrency (see Table 9). When $\theta = 2$, the expert's weight vector is obtained as $\widehat{\omega} = (\widehat{\omega}_1, \widehat{\omega}_2, \widehat{\omega}_3) = (1, 0, 0)$.

When choosing different values of parameter θ in the GIPFWGS operator, as shown in Table 10, the comprehensive preference value obtained from IPFWGGS, IPFWAGS, and IPFWQGS to cryptocurrency sustainability evaluation suggests that Bitcoin X_1 remains the most sustainable cryptocurrency.

Table 10
Comprehensive preference value based on three different GIPFWGS measures.

	IPFWGGS		IPFWAGS		IPFWQGS	
Alternatives	S_i	Rank	S_i	Rank	S_i	Rank
X_1 (Bitcoin)	1.3759	1	1.3760	1	1.3761	1
X_2 (Ethereum)	1.0368	6	1.0454	6	1.0539	6
X_3 (Ripple)	0.9960	7	0.9968	7	0.9976	7
X_4 (Litecoin)	1.1397	3	1.1414	3	1.1430	3
X_5 (Monero)	1.0857	4	1.0906	4	1.0956	4
X_6 (Stellar)	1.0710	5	1.0770	5	1.0829	5
X_7 (Dash)	0.9586	8	0.9620	8	0.9654	8
X_8 (NEM)	1.2798	2	1.2812	2	1.2825	2
Weight	$\widehat{\omega}$ (1, 0, 0)					

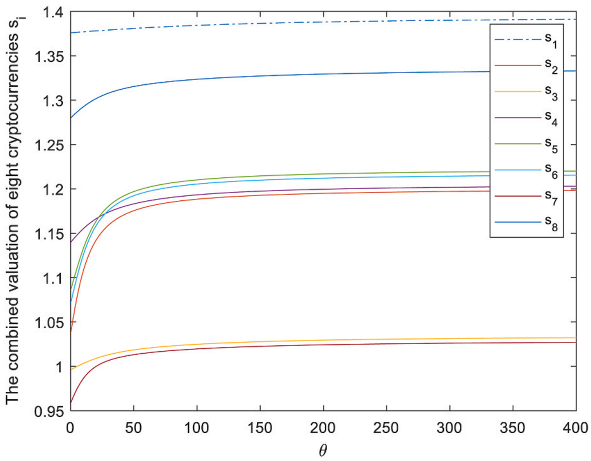

Fig. 6. Variations of comprehensive preference value s_i with changing values of θ.

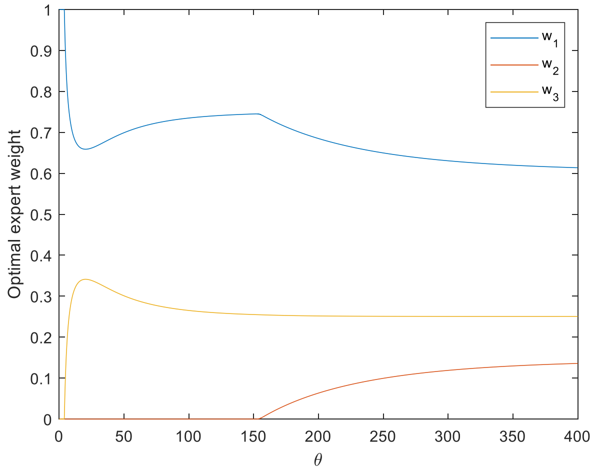

Fig. 7. Variations of the optimal expert's weight with changing values of θ.

Fig. 6 illustrates the variations of comprehensive preference value with changing values of θ. When $\theta \in [0, 400]$, each comprehensive evaluation value generally increases with increasing θ. However, it shows stable ranking results from $s_1 > s_8 > s_4 > s_5 > s_6 > s_2 > s_3 > s_7$ to $s_1 > s_8 > s_5 > s_6 > s_4 > s_2 > s_3 > s_7$ with only Litecoin (X_4) dropping from third to fifth place.

When considering variations of the optimal expert's weight with changing values of θ, as shown in Fig. 7, when $\theta \in [0, 400]$, $\widehat{\omega}_1$ (financial regulators) decreases from 1 to 0.61, $\widehat{\omega}_2$ (financial institutions) increases from 0 to 0.14. $\widehat{\omega}_3$ (academic economists) starts from 0, first increases and then decreases, and converges at 0.25. Therefore, the optimal experts weight vector is therefore obtained as $\widehat{\omega} = (\widehat{\omega}_1, \widehat{\omega}_2, \widehat{\omega}_3) = (0.61, 0.14, 0.25)$, which indicates the views from financial regulators are more important in this evaluation. The variation of optimal comprehensive evaluation value under optimal expert's weight vector (shown in Fig. 8) implies that the rank is eventually revalidated as $s_1 > s_8 > s_5 > s_6 > s_4 > s_2 > s_3 > s_7$.

Although the average value is the simplest method and involves fundamental calculation, it is not suitable for a multidimensional problem. In contrast to the results obtained using GIPFWGS, the fact that the similarity measures taking into account the ideal solution is ignored in the average value method because it only considers the expert's evaluation.

The Euclidean distance measure formula that is given below calculates the distance between the decision matrices of expert's evaluation and the ideal solution (see formula (27)):

$$ED\left(\mu_i^{(k)}, \nu^{(k)}\right) = \sqrt{\sum_{j=1}^{n} p_j \left[G\left(\mu_{ij}^{(k)}\right) - G\left(\nu_j^{(k)}\right)\right]^2} \tag{27}$$

In step 3, $H(\mu_i^{(k)}, \nu^{(k)})$ obtained in GIPFWGS is replaced by $1 - ED(\mu_i^{(k)}, \nu^{(k)})$. The comprehensive preference values are obtained as follows:

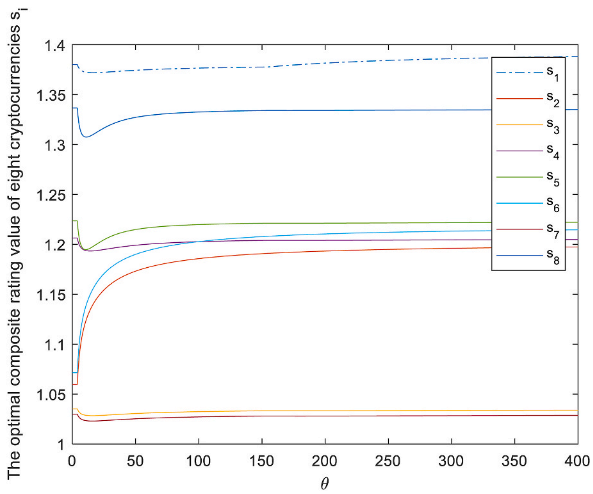

Fig. 8. Variations of $\widehat{s}_i$ with changing values of θ Euclidean distance.

Table 11
Sustainability evaluation results for major cryptocurrencies under Euclidean distance measure ($\theta = 2$).

Alternatives	Comprehensive Preference value *Si*	Rank
X_1 (Bitcoin)	0.4826	8
X_2 (Ethereum)	0.6225	6
X_3 (Ripple)	0.6313	5
X_4 (Litecoin)	0.7191	1
X_5 (Monero)	0.6999	2
X_6 (Stellar)	0.6793	3
X_7 (Dash)	0.5589	7
X_8 (NEM)	0.6413	4

Table 12
Comprehensive preference value based on three different GIPFWGS measures.

	IPFWGGS		IPFWAGS		IPFWQGS	
Alternatives	S_i	Rank	S_i	Rank	S_i	Rank
X_1 (Bitcoin)	0.4627	8	0.4724	8	0.4826	8
X_2 (Ethereum)	0.6159	6	0.6192	6	0.6225	6
X_3 (Ripple)	0.6282	5	0.6298	5	0.6313	5
X_4 (Litecoin)	0.7172	1	0.7182	1	0.7191	1
X_5 (Monero)	0.6975	2	0.6987	2	0.6999	2
X_6 (Stellar)	0.6761	3	0.6777	3	0.6793	3
X_7 (Dash)	0.5552	7	0.5570	7	0.5589	7
X_8 (NEM)	0.6412	4	0.6413	4	0.6413	4
Weight	$\widehat{\omega}$ (0, 1, 0)					

$s_1 = 0.4826,\ s_2 = 0.6225,\ s_3 = 0.6313,\ s_4 = 0.7191,\ s_5 = 0.6999,\ s_6 = 0.6793,\ s_7 = 0.5589,\ s_8 = 0.6413$

Hence all comprehensive preference values s_i $(i = 1, 2, ..., 8)$ in descending order are $s_4 > s_5 > s_6 > s_8 > s_3 > s_2 > s_7 > s_1$ under Euclidean distance method, which gives an analogous result (see Table 11) to that from GIPFWGS method. Table 12 reports robustness of comprehensive preference value when considering different values of parameter θ in the GIPFWGS operator. Sustainability evaluation under IPFWGGS, IPFWAGS, and IPFWQGS suggest that Litecoin (X4) is the most sustainable cryptocurrency.

When $\theta = 2$, the experts weight vector is obtained as $\widehat{\omega} = (\widehat{\omega}_1, \widehat{\omega}_2, \widehat{\omega}_3) = (0, 1, 0)$. With fixed experts weight vector, when discussing $\theta \in [0, 400]$, as can be seen in Fig. 9, the comprehensive preference again increases as θ increases. The overall comprehensive preference ranking is stable, with Ethereum (X2) and NEM (X8) change ranking with each other: $s_4 > s_5 > s_6 > s_2 > s_3 > s_8 > s_7 > s_1$.

Although the Euclidean distance method arrives at similar results, the GIPFWGS method that is proposed in this paper provides a more convenient way of calculation that incorporates the concept of membership with the distance measure. It also has higher fault tolerance to reduce the biasedness arising from outliers in questionnaire data. For example, when considering the underlying technical stability, given that the expert's evaluation is higher than the ideal solution, the GIPFWGS method takes the membership degree

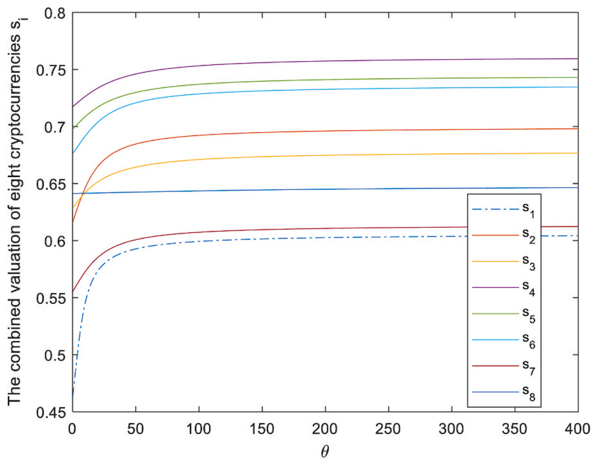

Fig. 9. Variations of comprehensive preference value s_i with changing values of θ When revalidating the optimal expert weight according to the value of θ, from Fig. 10 and 11, it is not difficult to find that the final ranking of comprehensive evaluation value obtained by the Euclidean distance method is with the optimal expert's weight $\widehat{\omega} = (\widehat{\omega}_1, \widehat{\omega}_2, \widehat{\omega}_3) = (0.11, 0.89, 0)$, where Litecoin (X4) remains the most sustainable cryptocurrency.

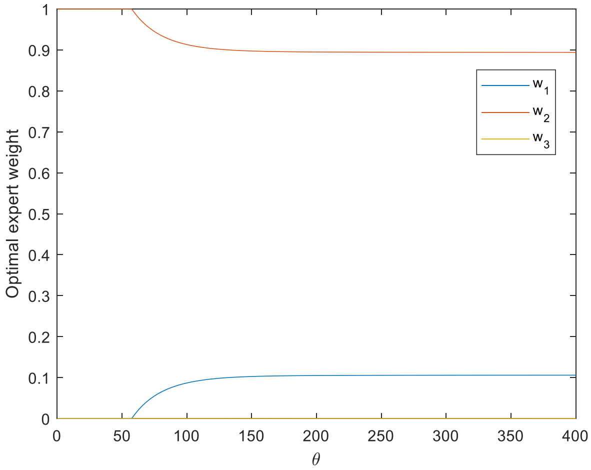

Fig. 10. Variations of the optimal expert's weight with changing values of θ.

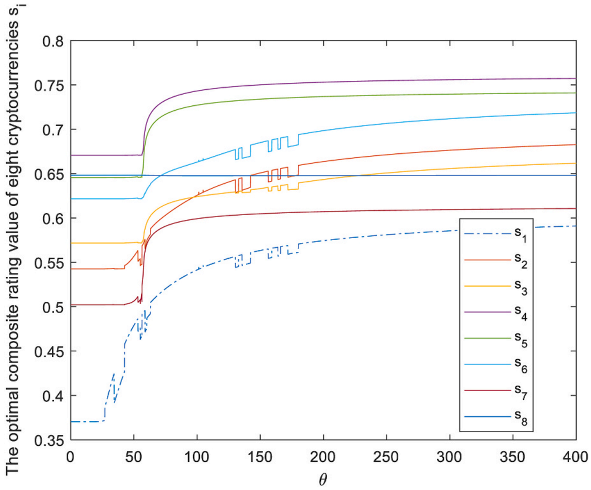

Fig. 11. Variations of $\widehat{s}_i$ with changing values of θ.

(similarity) as 1, while the Euclidean distance method calculates the distance between the expert's evaluation and the ideal solution, resulting in a similarity measure of less than 1, which makes the evaluation biased.

6. Conclusion

This study aimed to present a novel MAGDM approach to evaluate the sustainable development of eight major cryptocurrencies. Under the interval-valued Pythagorean fuzzy environment, we have proposed the concept of grey similarity measure for IVPFNs based on the whitenisation weight function and have developed a novel GIPFWGS measure approach to solve MAGDM problems. In comparison with other similarity measures and operators, such as the Heronian mean operator [34] and Hamming distance [35], the proposed approach provided an easy procedure to calculate with efficient and precise outcomes by combining the GIPFWGS measure and the GIPFOWA aggregation operator. With its implication, we demonstrated the applicability and effectiveness of the proposed method and found that Litecoin is selected as the best alternative in terms of sustainability evaluation under the three different similarity measures (i.e., IPFWGGS, IPFWAGS, IPFWQGS). We further perform a robustness assessment with different variations of the expert's weight to test how different values of parameter θ can affect the ranking results of the alternatives. The results suggest that Stellar becomes the most sustainable cryptocurrency when θ approaches 400. Furthermore, after resolving the optimal expert's weight with changing the value of θ, it is found that Stellar is still considered to be the most sustainable cryptocurrency.

A cryptocurrency with intensive energy consumption, high mining cost and high computing power would provide the least effective support for its sustainable development. Not surprisingly, Bitcoin remains the most pessimistic cryptocurrency in terms of its sustainability prospectus.

This research compares our GIPFWGS method with the popular average value method and Euclidean distance method. The results show that average value method finds it difficult to extract the information of the expert's expectation, which leads to a large gap in the final evaluations. Without involving the membership degree used in this paper, the Euclidean distance method calculates the distance of the obtained evaluation and the optimal evaluation when the evaluation meets the expectations of the experts, leading an obtained similarity of less than 1, which results in biased assessments. The comparison analysis gives evidence that the GIPFWGS method has the smallest gap between the size of the final evaluation value and best fault tolerance, including the concepts of distance and membership degree, which gives a convincing result for the assessment.

It should be noted that attributions considered for the assessment of the decision problem are evaluated based on the score expressed by experts, who must be objective and authoritative. Meanwhile, to reduce a certain cognitive bias in an evaluation, comparatively large sample data and multiple types of experts are needed, which complicates the data collection. Besides, the paper cannot apply exhaustion method. There may be better solution with some similarity functions in interval-valued Pythagorean fuzzy environment for the relevant problems.

There are open questions that we consider investigating in our future studies. Firstly, the method proposed is limited to a single family of fuzzy measures with variations of coefficient, while it would be advantageous to construct further time complexity studies of solving other fuzzy measures during the assessment of MAGDM problems with a large set of criteria in our future research to ensure good performance of the algorithm.

Secondly, due to the rapid changes in the cryptocurrency market, a multi-criteria decision-making approach is worth trying because it can deal with the indeterminate and inconsistent information that is introduced by Dombi operations on two single-valued trapezoidal neutrosophic numbers [36]. In this context, it would be of future interest to apply the proposed method by incorporating data from other markets, such as financial product investment decision making, green finance reputation evaluation, enterprise ESG evaluation, and supply chain management assessment.

Thirdly, existing Pythagorean fuzzy weighted geometric operator may generate irrational ranking orders of alternatives or fail to differentiate the order of alternatives. Future research can incorporate the method proposed by Paul et al. [29], which utilizes an advanced Pythagorean fuzzy weighted geometric operator for multi-attribute decision making to enhance the effectiveness and validity of decision-making processes. This method can provide a more comprehensive evaluation of alternatives and overcome the shortcomings of existing aggregation operators, resulting in more rational and discriminative ranking orders of alternatives compared to other methods.

Declaration of competing interest

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

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Appendix

Table A1
Sustainability Evaluation Questionnaire for Major Cryptocurrencies

[Attributes Cryptocurrencies	Underlying Technology Stability	Transaction Anonymity	Public Attention Level	Market Liquidity	Price Stability	Market Share	Regulatory Continuity	Energy Consumption	Mining Cost	Network Hash Rate
Bitcoin										
Ethereum										
Ripple										
Litecoin										
Monero										
Stellar										
Dash										
NEM										

Instructions for filling the Questionnaire: The scoring range of the above attributes is 1–10 points. A score of 1 represents the lowest degree and a score of 10 represents the highest degree.

Table A2
Weight Assignment Table for Sustainability Evaluation Indicators of Major Cryptocurrencies

	Underlying Technology Stability	Transaction Anonymity	Public Attention Level	Market Liquidity	Price Stability	Market Share	Regulatory Continuity	Energy Consumption	Mining Cost	Network Hash Rate
Weight Values										

Instructions for filling the Questionnaire: The weight values for each indicator is expressed as percentages, and the sum of all weight values is 100%.

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