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A Decision Cloud Ranking Approach Based on Privacy and Security in Blockchain E-Health Industry 4.0 Systems

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Abstract

E-health Industry 4.0 systems ranking based on Blockchain is a multi-criteria decision-making (MCDM) problem, considering the multiple evaluation properties, their significance, and data variety. The final closeness between the evaluation sample and ideal solutions also constitutes an optimisation problem. To the authors' knowledge, no study has provided a multi-privacy and security ranking approach solution for E-health Industry 4.0 systems based on Blockchain. Consequently, this study proposes and discusses a multi-privacy and security ranking approach solution for E-health Industry 4.0 systems, utilising the SFS-FWZIC method to address the significance of properties issue and the Grey-TOPSIS method to tackle data variation, multiple evaluation properties, and the ideal solutions optimisation problem. The methodology of the proposed approach consists of three sections. First, three decision matrices are constructed based on the intersection of E-health systems with the mentioned properties, intersecting Electronic Health Records (EHRs), Electronic Medical Records (EMRs), and Personal Health Records (PHRs) with seven properties. Second, the weights of each privacy and security property are calculated using the SFS-FWZIC method. Finally, the weights determined by the SFS-FWZIC method and the three decision matrices are input into the Grey-TOPSIS method to rank E-health systems across the three categories. The findings reveal the following: (1) The SFS-FWZIC method effectively assigned weights to privacy and security properties, with access control achieving the highest significance weight (0.1934) and Secure-search receiving the lowest weight (0.0603). (2) The Grey-TOPSIS method efficiently ranked E-health systems across the three categories based on various parameters, including α=0.1,α=0.3,α=0.5,α=0.7,and α=0.9. Sensitivity and correlation analysis were conducted to evaluate the results, revealing high correlation results based on each α value across all discussed scenarios of changing property weights. The implications of this study can lead to better decision-making, improved security and privacy, increased competition, and widespread adoption, ultimately contributing to more efficient and effective healthcare delivery.

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Keywords: E-Health Systems; Industry 4.0; Multi-Criteria Decision-Making; Security; Privacy.

1. Introduction

E-health Industry 4.0 is among the fastest growing and most prominent industries globally [1, 2], yet it has faced significant socio-economic challenges in many countries over the past decade [1]. According to the United States Department of Health and Human Services (HHS), personal healthcare expenditures increased from $2.01 trillion to $3.08 trillion between 2008 and 2018, with a 4.4% growth rate [3]. National health expenditures are projected to increase at an average annual rate of 5.4% from 2019 to 2028, accounting for 19.7% of the gross domestic product [4]. These statistics indicate that healthcare industry expenditures are expected to grow faster than anticipated.

Earlier iterations of the E-health Industry, such as 1.0, 2.0, and 3.0, faced challenges and complexities, including duplicate healthcare records, maintenance issues, hospital-centric systems, and managing large volumes of real-time medical records [5]. In contrast, E-health Industry 4.0 has been significantly revolutionised by cloud storage, biomedical sensors, and wireless body area networks, enabling efficient patient data transfer [6]. In times of crisis, such as the COVID-19 pandemic, it is imperative to implement an E-health Industry 4.0 system to reduce per capita medication expenses and provide care focused on both the institution and the patient. Moreover, medical facilities worldwide have been overwhelmed with patients who have contracted the disease. Consequently, seeking medical attention at these facilities for disease diagnosis may pose significant challenges in terms of time, expense, and severity of the condition for the individual [7, 8].

Nomenclature & Symbols			
HHS	Health and Human Services	FWZIC	Fuzzy Sets Weighted with Zero Inconsistency
IoT	Internet of Things	SFS	Spherical-Fuzzy-Set
MCDM	Multiple Criteria Decision-Making	EHRs	Electronic Health Records
BWM	Best-Worst Method	EMRs	Electronic Medical Records
AHP	Analytic Hierarchy Process	PHRs	Personal Health Records
TOPSIS	Technique For Order of Preference by Similarity to The Ideal Solution		

The E-health Industry 4.0 is poised to meet the abovementioned needs, encompassing remote monitoring, diagnosis, and treatment [9]. The E-health Industry 4.0 systems facilitate the connection between patients and wearable biomedical sensors, enabling remote monitoring of patients and early detection of illnesses. The patients' electronic records obtained from the sensors are stored in either distributed/centralised location. Nonetheless, the susceptibility of centralised locations to a range of attacks, such as confidentiality, single point of failure, availability, and integrity, are pertinent concerns [9]. In addition, it is imperative to ensure the secrecy of the patient's medical information during the entire transaction process, limiting access solely to authorised individuals [10].

Addressing these challenges and concerns involves leveraging Blockchain technology supported by Industry 4.0 to prevent single-point failures and tampering, ensuring data integrity [11]. Blockchain technology presents a viable solution for addressing privacy and security concerns [12], [13]. The utilisation of blockchain technology has facilitated the advancement of E-health Industry 4.0 by improving transparency and communication among healthcare providers and patients [14]. It facilitates trustworthy and immutable transactions by utilising a distributed-decentralised system, thereby eliminating the need for centralisation or mediation by a central authority [15]. Numerous researchers have reviewed and examined the impact of Blockchain on the E-health Industry 4.0, primarily focusing on enhancing data sharing, security, privacy, and prevention of unauthorised access through the utilisation of Blockchain [16].

The rest of this paper is organised as follows. The most related ranking issues and techniques are presented in Section 2. The methodology of ranking E-healthcare Industry 4.0 systems is proposed in Section 3. In Section 4, the overall results are presented and discussed. The evaluation of the proposed method is presented in Section 5. Finally, Section 6 concludes this paper.

2. Related Works

E-healthcare Industry 4.0 systems that rely on blockchain technology can be evaluated by assessing various privacy and security properties, as indicated by [16]. In addition, a review proposed by [16] has segmented E-healthcare Industry 4.0 systems that utilise blockchain technology into two distinct categories: telecare-medical-information-systems and E-health systems. The literature review by [17] demonstrates that previous research efforts have incorporated privacy and security features creating E-healthcare Industry 4.0 systems dependent on blockchain technology. Nevertheless, no study utilised these properties as evaluation criteria to establish a standard of comparison for the existing systems. A decision matrix for telecare-medical-information systems was proposed by [18]. The systems within this category were subsequently evaluated and ranked based on six distinct privacy and security properties. The telecare-medical-information systems in this study were based on utilising Internet of Things (IoT) technology in conjunction with blockchain. To date, no scholarly investigation has evaluated cloud-based E-health systems incorporating blockchain technology and employing the seven fundamental privacy and security properties [17], representing a notable research gap in the existing literature.

Assessing E-health systems' privacy and security levels is a crucial and challenging undertaking, particularly in determining their respective rankings. Although multiple systems are reported in the academic literature, a singular system that fulfils all fundamental privacy and security properties has not yet been determined. The complexity of ranking E-health systems based on their privacy and security properties is compounded by the diversity of these properties in each system. Based on these delineations, comparing the current systems from a single point of view would be unjust. Furthermore, the ranking of E-health systems is challenged by three important issues [19-22], namely, the presence of multiple evaluation properties [23-25], the significance of these properties [26-28], and the variety of data [29]. These issues must be addressed to fill the research gap that has been identified [30-32]. Previous studies incorporated certain privacy and security properties during the design phase of E-health systems. Therefore, these properties must be taken into account simultaneously while ranking E-health systems. The significance of these properties exhibits variability as the literature amalgamates them in diverse configurations.

Furthermore, such properties exhibited variability across E-health systems, escalating with the complexity of tasks within each system. Hence, the ranking of E-health systems to identify the most private and secure system falls under multiple criteria decision-making (MCDM) problems due to the issues above [33]. The decision-making process can be defined as a systematic and rational strategy for choosing the optimal option among a range of feasible options [34-37].

Numerous MCDM techniques have been devised and implemented across various domains, encompassing the ranking of alternatives and the weighting of criteria [38, 39]. The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) is a popular MCDM method used to identify the best alternative from a set of alternatives evaluated based on multiple properties. It ranks alternatives by comparing their similarity to a positive-ideal solution and the distance from the negative-ideal solution. However, the classical TOPSIS method's use of Euclidean distance is associated with certain limitations, including the insensitivity to small values, the distortion of original information, The distance between the positive-ideal-solution and negative-ideal-solution relatively small [40], and the rank reversal flaws [41]. Several enhanced forms of TOPSIS have been introduced in scholarly works to address these limitations [38-46]. For instance, [42] used the Canberra distance as an alternative to the Euclidean distance. Similarly, [43] and [51] used contact-vector-distance, generalised-hybrid-distance, and hamming distance for the same purpose. In pursuit of the same objective, additional groups of scholars have incorporated grey relational analysis with TOPSIS, as demonstrated in sources [42-46].

The primary advantages of the Grey relational analysis method include its simplicity in calculations, reliance on original data, and effectiveness in making business decisions [52]. In addition, Grey relational analysis can handle uncertain, incomplete, or vague data by using grey numbers, which makes it suitable for situations where precise data is not available [52, 53] [48]. Recently, a hybrid ranking approach was introduced to assess and compare the daily performance of the electricity market, enhancing the Grey-TOPSIS method by employing an optimisation model to determine the final proximity between the different samples and the ideal one [49]. Later, [18] adopted this version of the Grey-TOPSIS method and combined it with the Bald-Eagle-Search (BES) algorithm [54] to rank IoT healthcare systems. However, their proposed ranking method faced limitations in determining the evaluation criteria's weighting. Therefore, an external approach is necessary to achieve this objective [55].

Analytic hierarchy process (AHP), best-worst method (BWM), and fuzzy sets weighted with zero inconsistency (FWZIC) method [56] are widely used methods in determining the evaluation criteria's weighting. AHP has been used with the Grey-TOPSIS method in many studies and solved multiple MCDM problems [40], [46-50]. However, there has been no recent study integrated BWM and Grey-TOPSIS. Furthermore, the lack of consistency in AHP and BWM remains a significant concern [57]. The inconsistency arises due to pairwise comparisons, whereby the quantity of comparisons gradually increases in line with the number of criteria. Furthermore, the issue of high dependency among criteria is a concern in both AHP and BWM methods. The addition or removal of a criterion necessitates the repetition of pairwise comparisons. In contrast, the FWZIC method can estimate criteria weight with zero inconsistency regardless of their number [56-58]. Thus, [18] combined the FWZIC method with spherical-fuzzy-set (SFSs) [59] to estimate the weight of six privacy and security properties and solve informational vagueness, hesitancy, and uncertainty.

The healthcare industry 4.0 can greatly benefit from ranking the available E-health systems, such as Electronic Health Records (EHRs), Electronic Medical Records (EMRs), and Personal Health Records (PHRs), in several ways. By evaluating and comparing these systems based on various privacy and security properties, healthcare organisations can make more informed decisions to optimise patient care, streamline operations, and reduce costs. The following points summarise the study's contributions:

- This study formulates three decision matrices based on the intersection of E-health systems (EHRs, EMRs, and PHRs) with seven privacy and security properties.
- This study adopted the SFSs-FWZIC method to estimate the weight of the seven security properties and solve the criteria Importance issue.
- This study adopted the Grey-TOPSIS method to rank E-health systems across the EHRs, EMRs, and PHRs.
- This study developed a ranking approach for E-health systems using constructed decision matrices and combining SFSs-FWZIC and Grey-TOPSIS methods.

3. Proposed E-Health Systems Ranking Approach

The proposed ranking approach of E-health systems is explained as follows: Section 3.1 presents the formulation of three decision matrices (EHRs, EMRs, and PHRs). In Section 3.2, the adopted SFSs-FWZIC method is introduced. Finally, the adoption of the Grey-TOPSIS method is explained in Section 3.3.

3.1. Decision matrices formulation

In the proposed approach, decision matrices are regarded as the primary component, where three decision matrices are formulated to rank E-health systems within EHRs, EMRs, and PHRs categories. The formulation of the E-health systems decision matrices conducted as follows:

The first step involves the identification of potential privacy and security properties that can be utilised to rank and prioritise E-health systems. The development of E-health systems involved the utilisation of seven privacy and security properties, namely user-authentication (UA), access control (AC), privacy-preservation (PP), secure-search (SS), integrity (Int), availability (Ava), and anonymity (Ano), as stated in [17]. To date, no research has utilised them to rank the existing systems. Thus, the current investigation employed stated properties during the process of ranking. The definitions of the privacy and security properties in E-health systems are stated below:

- User Authentication (UA): This process verifies the identity of users, such as patients or medical providers, to ensure that only legitimate users can access the E-health systems and perform actions within their authorised scope.
- Access-Control (AC): In the context of E-health systems, access control is a crucial security measure that restricts patients' and medical providers' actions in the ledger, ensuring that only authorised individuals can access sensitive information [60].
- Privacy-Protection (PP): Within E-health systems, privacy refers to a patient's right to determine when, how, and to what extent their personal information is shared or accessed by others. The primary goal of integrating patient health information into E-health systems is to protect patient privacy [61].
- Secure Search (SS): A secure search capability in E-health systems allows only authorised medical providers to search for the intended patient's pseudo identities, facilitating improved diagnosis and treatment while maintaining patient privacy [62].
- Integrity (Int): This attribute relates to the system's capacity to maintain the originality, accuracy, completeness, and continuity of patient data and healthcare information, ensuring that the information remains unaltered and reliable.
- Availability (Ava): In E-health systems, availability denotes continuous access to information (24/7) and the ability to perform data transactions at any time and from any location [16].
- Anonymity (Ano): Anonymity in E-health systems refers to the removal of patients' actual identities from their records. Since medical records may contain sensitive patient information, data must be anonymised before being transmitted across a network.

The second step involves the identification of the existing E-health systems. According to [17], sixteen systems are found under EHRs, six systems under EMRs, and four systems under PHRs. The representation of E-health systems decision matrices is illustrated in Fig. 1.

The third step intersects the systems within EHRs, EMRs, and PHRs categories with the seven privacy and security properties (i.e., UA, AC, PP, SS, Int, Ava, and Ano) to build the decision matrices.

The SFS-FWZIC Method is utilised to assign a weight value to the seven properties, thereby establishing their respective levels of importance. Subsequently, the computed weights and the three decision matrices are utilised in the Grey-TOPSIS method to rank the systems within each category.

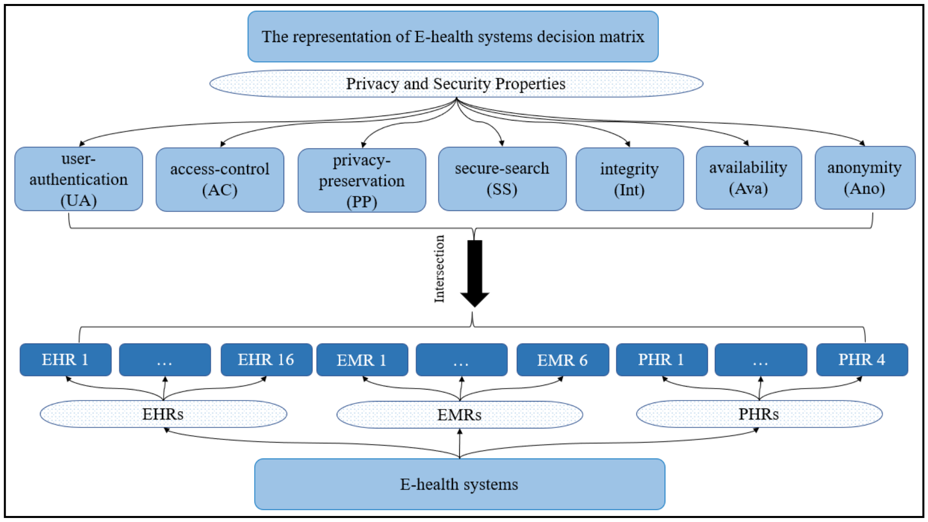

Fig. 1. The representation of E-health systems decision matrices

3.2. SFS-FWZIC method adaptation

Following [18], the SFS-FWZIC method is adopted to calculate the weight of the privacy and security properties and determine the importance level of each property. It can be implemented as follows:

Step 1: The privacy and security properties are defined in this step. Subsequently, the next step involves identifying and selecting a panel of specialists to evaluate these properties.

Step 2: This step involves identifying and selecting specialists within the same domain of study to build Structured-Expert-Judgment (SEJ) for evaluating and determining the importance level of the defined properties. The target population comprises experts in E-health systems based on blockchain technology and security. This process consists of five sub-steps:

- Identifying knowledgeable individuals (experts) in the research topic who have recognition from their peers. To select experts, a bibliometric analysis is conducted on all authors and co-authors in the study field (i.e., E-health systems). This analysis identifies numerous specialists from various laboratory groups worldwide.
- After identifying potential experts, a panel of 10 to 16 experts is chosen, with a minimum of four experts required for each subject. All selected experts are contacted via email to estimate their interest in participating on the panel and confirm their expertise in the field. Following this process, 17 experts have agreed to serve on the SEJ panel.
- The development of an evaluation form is deemed an essential step in the acquisition of data from experts. The experts chosen in the prior step are responsible for assessing the validity and reliability of the form.
- The process of evaluating the importance of each property is carried out in this step. The importance of properties is assessed by experts utilising a Likert scale consisting of five points. The Likert scale is employed due to its reliable quantitative data, ease of analysis, and minimal bias [63].
- The process of transforming a linguistic scale into corresponding numerical values is performed in this step, as demonstrated in Table 1. The experts' preferences are converted into numerical values to enable subsequent analysis in the next steps.

Table 1. Linguistic scale and equivalent numerical values

Linguistic scale	Numerical values
Very low importance (VLI)	1
Low important (LI)	2
Medium importance (MI)	3
Important (I)	4
Very important (VI)	5

Step 3: In this step, an Expert-Decision-Matrix (EDM) is formulated by integrating the SEJ panel and the seven privacy and security properties. A cross-referencing of the SEJ panel and these attributes has been established. The intersection between each property (Pj) and each selected expert (Ei) is established, whereby the experts allocate levels of importance to all properties, as illustrated in (1).

$$EDM = \begin{array}{c c} & \begin{array}{ccc} P1 & \dots & Pn \end{array} \\ \begin{array}{c} E_1 \\ \vdots \\ E_{fn} \end{array} & \begin{bmatrix} P_1/E_1 & \cdots & P_{1n}/E_{1n} \\ \vdots & \ddots & \vdots \\ P_{f1}/E_{f1} & \cdots & P_{fn}/E_{fn} \end{bmatrix} \end{array} \tag{1}$$

Step 4: This step involves the creation of the SFS–EDM by applying the SFSs on the EDM. In this step, the numerical values are swapped with spherical fuzzy numbers (SFNs), as shown in Table 2. According to [64], SFSs and SFNs can be defined as follows:

Definition 1 [65]: Let the universe set be U. Then the set $\tilde{A}_s = \{\langle u, \mu_{\tilde{A}_s}(u), \nu_{\tilde{A}_s}(u), \pi_{\tilde{A}_s}(u)\rangle | u \in U\}$ is said to be SFS, where $\mu_{\tilde{A}_s}(u): U \to [0,1]$, $\nu_{\tilde{A}_s}(u): U \to [0,1]$, and $\pi_{\tilde{A}_s}(u): U \to [0,1]$ are said to be positive-membership-degree of u in U, neutral-membership-degree of u in U, and negative-membership-degree of u in U, respectively. The $\mu_{\tilde{A}_s}$, $\nu_{\tilde{A}_s}$, and $\pi_{\tilde{A}_s}$ must meet the condition:$(\forall u \in U)\left(0 \leqslant \left(\mu_{\tilde{A}_s}(u)\right)^2 + \left(\nu_{\tilde{A}_s}(u)\right)^2 + \left(\pi_{\tilde{A}_s}(u)\right)^2 \leqslant 1\right)$.

Definition 2 [64]: For SFS $\{\langle u, \mu_{\tilde{A}_s}(u), \nu_{\tilde{A}_s}(u), \pi_{\tilde{A}_s}(u)\rangle | u \in U\}$, which is triple components $\langle \mu_{\tilde{A}_s}, \nu_{\tilde{A}_s}, \pi_{\tilde{A}_s}\rangle$ are said to be SFN, and each SFN can be represented by $e = \langle \mu_e, v_e, \pi_e\rangle$, where μ_e, v_e and $\pi_e \in [0,1]$, with the condition that $0 \leqslant \mu_e^2 + v_e^2 + \pi_e^2 \leqslant 1$.

Table 2. Linguistic scale and their corresponding SFNs [64]

Linguistic scale	μ	v	π
Very low importance (VLI)	0.15	0.85	0.1
Low important (LI)	0.25	0.75	0.2
Medium importance (MI)	0.55	0.5	0.25
Important (I)	0.75	0.25	0.2
Very important (VI)	0.85	0.15	0.1

Step 5: The present step involves the computation of the final weight values for the seven properties $(w_1, w_2 \ldots, w_n)^{\mathrm{T}}$ by utilising the SFNs obtained from the preceding step. The calculation is performed in the following manner:

- Compute the ratio of the SFNs within SFS–EDM using (2) and (3) [65, 66].

$$\tilde{A}_s \oslash \tilde{B}_s = \left(\left(\frac{\left(\mu_{\tilde{A}_s}^2(2-\mu_{\tilde{B}_s}^2)\right)}{1-\left(1-\mu_{\tilde{A}_s}^2\right)\cdot\left(1-\mu_{\tilde{B}_s}^2\right)}\right)^{\frac{1}{2}}, \frac{\left(\nu_{\tilde{A}_s}^2-\nu_{\tilde{B}_s}^2\right)^{\frac{1}{2}}}{\left(1-\nu_{\tilde{A}_s}^2\cdot\nu_{\tilde{B}_s}^2\right)^{\frac{1}{2}}}, \frac{\left(\pi_{\tilde{A}_s}^2-\pi_{\tilde{B}_s}^2\right)^{\frac{1}{2}}}{\left(1-\pi_{\tilde{A}_s}^2\cdot\pi_{\tilde{B}_s}^2\right)^{\frac{1}{2}}}\right), \tag{2}$$

$$if\ \frac{\mu_{\tilde{B}_s}^2}{\mu_{\tilde{A}_s}^2} \geq \frac{1-\pi_{\tilde{B}_s}^2}{1-\pi_{\tilde{A}_s}^2}\frac{1+\pi_{\tilde{A}_s}^2}{1+\pi_{\tilde{B}_s}^2} \geq 1.$$

$$SAM(\tilde{A}_{S1}, \ldots, \tilde{A}_{Sn}) = \tilde{A}_{S1} + \tilde{A}_{S1} + \cdots + \tilde{A}_{Sn} = \left\{\left[1 - \prod_{i=1}^{n}(1-\mu_{\tilde{A}_{Si}}^2)\right]^{1/2}, \prod_{i=1}^{n}\nu_{\tilde{A}_{Si}}, \left[\prod_{i=1}^{n}(1-\mu_{\tilde{A}_{Si}}^2) - \prod_{i=1}^{n}(1-\mu_{\tilde{A}_{Si}}^2-\pi_{\tilde{A}_{Si}}^2)\right]^{1/2}\right\}. \tag{3}$$

- The final fuzzy weight values of the seven properties are represented as $(\widetilde{w1}, \widetilde{w2}, \ldots, \widetilde{wn})^T$, and are obtained through the calculation of mean values utilising (3) and (4) [65].

$$\tilde{A}_s / \lambda = \left\{(1-\left(1-\mu_{\tilde{A}_s}^2\right)^{1/\lambda})^{1/2}, \nu_{\tilde{A}_s}^{1/\lambda}, \left((1-\mu_{\tilde{A}_s}^2)^{1/\lambda} - (1-\mu_{\tilde{A}_s}^2-\pi_{\tilde{A}_s}^2)^{1/\lambda}\right)^{1/2}\right\} \text{ for } \lambda > 0, \tag{4}$$

- Defuzzify the SFNs to find the final crisp weight values of the seven properties using (5) [59].

$$Def\ (\tilde{A}_s) = \left(\mu_{\tilde{A}_s} - \pi_{\tilde{A}_s}\right)^2 - \left(\nu_{\tilde{A}_s} - \pi_{\tilde{A}_s}\right)^2. \tag{5}$$

- The sum of attribute weights must be equivalent to 1. Equation (6) is utilised to rescale the weights accordingly if this requirement is not satisfied.

$$\mathrm{w_j} = s(\aleph) / \sum_{\mathrm{j}=1}^{\mathrm{J}} s(\aleph). \tag{6}$$

3.3. Grey-TOPSIS method adaptation

The overall weights are derived from the SFS-FWZIC method to address the primary limitations of Grey-TOPSIS, which include the lack of weight calculation. Nevertheless, the utilisation of TOPSIS or GRA individually captures only a fraction of the information provided by the data. Consequently, the Grey-TOPSIS approach is utilised in this section to rank E-health systems across the three identified categories based on the acquired property weights. The Grey-TOPSIS method consists of the following steps [18], [49]:

Step 1: TOPSIS's fundamental premise is that the optimal solution should be the one that is closest to the positive-ideal-solution A^+ And the one that is farthest from the negative-ideal-solution A^- [67]. The basic processes of TOPSIS are illustrated as follows:

- Normalise the decision matrices using (7).

$$S_{ij} = x_{ij} / \left(\sum_{i=1}^{k}\left(x_{ij}\right)^2\right)^{1/2}, \tag{7}$$

where x_{ij} represents the evaluation of certain systems at the intersection of the i_{th} row, which pertains to E-health systems, and the j_{th} column pertains to the seven privacy and security properties in the decision matrices. Whereas k represents the aggregate quantity of E-health systems under consideration, the variable m represents the total number of properties.

- Apply the weight values of the properties computed using the SFS-FWZIC method to create the weighted matrix by (8).

$$V_{ij} = w_i * S_{ij}, \text{ where } w = [w_1 \quad w_2 \quad \cdots \quad w_m], \tag{8}$$

- Determine the positive-ideal-solution A^+ and negative-ideal-solution A^- using (9) and (10), respectively.

$$A^+ = (v_1^+, v_2^+, v_3^+, \ldots\ldots, v_m^+) = \left(\left(\max v_{ij} | \mathrm{j} \in \mathrm{I}\right), \left(\min v_{ij} | \mathrm{j} \in \mathrm{J}\right)\right), \tag{9}$$

$$A^- = (v_1^-, v_2^-, v_3^-, \ldots\ldots, v_m^-) = \left(\left(\min v_{ij} | \mathrm{j} \in \mathrm{I}\right), \left(\max v_{ij} | \mathrm{j} \in \mathrm{J}\right)\right), \tag{10}$$

Where I refer to the beneficial properties, and J refers to the non-benefit properties, $i = 1, 2, 3, \ldots, k;\ j = 1, 2, 3, \ldots, m$.

- Compute Euclidean distance which involves the computation of the D_i^+ and D_i^- for all E-health systems in the weighted matrix based on the A^+ and A^- using (11).

$$D_i^{\mp} = \left(\sum_{j=1}^{k}\left(V_{ij} - v_j^{\mp}\right)^2\right)^{1/2}. \tag{11}$$

Step 2: Grey relational analysis is a method that involves the computation of the grey matrix of the A^{+} and A^{-} as a means of distance determination. The mathematical expression for Grey relational analysis $(G_i^{\mp})$ is presented as follows:

$$G_i^{\mp} = \frac{\sum_{j=1}^{m} r_{ij}^{\mp}}{m}, \tag{12}$$

where

$r_{ij}^{\mp} = \frac{\min_{1\le i\le k}\min_{1\le j\le m}|v_j^{\mp} - V_{ij}| + \rho \max_{1\le i\le k}\max_{1\le j\le m}|v_j^{\mp} - V_{ij}|}{|v_j^{\mp} - V_{ij}| + \rho \max_{1\le i\le k}\max_{1\le j\le m}|v_j^{\mp} - V_{ij}|}$ and ρ is typically assigned a value of 0.5.

Step 3: Compute the hybrid distance and hybrid closeness $(Score_i)$ using (13) and (14), respectively.

$$min\, Z^{\mp} = \sum_{i=1}^{k} \alpha \cdot H_i^{\mp} \ln\left(\frac{H_i^{\mp}}{nrm(D_i^{\mp})}\right) + \sum_{i=1}^{k}(1-\alpha).H_i^{\mp}\ln\left(\frac{H_i^{\mp}}{nrm(G_i^{\mp})}\right), \tag{13}$$

where

$\sum_{i=1}^{k} H_i^{\mp} = 1,\ 0 \le H_i^{\mp} \le 1$, and α and $1-\alpha$ represent the decision maker's preference for TOPSIS and Grey relational analysis methods, respectively, $\alpha \in [0;\ 1]$.

$$Score_i = \frac{H_i^{-}}{H_i^{+} + H_i^{-}}. \tag{14}$$

E-health systems across the EHRs, EMRs, and PHRs categories are ranked in descending order based on their score values, and the system with the highest score is considered the optimal system.

4. Results and discussion

This section presents the outcomes of the proposed approach utilised for ranking E-health systems. It is composed of three subsections. The decision matrices of EHRs, EMRs, and PHRs categories are presented in Section 4.1. Section 4.2 presents the outcomes of the SFS-FWZIC approach, along with an estimation of the weight of the properties. The ranking outcomes for E-health systems in each category are presented in Section 4.3.

4.1. E-health systems decision matrices results

The decision matrices were constructed by intersecting the lists of E-health systems across the three categories (i.e. EHRs, EMRs, and PHRs) and their assessment privacy and security properties. Tables 2-4 report the proposed decision matrices that rank each system across the mentioned categories. The absence of properties from certain systems is indicated by "No," while their presence is indicated by "Yes,". The constructed matrices are fed to the Grey-TOPSIS method to rank the systems concerning the properties' weight. The following section reports the weighting findings of the privacy and security properties derived using the SFS–FWZIC method.

Table 2. Decision Matrix of EHRs

E-health systems/ properties	UA	AC	PP	SS	Int	Ava	Ano
EHR 1 [68]	No	Yes	No	Yes	Yes	No	No
EHR 2 [69]	Yes	Yes	Yes	No	Yes	No	No
EHR 3 [70]	Yes	No	Yes	No	Yes	Yes	Yes
EHR 4 [71]	Yes	No	Yes	No	Yes	No	No
EHR 5 [72]	Yes	No	Yes	No	Yes	No	No
EHR 6 [73]	Yes	No	Yes	No	Yes	No	No
EHR 7 [74]	No	Yes	Yes	No	Yes	Yes	Yes
EHR 8 [75]	No	No	Yes	No	Yes	No	No
EHR 9 [76]	No	Yes	No	No	Yes	Yes	No
EHR 10 [77]	No	Yes	Yes	Yes	Yes	Yes	No
EHR 11 [78]	No	Yes	Yes	Yes	Yes	No	No
EHR12 [79]	Yes	Yes	Yes	No	Yes	Yes	No
EHR 13 [80]	No	Yes	Yes	No	Yes	Yes	No
EHR 14 [81]	No	No	Yes	No	Yes	Yes	No
EHR 15 [82]	No	No	No	No	Yes	Yes	No
EHR 16 [83]	No	Yes	Yes	No	Yes	Yes	Yes

Table 3. Decision Matrix of EMRs

E-health systems/ properties	UA	AC	PP	SS	Int	Ava	Ano
EMR 1 [84]	No	No	Yes	No	Yes	No	No
EMR 2 [85]	No	No	Yes	No	Yes	No	No
EMR 3 [86]	No	No	Yes	No	Yes	No	Yes
EMR 4 [87]	No	No	Yes	No	Yes	No	No
EMR 5 [88]	No	Yes	Yes	No	Yes	No	No
EMR 6 [89]	Yes	Yes	Yes	No	Yes	Yes	No

Table 4. Decision Matrix of PHRs

E-health systems/ properties	UA	AC	PP	SS	Int	Ava	Ano
PHR 1 [90]	No	No	Yes	Yes	Yes	No	No
PHR 2 [91]	No	Yes	Yes	No	Yes	No	No
PHR 3 [92]	No	Yes	Yes	No	Yes	No	No
PHR 4 [93]	No	No	Yes	No	Yes	Yes	No

4.2. Properties weight results

This section describes the weight outcomes of the privacy and security properties constructed in Section 3.2, utilising the SFS-FWZIC method. Upon completion of the prescribed procedures, the SFS-FWZIC method yielded consistent weight sets. Following SFS-FWZIC's approach, the initial step involves identifying a predetermined set of properties, as outlined in Section 3.1. Subsequently, the specialists gather data, as delineated in the second step of the SFS-FWZIC method. Seventeen experts in the field of E-health systems completed an established evaluation form for expressing their proficiency in evaluating the relative importance of all the privacy and security properties, as illustrated in Table 5. Subsequently, the experts' preferences are converted from the linguistic scale to their corresponding numerical values. Furthermore, the EDM of E-health systems is constructed by the information presented in Table 1, as outlined in the third step and illustrated in Table 6.

Table 5. Experts' preferences of seven properties for E-health systems on the linguistic scale

Properties/Experts	E1	E2	E3	E4	E5	E6	E7	E8	E9	E10	E11	E12	E13	E14	E15	E16	E17
UA	I	VI	VI	VI	VI	I	MI	VI	VI	I	VI	VI	VI	VI	VI	I	I
AC	I	VI	VI	I	VI	VI	I	VI	VI	VI	VI	I	VI	I	I	VI	VI
PP	VI	VI	VI	VI	I	I	I	I	VI	I	VI	I	VI	VI	VI	I	I
SS	I	MI	VI	MI	MI	I	VI	I	MI	MI	MI	I	VI	MI	LI	I	LI
Int	MI	VI	VI	MI	VI	VI	I	VI	I	VI	VI	I	VI	MI	VI	VI	VI
Ava	MI	VI	VI	VI	I	VI	I	I	VI	VI	VI	I	VI	MI	I	I	MI
Ano	MI	MI	VI	VI	MI	VI	MI	MI	LI	VI	VI	MI	VI	MI	MI	I	LI

Table 6. EDM of E-health systems

Properties / Experts	E1	E2	E3	E4	E5	E6	E7	E8	E9	E10	E11	E12	E13	E14	E15	E16	E17
UA	4	5	5	5	5	4	3	5	5	4	5	5	5	5	5	4	4
AC	4	5	5	4	5	5	4	5	5	5	5	4	5	4	4	5	5
PP	5	5	5	5	4	4	4	4	5	4	5	4	5	5	5	4	4
SS	4	3	5	3	3	4	5	4	3	3	3	4	5	3	2	4	2
Int	3	5	5	3	5	5	4	5	4	5	5	4	5	3	5	5	5
Ava	3	5	5	5	4	5	4	4	5	5	5	4	5	3	4	4	3
Ano	3	3	5	5	3	5	3	3	2	5	5	3	5	3	3	4	2

According to Step 4, the creation of SFS-EDM involves the application of SFNs on the EDM, as illustrated in Table 7. Equations (2) and (3) are utilised in Step 5 to determine the ratio values of the seven properties. Subsequently, the fuzzy weight values ($\tilde{w}$) are determined by calculating the mean of the experts' preference for each property through the utilisation of Equations (3) and (4). All seven properties' final weight is computed using Equation (5). Finally, Equation (5) is employed to appropriately adjust the resultant weights to satisfy the required condition that the summation of attribute weights is equal to 1. Table 9 displays the calculated ratio and fuzzy value of the final weights assigned to the evaluation properties of E-health systems.

Table 7. SFS-EDM of E-health systems

Properties/Experts		E1	E2	E3	E4	E5	E6	E7	E8	E9	E10	E11	E12	E13	E14	E15	E16	E17
UA	μ	0.75	0.85	0.85	0.85	0.85	0.75	0.55	0.85	0.85	0.75	0.85	0.85	0.85	0.85	0.85	0.75	0.75
	v	0.25	0.15	0.15	0.15	0.15	0.25	0.5	0.15	0.15	0.25	0.15	0.15	0.15	0.15	0.15	0.25	0.25
	π	0.2	0.1	0.1	0.1	0.1	0.2	0.25	0.1	0.1	0.2	0.1	0.1	0.1	0.1	0.1	0.2	0.2
AC	μ	0.75	0.85	0.85	0.75	0.85	0.85	0.75	0.85	0.85	0.85	0.85	0.75	0.85	0.75	0.75	0.85	0.85
	v	0.25	0.15	0.15	0.25	0.15	0.15	0.25	0.15	0.15	0.15	0.15	0.25	0.15	0.25	0.25	0.15	0.15
	π	0.2	0.1	0.1	0.2	0.1	0.1	0.2	0.1	0.1	0.1	0.1	0.2	0.1	0.2	0.2	0.1	0.1
PP	μ	0.85	0.85	0.85	0.85	0.75	0.75	0.75	0.75	0.85	0.75	0.85	0.75	0.85	0.85	0.85	0.75	0.75

	v	0.15	0.15	0.15	0.15	0.25	0.25	0.25	0.25	0.15	0.25	0.15	0.25	0.15	0.15	0.15	0.25	0.25
	π	0.1	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.1	0.2	0.1	0.2	0.1	0.1	0.1	0.2	0.2
SS	μ	0.75	0.55	0.85	0.55	0.55	0.75	0.85	0.75	0.55	0.55	0.55	0.75	0.85	0.55	0.25	0.75	0.25
	v	0.25	0.5	0.15	0.5	0.5	0.25	0.15	0.25	0.5	0.5	0.5	0.25	0.15	0.5	0.75	0.25	0.75
	π	0.2	0.25	0.1	0.25	0.25	0.2	0.1	0.2	0.25	0.25	0.25	0.2	0.1	0.25	0.2	0.2	0.2
Int	μ	0.55	0.85	0.85	0.55	0.85	0.85	0.75	0.85	0.75	0.85	0.85	0.75	0.85	0.55	0.85	0.85	0.85
	v	0.5	0.15	0.15	0.5	0.15	0.15	0.25	0.15	0.25	0.15	0.15	0.25	0.15	0.5	0.15	0.15	0.15
	π	0.25	0.1	0.1	0.25	0.1	0.1	0.2	0.1	0.2	0.1	0.1	0.2	0.1	0.25	0.1	0.1	0.1
Ava	μ	0.55	0.85	0.85	0.85	0.75	0.85	0.75	0.75	0.85	0.85	0.85	0.75	0.85	0.55	0.75	0.75	0.55
	v	0.5	0.15	0.15	0.15	0.25	0.15	0.25	0.25	0.15	0.15	0.15	0.25	0.15	0.5	0.25	0.25	0.5
	π	0.25	0.1	0.1	0.1	0.2	0.1	0.2	0.2	0.1	0.1	0.1	0.2	0.1	0.25	0.2	0.2	0.25
Ano	μ	0.55	0.55	0.85	0.85	0.55	0.85	0.55	0.55	0.25	0.85	0.85	0.55	0.85	0.55	0.55	0.75	0.25
	v	0.5	0.5	0.15	0.15	0.5	0.15	0.5	0.5	0.75	0.15	0.15	0.5	0.15	0.5	0.5	0.25	0.75
	π	0.25	0.25	0.1	0.1	0.25	0.1	0.25	0.25	0.2	0.1	0.1	0.25	0.1	0.25	0.25	0.2	0.2

Table 8 presents the final weight results for ranking E-health systems, highlighting the importance of the seven privacy and security properties. Access control (AC) earned the greatest weight value of 0.1934, followed by user authentication (UA) with 0.1847 and privacy protection (PP) with 0.1806. Integrity (Int) and availability (Ava), the fifth and sixth properties, had weight values of 0.1670 and 0.1483, respectively. The fourth and seventh properties, anonymity (Ano) and secure-search (SS) had the lowest weight values, with 0.0657 and 0.0603, respectively.

Table 8. Data ratio and final weights of E-health systems

Properties/ Experts		E1	E2	E3	E4	E5	E6	E7	E8	E9	E10	E11	E12	E13	E14	E15	E16	E17	$\tilde{w}$	Def. of $\tilde{w}$	Final weights
UA	μ	0.754	0.85	0.85	0.851	0.851	0.75	0.552	0.851	0.851	0.75	0.85	0.852	0.85	0.854	0.851	0.751	0.755	13.6744		
	v	0.25	0.15	0.15	0.15	0.15	0.25	0.5	0.15	0.15	0.25	0.15	0.15	0.15	0.15	0.15	0.25	0.25	3.4	128.5444	0.1847
	π	0.191	0.099	0.1	0.098	0.096	0.2	0.245	0.098	0.097	0.199	0.1	0.093	0.1	0.082	0.095	0.199	0.192	2.2816		
AC	μ	0.754	0.85	0.85	0.751	0.851	0.85	0.753	0.851	0.851	0.85	0.85	0.752	0.85	0.754	0.751	0.851	0.855	13.8747		
	v	0.25	0.15	0.15	0.25	0.15	0.15	0.25	0.15	0.15	0.15	0.15	0.25	0.15	0.25	0.25	0.15	0.15	3.15	134.6313	0.1934
	π	0.191	0.099	0.1	0.199	0.096	0.099	0.194	0.098	0.097	0.099	0.1	0.196	0.1	0.191	0.198	0.097	0.082	2.23567		
PP	μ	0.854	0.85	0.85	0.851	0.751	0.75	0.753	0.751	0.851	0.75	0.85	0.752	0.85	0.854	0.851	0.751	0.755	13.6747		
	v	0.15	0.15	0.15	0.15	0.25	0.25	0.25	0.25	0.15	0.25	0.15	0.25	0.15	0.15	0.15	0.25	0.25	3.35	125.6656	0.1806
	π	0.08	0.099	0.1	0.098	0.198	0.2	0.194	0.199	0.097	0.199	0.1	0.196	0.1	0.082	0.095	0.199	0.192	2.42671		
SS	μ	0.754	0.55	0.85	0.551	0.551	0.75	0.853	0.751	0.551	0.55	0.55	0.752	0.85	0.554	0.251	0.751	0.252	10.6701		
	v	0.25	0.5	0.15	0.5	0.5	0.25	0.15	0.25	0.5	0.5	0.5	0.25	0.15	0.5	0.75	0.25	0.75	6.7	41.96577	0.0603
	π	0.191	0.25	0.1	0.249	0.248	0.2	0.088	0.199	0.249	0.249	0.25	0.196	0.1	0.243	0.198	0.199	0.192	3.39988		
Int	μ	0.554	0.85	0.85	0.551	0.851	0.85	0.753	0.851	0.751	0.85	0.85	0.752	0.85	0.554	0.851	0.851	0.855	13.2735	116.1989	0.167
	v	0.5	0.15	0.15	0.5	0.15	0.15	0.25	0.15	0.25	0.15	0.15	0.25	0.15	0.5	0.15	0.15	0.15	3.9		

	π	0.243	0.099	0.1	0.249	0.096	0.099	0.194	0.098	0.199	0.099	0.1	0.196	0.1	0.243	0.095	0.097	0.082	2.38848		
	μ	0.554	0.85	0.85	0.851	0.751	0.85	0.753	0.751	0.851	0.85	0.85	0.752	0.85	0.554	0.751	0.751	0.554	12.9729		
Ava	v	0.5	0.15	0.15	0.15	0.25	0.15	0.25	0.25	0.15	0.15	0.15	0.25	0.15	0.5	0.25	0.25	0.5	4.2	103.2103	0.1483
	π	0.243	0.099	0.1	0.098	0.198	0.099	0.194	0.199	0.097	0.099	0.1	0.196	0.1	0.243	0.198	0.199	0.243	2.7041		
	μ	0.554	0.55	0.85	0.851	0.551	0.85	0.552	0.551	0.25	0.85	0.85	0.551	0.85	0.554	0.551	0.751	0.252	10.7693		
Ano	v	0.5	0.5	0.15	0.15	0.5	0.15	0.5	0.5	0.75	0.15	0.15	0.5	0.15	0.5	0.5	0.25	0.75	6.65	45.7414	0.0657
	π	0.243	0.25	0.1	0.098	0.248	0.099	0.245	0.249	0.199	0.099	0.1	0.247	0.1	0.243	0.248	0.199	0.192	3.15754		

4.3. E-health systems ranking results

The Grey-TOPSIS method, described in Section 3.3, determines the ranking results for each e-health system category. The estimated weight values of the privacy and security properties are fed to the Grey-TOPSIS method and the three decision matrices for ranking e-health systems. The positive (D_i^+) and negative (D_i^-) ideal solutions in Euclidean distances calculation are obtained using Equation (11), whereas the positive (G_i^+) and negative (G_i^-) ideal solutions in Grey relational analysis distances are calculated by Equation (12). The calculated ideal solutions are combined to compute the positive (H_i^+) and negative (H_i^-) ideal solutions for the hybrid distance using Equation (13). Finally, the score values of the E-health system across EHRs, EMRs, and PHRs are computed using Equation (14). The relative closeness ranged from 0 to 1, with a value closer to 0 indicating a more optimal system. Therefore, the most favourable system would have the lowest score, while the least favourable system would have the highest score. In this study, α values of 0.1, 0.3, 0.5, 0.7, and 0.9 were set to examine the changes in the final rankings. Table 9 displays the overall results when $\alpha = 0.1$ for the E-health system subcategories, including EHRs, EMRs, and PHRs. Table A.1 in Appendix A reports the results of the E-health system subcategories for the remaining α values (i.e., 0.3, 0.5, 0.7, and 0.9).

Table 9. Overall ranking results of EHRs, EMRs, and PHRs using the Grey-TOPSIS method when α = 0.1

				α = 0.1					
EHRs	**Alternatives**	**D+**	**D-**	**G+**	**G-**	**H+**	**H-**	**Score**	**Rank**
	EHR 1 [68]	0.0735	0.0512	0.0958	0.0338	0.0131	0.0344	0.7245	14
	EHR 2 [69]	0.0477	0.0777	0.0410	0.0810	0.0297	0.0153	0.3410	6
	EHR 3 [70]	0.0490	0.0769	0.0094	0.1082	0.0387	0.0049	0.1126	2
	EHR 4 [71]	0.0643	0.0633	0.0867	0.0417	0.0161	0.0311	0.6583	9
	EHR 5 [72]	0.0643	0.0633	0.0867	0.0417	0.0161	0.0311	0.6583	9
	EHR 6 [73]	0.0643	0.0633	0.0867	0.0417	0.0161	0.0311	0.6583	9
	EHR 7 [74]	0.0556	0.0718	0.0119	0.1060	0.0377	0.0060	0.1372	3
	EHR 8 [75]	0.0818	0.0350	0.1349	0.0002	0.0014	0.0477	0.9724	15
	EHR 9 [76]	0.0697	0.0568	0.0895	0.0393	0.0151	0.0322	0.6809	12
	EHR 10 [77]	0.0565	0.0711	0.0135	0.1046	0.0373	0.0065	0.1494	5
	EHR 11 [78]	0.0654	0.0621	0.0545	0.0693	0.0252	0.0205	0.4478	8
	EHR12 [79]	0.0344	0.0851	0.0000	0.1163	0.0416	0.0013	0.0296	1
	EHR 13 [80]	0.0611	0.0668	0.0482	0.0748	0.0272	0.0182	0.4010	7
	EHR 14 [81]	0.0748	0.0492	0.0939	0.0355	0.0136	0.0338	0.7138	13
	EHR 15 [82]	0.0819	0.0346	0.1352	0.0000	0.0013	0.0478	0.9741	16
	EHR 16 [83]	0.0556	0.0718	0.0119	0.1060	0.0377	0.0060	0.1372	3
				α = 0.1					
EMRs	**Alternatives**	**D+**	**D-**	**G+**	**G-**	**H+**	**H-**	**Score**	**Rank**
	EMR 1 [84]	0.1968	0.0002	0.2196	0.0000	0.0000	0.0799	0.9999	4
	EMR 2 [85]	0.1968	0.0002	0.2196	0.0000	0.0000	0.0799	0.9999	4
	EMR 3 [86]	0.1916	0.1361	0.1794	0.1265	0.0469	0.0665	0.5863	3
	EMR 4 [87]	0.1968	0.0002	0.2196	0.0000	0.0000	0.0799	0.9999	4
	EMR 5 [88]	0.1731	0.2833	0.1619	0.1816	0.0706	0.0600	0.4595	2
	EMR 6 [89]	0.0450	0.5801	0.0000	0.6919	0.2504	0.0017	0.0066	1
				α = 0.1					
PHRs	**Alternatives**	**D+**	**D-**	**G+**	**G-**	**H+**	**H-**	**Score**	**Rank**
	PHR 1 [90]	0.2886	0.2072	0.4276	0.0000	0.0076	0.1522	0.9523	4
	PHR 2 [91]	0.2267	0.2805	0.1720	0.3598	0.1295	0.0653	0.3352	2
	PHR 3 [92]	0.1958	0.3055	0.0000	0.6019	0.2105	0.0072	0.0331	1
	PHR 4 [93]	0.2889	0.2067	0.4004	0.0383	0.0203	0.1432	0.8759	3

Tables 9 and A.1 (Appendix A) show the E-health systems subcategory results. In the EHRs subcategory, among the 16 systems, system 12 ranked first for all α values. Then, the score values of EHR12 for the $\alpha = 0.1,\ \alpha = 0.3,\ \alpha = 0.5,\ \alpha = 0.7,$ and $\alpha = 0.9$ were 0.0296, 0.0882, 0.1461, 0.2034, and 0.2601, respectively. In addition, the last rank went to EHR15 for all α values, where the score values received by this system were 0.9741, 0.9200, 0.8626, 0.8018, and 0.7372 for the $\alpha = 0.1,\ \alpha = 0.3,\ \alpha = 0.5,\ \alpha = 0.7,$ and $\alpha = 0.9$, respectively. Some differences in the final ranking results were detected among the α values in this subcategory. EHR7 and 16 had the same rank results (rank = 3) for $\alpha = 0.1,\ \alpha = 0.3,\ \alpha = 0.5,$ and $\alpha = 0.7$ and dropped to the fourth rank for $\alpha = 0.9$. Similarly, EHR10 received the fifth rank for $\alpha = 0.1,\ \alpha = 0.3,\ \alpha = 0.5,$ and $\alpha = 0.7$ and dropped to the sixth rank ($\alpha = 0.9$). EHR2 got the sixth rank for $\alpha = 0.1,\ \alpha = 0.3,\ \alpha = 0.5,$ and $\alpha = 0.7$ and jumped to the third rank for $\alpha = 0.9$. The ranking results for EHRs 14 and 1 were 13th and 14th for $\alpha = 0.1,\ \alpha = 0.3,\ \alpha = 0.5,$ and $\alpha = 0.7$, respectively. These systems swapped positions for $\alpha = 0.9$. The ranks of the rest eight systems were the same for all α values and distributed between the first and last systems. In the EMRs subcategory, EMR6 received the highest rank for all α values. The score values of this system were 0.0066, 0.0201, 0.0341, 0.0488, and 0.0640 when $\alpha = 0.1,\ \alpha = 0.3,\ \alpha = 0.5,\ \alpha = 0.7,$ and $\alpha = 0.9$, respectively. Then, the lowest and same rank went to EMRs 1, 2, and 4 for all α values, as these systems employed the same criteria of privacy protection and integrity. They received scores of 0.9999, 0.9998, 0.9996, 0.9995, and 0.9993 for the $\alpha = 0.1,\ \alpha = 0.3,\ \alpha = 0.5,\ \alpha = 0.7,$ and $\alpha = 0.9$, respectively. EMRs 5 and 3 receive the second and third ranks for all α values, respectively. Last, in the PHR subcategory, PHRs 3 and 1 achieved the best and worst ranks, and the rest were spread in between for all α values. However, PHR3 had score values of 0.0331, 0.1028, 0.1775, 0.2579, and 0.3446, and PHR1 had score values of 0.9523, 0.8613, 0.7756, 0.6948, and 0.6186 for $\alpha = 0.1,\ \alpha = 0.3,\ \alpha = 0.5,\ \alpha = 0.7,$ and $\alpha = 0.9$, respectively.

Overall, in the E-health system categories, the α values were set to 0.1, 0.3, 0.5, 0.7, and 0.9 to explore the changes in the final ranking results. However, the final rankings of two decision matrices (i.e., EMRs, and PHRs) remained the same across all α values except for the EHRs subcategory. The reason is that the binary nature of the decision matrices data (i.e., Yes and No), the variation of the properties, and the decrease in the number of alternatives led to relatively tiny differences in the score values of these systems.

In addition, each property weight significantly affects E-health systems' ranking results. For instance, in the PHR subcategory, PHR3 is characterised by three distinct properties, namely access control (w = 0.1934), privacy protection (w = 0.1806), and integrity (w = 0.1670). The PHR1 exhibits three distinct properties, namely privacy-protection (w = 0.1806), secure-search (w = 0.0603), and integrity (w = 0.1670). Despite having an equal number of properties, PHR3 is considered more desirable than PHR1 due to its higher rank. Therefore, it is imperative to identify the importance of properties to choose and prioritise E-health systems effectively.

5. Evaluation

The weights of the properties can significantly affect the results of multiple properties models. Therefore, assessing the impact of changes in property weights on the proposed approach's results is crucial to determining the approach's strength and the accuracy of the outcomes. Consequently, this section of the study conducts a sensitivity analysis of the e-health system rankings concerning changes in property weights.

The initial step in sensitivity analysis involves identifying the most influential property according to the SFS-FWZIC method. Next, the impact of changing property weights is examined by creating five scenarios using Equation (15) [94]. The elasticity coefficient (α_c) is employed to determine the weight change of each property compared to the most significant one, and the threshold values for altering the weight of the most influential property are identified. Finally, an analysis is carried out to compare the rankings achieved through the alterations of properties weight in the generated scenarios with the initial ranking produced by the Grey-TOPSIS method.

$$w_c = (1 - w_s) \times (w_c^o / W_c^0) = w_c^o - \Delta x \alpha_c, \tag{15}$$

where

w_s is the most influential property.
w_c^o is the initial weight calculated by the SFS-FWZIC method.
W_c^0 is the summation of the initial weights.
Δx is the threshold value for modifying the weight of the most influential property.

As indicated in Table 8, access control was deemed the most influential property among the seven, with a weight value of 0.1934. Utilising (15), the weights of each property yielded five distinct scenarios. The computation of the elasticity coefficient (α_c) for all properties is demonstrated in Table 10.

Table 10. The elasticity coefficient of the privacy and security properties for sensitivity analysis

Properties	**UA**	**AC**	**PP**	**SS**	**Int**	**Ava**	***Ano***
α_c	0.229	0.2398	0.2239	0.0748	0.207	0.1839	0.0815

The access-control property's threshold values were within the range of $-0.1934 \le \Delta x \le 0.8066$. The defined threshold values were divided into five scenarios (S1, S2, …, S5), generating novel weight values. These weight values are presented in Fig. 2.

The generated weight values were employed to evaluate the sensitivity of ranking E-health systems. The objective is to ascertain the impact of modifying the weights on the final ranking outcomes across all five scenarios. The significance of privacy and security properties is a crucial factor that can impact the ranking of E-health systems across the three categories. For the EHRs, the ranks of the 16 systems were compared across all α values, as shown in Fig. 3. Similar to the initial rank, EHR12 took the first rank for all α values in the S2, S3, and S4 plus S5 when $\alpha = 0.9$. EHRs 7 and 16 remained stable in S1 for $\alpha = 0.1,\ \alpha = 0.3,\ \alpha = 0.5,$ and $\alpha = 0.7$. Similarly, EHR10 had the same ranking results (rank = 5) as the initial rank in the S1 for the $\alpha = 0.3,\ \alpha = 0.5,$ and $\alpha = 0.7$. EHR2 ranked sixth in the S1, S2, and S5 for $= 0.1,\ \alpha = 0.3,$ and $\alpha = 0.5$, including S1 and S5 for $\alpha = 0.7$. This EHR received the third rank in S1 for $\alpha = 0.9$. For all α values, EHRs 11 and 13 ranked eighth and seventh in S2, respectively, in addition to S5 for $\alpha = 0.3$. EHR14 got the same result as the initial rank only in S2 for $\alpha =$

0.3. For $\alpha = 0.5$, $\alpha = 0.7$, and $\alpha = 0.9$, EHR1 remained stable in the S2, S3, and S4 plus S5 for $\alpha = 0.9$. In all α values, EHRs 8 and 15 remained unchanged in S2, S3, and S4. All other EHRs in this subcategory had a significant change in their rankings. For the EMRs, the ranks of the six systems were compared across all α values, as shown in Fig. 3. The most desirable EMR in this category (EMR6) remained stable in all scenarios and across all α values. EMR1, EMR2, EMR3, EMR4, and EMR5 showed minimal changes in S1 and received the same ranking results as the initial rank in S2–S5 for all α values. For the PHRs, the ranks of the four systems were compared across all α values, as shown in Fig. 3. PHRs 2 and 3 were stable in S1 and S2 for all α values except for $\alpha = 0.9$ in S2, where their positions swapped. PHR1 remained with no change in S1 only for all α values. The ranking results of PHR4 did not match the initial rank in all scenarios across all α values.

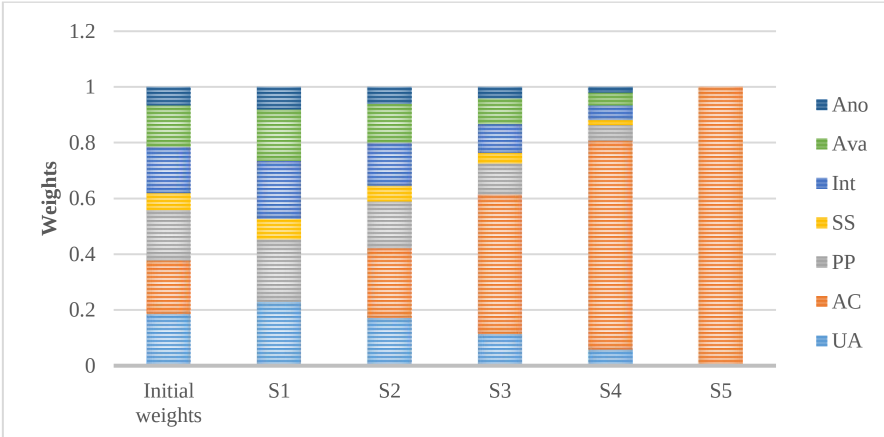

Fig. 2. The new properties weights for sensitivity analysis

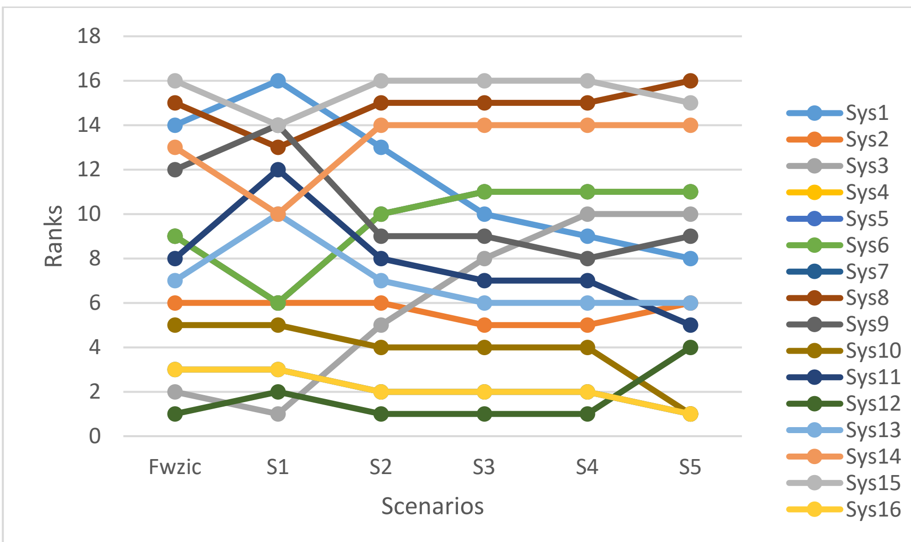

Fig. 3. Sensitivity analysis of the ranking of EHRs alternatives in 5 scenarios ($\alpha = 0.1$)

Finally, the Spearman correlation coefficient (SCC) was utilised to statistically assess the correlation between the results of the five scenarios[94]. Fig. 4 shows the correlation analysis results for the ranking of the EHRs subcategory, where the correlations between the initial ranks and the five scenarios were found to be strong and positive across all α values. For $\alpha = 0.1$, S2 had the highest SCC value of 1.0, whereas S1 and S3 had values of approximately 0.9, and S4 and S5 had values of approximately 0.8 with a mean value of 0.862 for all scenarios. The SCC value for $\alpha = 0.3$ was identical to that for $\alpha = 0.1$, except for the S5 scenario, which obtained an SCC value of 0.7 with a mean value of 0.850 for all scenarios. SCC values (0.9, 0.8, 0.8, and 0.7) were similar in S1, S3, S4, and S5 for $\alpha = 0.5$ and $\alpha = 0.7$. Then, the SCC values were 1.0 and 0.9 in the S2 with mean values of 0.845 and 0.836, respectively, for $\alpha = 0.5$, and $\alpha = 0.7$ for all scenarios. For $\alpha = 0.9$, S3 and S4 had an SCC value of 0.8, whereas S1, S2, and S5 had an SCC value of 0.7, 0.9, and 0,6, respectively, with a mean value of 0.776 for all scenarios.

Fig. 4 presents the obtained correlation analysis for the ranking of EMRs subcategory for all α values, which proved to have a strong and positive correlation (mean = 0.951) among four scenarios (i.e., S2, S3, S4, and S5) for all α values and one scenario (i.e., S1) for all α values with SCC values of 1.0 and 0.8, respectively. For the PHRs subcategory, Fig. 4 present the correlation analysis result between the initial ranks and the five scenarios across all α values. In S1 and S2, SCC values were strong and positive 0.9 and 0.8, respectively, for all α values except $\alpha = 0.9$ (SCC = 0.6). The S3 obtained moderate and positive SCC values of 0.6 for $\alpha = 0.1$ and $\alpha = 0.3$, whereas no relationship was observed (SCC = 0) for $\alpha = 0.5$, $\alpha = 0.7$, and $\alpha = 0.9$. SCC values were zero in S4 across all α values, indicating no relationship between the initial ranks and S4. Similar SCC values were received in S5 for $\alpha = 0.1$ and $\alpha = 0.5$, whereas weak and negative SCC values (−0.3) were received for $\alpha = 0.3$, $\alpha = 0.7$, and $\alpha = 0.9$. The mean values were 0.465, 0.413, 0.345, 0.293, and 0.253 for $\alpha = 0.1$, $\alpha = 0.3$, $\alpha = 0.5$, $\alpha = 0.7$, and $\alpha = 0.9$, respectively.

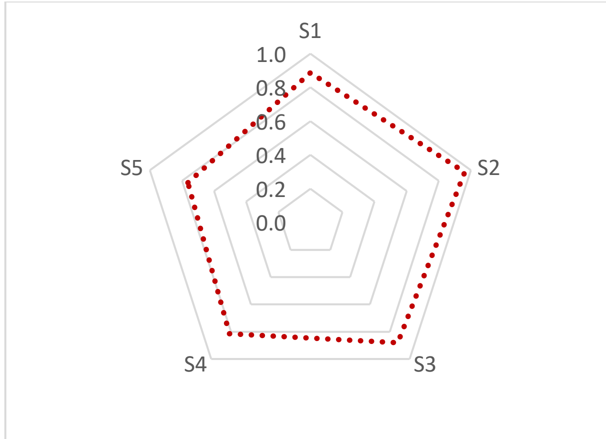

Fig. 4. Correlation of ranks among five scenarios for EHRs ($\alpha = 0.1$)

6. Conclusion

Ranking E-health systems, including EHRs, EMRs, and PHRs, can have numerous implications within the healthcare sector. First, ranking healthcare systems facilitates informed decision-making among healthcare providers, policymakers, and patients, enabling them to compare different systems' security and privacy properties. Second, through comparing and prioritising these systems, developers, and vendors can pinpoint specific areas that require enhancement regarding security and privacy. Third, the ranking process creates a competitive environment among E-health system developers, leading to continuous improvements in features, security, and efficiency. This competition ultimately benefits healthcare providers and patients by providing more advanced and reliable solutions. Fourth, ranking E-health systems can help build trust and confidence in these technologies, encouraging healthcare providers and patients to adopt them. Widespread adoption of EHRs, EMRs, and PHRs can lead to more efficient healthcare processes, reduced medical errors, and better patient outcomes.

Notwithstanding these benefits, the suggested approach exhibits certain shortcomings: The assessment of privacy and security properties in E-health systems was limited to binary categorisation, with only two options available (i.e., Yes and No). Additionally, the properties were evaluated using a five-point Likert scale only for weighting purposes. More so, the prioritisation process was not based on the experts' personal experiences. Many possible directions for investigation can be explored in the future, including assessing E-health systems' privacy and security properties through various Likert scales, such as those with seven or eleven scales. An alternative version of the Grey-TOPSIS method could be investigated and compared with the present study.

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