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Evaluation of human resource information systems using grey ordinal pairwise comparison MCDM methods

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ABSTRACT

This paper evaluates the human resource information systems provided by different vendors using two new hybrid multicriteria decision-making methods that require ordinal data as inputs. First, the grey-point-allocation full-consistency (Grey-PA-FUCOM) weighting method is proposed. The Grey-PA-FUCOM combines the simple point-allocation method widely used by human resource managers and the advanced FUCOM method widely accepted by scholars in grey system theory. Second, the grey-regime method, an extension of the classical regime method based on grey system theory, is used to account for the uncertainty in the evaluation. Next, the Grey-PA-FUCOM weights are applied in conjunction with the grey-regime scheme to evaluate the five vendors. Finally, to validate the results of this study, grey relational analysis with grey numbers, the grey weighted sum model, and a technique for order performance based on the similarity to the ideal solution with grey values are used.

1. Introduction

The People's Republic of China (PRC) has grown over the years to become one of the top economies in the world. Human resources (HR) have been a vital resource for developing the economy. New workforce types have emerged as the Chinese human resource management (HRM) has developed from an administrative to a supportive role, and now, to a strategic role (Zhao & Du, 2012). Generally, companies aim to grow, and systems should be put in place to support this goal. As an organisation grows, there is a need to simplify the system for viewing the whole organisation to know who is managing the various groups of employees and resources. For instance, manually computing appraisals and tracking the time for the compensation and benefits of employees are achievable. However, this can be swiftly done using a human resource information system (HRIS).

HRM can be described as the process of planning, organizing, staffing, leading, and controlling the activities of an organization by acquiring, training, appraising, and compensating employees to build and maintain the relationships between employees and the organization to achieve the company goals and employee expectations (Dessler, 2016). Moreover, a management-information system (MIS) is the software and hardware for efficiently running an organization by interpreting the situation of the organization, decision-making, and strategically formulating plans to improve the organization (Laudon & Laudon, 2019). Hence, the blend of HRM and a MIS is described as an HRIS in this paper. In other words, an HRIS is an integrated system that assists with the planning and controlling of employees by aligning them with the organization so that they efficiently work for the organization. Primarily, an HRIS should be capable of capturing, storing, processing, and distributing data with information that can be used in making useful decisions for people and the organization, such as prediction and forecasting.

Management decisions in organisations can be addressed as a Multicriteria decision-making (MCDM) problem; an MCDM is a systematic process of selecting the best or optimal alternative after comprehensively evaluating numerous and conflicting criteria (Tzeng & Huang, 2011). A prevalent MCDM approach of assigning the weights used by HR managers is the point-allocation (PA) method that is computationally less intensive. However, researchers have improved various pairwise comparison methods, among which the full-consistency method (FUCOM) is widely accepted by the academic community in recent years (Pamučar, Stevi, & Sremac, 2018). Although HR managers and

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academia share the common goal of weighting, the PA method and FUCOM result in different weights, which lead to uncertainty in the evaluations. Furthermore, the regime method introduced by Hinloopen, Nijkamp, and Rietveld (1983), which is a pairwise ordinal MCDM evaluation method, has been extended using grey system theory (GST), and the grey-regime method has been proposed. The GST is used to account for the uncertainty in decision-making. For simplicity, the GST is the principle of analysing systems with incomplete information (Deng, 1989).

This paper mainly aims to bridge the gap between academia and HR managers' decision-making by combining both worlds with GST. This paper makes two primary contributions. First, it proposes the hybrid MCDM weighting method that combines the PA and FUCOM with GST. This proposed method is called the Grey-PA-FUCOM weighting method. Second, it extends the regime method for uncertain decision-making by developing the grey-regime method. Another contribution of this paper is the hierarchical diagram for HRIS evaluation, which can be adopted and modified for software selection problems.

The rest of this paper is organised as follows. Section 2 presents a literature review of HRM and some MCDM methods with GST. Section 3 describes the evaluation criteria for an HRIS using the methods utilised in this research. Section 4 outlines an HRIS evaluation with some confirmatory ranking results and analysis. Section 5 presents some managerial implications. Lastly, Section 6 presents the conclusions of this paper.

2. Literature review

This literature review examines the research trends in HR and HRM software selection. The latter is an additional focus because HRM can be supported through the software packages used. In addition, some related works that present hybrid MCDM methods based on GST are reviewed.

2.1. HRM and software selection

Liff (1997) conducted one of the earlier studies on HRIS. Liff's study highlighted HRIS as an instrument for effective decision-making, a new viewpoint to approach the same, and a map for to help managers achieve organisation goals. For example, as a proxy for the increasing need to achieve organisational sustainability goals, green and sustainable HRM has been one of the major trends in HR. To identify the best green HRM (GHRM) practices, Gupta (2018) applied the best worst method with fuzzy technique for order performance based on the similarity (TOPSIS). Ahammad, Glaister, and Gomes (2019) also presented the need for an organisation to be strategically agile, including its ability to seize opportunities, change direction, and avoid collisions. Ability, motivation, and opportunity (AMO) theory can be used to enhance HRM practices to match HR with multinational corporations and with the chief executive officer's leadership styles. Yu, Chavez, Feng, Wong, and Fynes (2020) analysed 126 automobile-manufacturing companies in China to examine the value of GHRM in supporting environmental cooperation with customers and suppliers. They discovered that GHRM has a positive and significant role in environmental cooperation with customers and suppliers. This suggests that GHRM provides training with incentives under a conducive environment, thereby embracing AMO theory to promote ecological collaboration. Fuenzalida and Riccucci (2019) empirically validated the negative impact of politicisation on organisational performance, and these effects could be controlled with proper HRM practices such as recruitment, training, and performance appraisal.

HRM practices can impact the behaviour of employees. Gharibeh (2019) investigated the impact of green HR (GHR) practices when considering green selection recruitment, training, and development with a reward system. Gharibeh showed that GHR has a positive relation with increasing the competitive advantage of educational organisations in Jordan. By empirically analysing GHRM practices in Palestinian healthcare organisations and their impact on organisational performance, Mousa and Othman (2020) developed a framework for influencing and implementing GHRM practices for maximising an organisation's sustainable performance. An organisation can increase employee commitment by increasing their positive perception towards GHRM. Kim, Kim, Choi, and Phetvaroon (2019) examined the effect of GHRM on hotel employees' eco-friendly behaviour and environmental performance, and found supporting evidence on the relationship between GHRM and employees' organizational commitment based on the social-identity theory. Similarly, Pham, Tučkovš, and Chiappetta Jabbour (2019) found a direct effect of GHRM practices on organisational citizenship behaviour for the environment.

Since HRIS is generally a specialised software, some researchers have developed approaches to address software selection problems. Regarding enterprise resource planning (ERP) software selection, Yazgan, Boran, and Goztepe (2009) applied the analytic network process (ANP) using artificial neural networks that would predict the priorities of the ERP software. Zhang, Wu, Feng, and Yu (2011) developed the grey relative correlation analysis method to assess the primary factors influencing the enterprise informatisation and applied the grey clustering method to evaluate the information system's functional requirements. Chin and Fu (2014) proposed the integrated evidential reasoning method for solving MCDM problem in an uncertain decision environment and applied it in the selection of the best product lifecycle management software. Kovačević, Madić, Radovanović, and Rančić (2014) presented a software prototype for solving a multi-objective optimisation problem. This prototype can be used as a reference in the design of a HRIS e.g., estimating the compensation of employees considering the conflicting objectives of minimising operational cost of the company while maximising their salary to retain employees in a globally competitive business environment.

The idea of managing an enterprise with the assistance of software began with simple inventory-management software. Then, material-requirement planning evolved into material-resource planning and was further developed to become the ERP system (Monk & Wagner, 2012). Most ERP systems are modular and have an HR software package. However, the use of the HR module bundle with an ERP system may not be comprehensive enough for HR management compared to a system specifically designed to address HR problems, such as an HRIS. For example, Karaarslan and Gundogar (2009) applied the AHP to evaluate modular ERP software based on the features that fit the function of a marble-machine factory. Karsak and Özogul (2009) developed a framework for ERP software selection that combined quality function deployment (QFD) and a fuzzy linear regression with binary goal programming. This approach ensures a company's demands and considers ERP system functionalities. Şen and Baraçlí (2010) evaluated ERP software for an audio-electronics company based on fuzzy QFD by considering non-functional criteria like quality, technological, and socioeconomic factors. Zeng, Wang, and Xu (2017) presented an integrated model for selecting the best ERP system for small and medium-sized enterprises in China. The Delphi, AHP, fuzzy, and grey relational analysis (GRA) methods were combined to conduct the evaluation under uncertainty.

In summary, HRM practices should encompass green and sustainable development, and include setting up a platform to implement it. An HRIS can be used for automating the HR department and working towards a paperless office that contributes to less use of trees and a greener environment.

2.2. MCDM methods with grey system theory

GST was theorised by Deng (1989), who is known as the father of GST. GST realises system cognition by mining known information (Liu, 2018). GST is well-suited for decision-making with small sample sizes. With certainty, all systems in a natural environment can be classified as grey systems since we cannot wholly mathematically account for and represent the systems in an environment. In GST, systems with completely known information are classified as white systems, and systems with entirely unknown information are classified as black systems; thus, systems with partially known information are classified as grey systems. In this research, interval grey numbers are used. Note that not all numbers represented in grey interval number notation are grey numbers.

Several studies have integrated GST with numerous MCDM methods. Hsu, Liou, and Chuang (2013) proposed a hybrid decision-making trial and evaluation laboratory (DEMATEL) and ANP method, combined with a modified traditional GRA, for outsourcing airline-provider services in Taiwan to reflect the realities in the actual world. They modified conventional GRA by replacing the reference series with one that is obtainable in the real world. Zakeri and Keramati (2015) applied both fuzzy and grey TOPSIS in the selection of electrical–wire manufacturers. Nguyen, Dawal, Nukman, and Aoyama (2014) presented the fuzzy ANP and complex proportional assessment of alternatives (COPRAS) with the grey relations hybrid MCDM method for selecting machine tools. The evaluation result was compared using the TOPSIS–grey and SAW–grey hybrid methods, as well as the GRA method. Regardless of choosing the best machine, it should be well-maintained. Kirubakaran and Ilangkumaran (2016) combined the fuzzy AHP, GRA, and TOPSIS techniques to choose the best maintenance scheme for the pumps used in paper manufacturing. The fuzzy AHP method was used to determine the criteria weights, and the GRA-TOPSIS method was used to evaluate the maintenance scheme. Yazdani, Kahraman, Zarate, and Onar (2019) integrated QFD with the GRA to model the core supply–chain criteria in an uncertain environment, and applied this approach to an agricultural-production system project. Kaviani, Yazdi, Ocampo, and Kusi-Sarpong (2020) combined the grey–Delphi method to determine the evaluation criteria for supply selection in the oil and gas industry and applied the grey–Shannon entropy weighting method and the grey-EDAS method to select the best contractor.

Furthermore, Zhao and Guo (2015) used linguistic superiority ratings with entropy weighting and fuzzy GRA to evaluate alternative energy sources such as wind, solar photovoltaic, and biomass renewable-power systems. Chithambaranathan, Subramanian, Gunasekaran, and Palaniappan (2015) presented two hybrids, the grey ELECTRE (elimination et choix traduisant la realité-elimination and choice expressing reality) and grey VIKOR (vlsekriterijumska optimizacijia I kompromisno resenje-multicriteria optimisation and compromise solution) methods. ELECTRE and VIKOR were combined with grey linguistic variables to measure criteria weights and to evaluate service supply chains based on their environmental performances. Bekar, Cakmakci, and Kahraman (2016) integrated AHP and grey correlation with TOPSIS to evaluate grey decoration materials. Liou, Tamošaitienė, Zavadskas, and Tzeng (2016) applied the DEMATEL technique to construct an influential network relationship, where the ANP was used to determine the criteria weights, and COPRAS with grey relations was used to evaluate the green suppliers in an electronics company in Taiwan. Cao, Esangbedo, Bai, and Esangbedo (2019) selected the most suitable contractor for a floating solar panel installation based on the grey stepwise weight analysis ratio assessment weighting (SWARA)-FUCOM method with the GRA. Furthermore, Ghoushchi, Ab Rahman, Raeisi, Osgooei, and Ghoushji (2020) conducted the failure mode and effect analysis of solar panel and evaluated the priority of installation risk using the SWARA method and GRA. Similarly, Esangbedo and Bai (2020) applied the SWARA with the GRA using grey numbers to compute the compensation and benefits as a lump sum paid to expatriates for the work done overseas. Javed, Mahmoudi, and Liu (2020) developed the grey absolute decision analysis method for group decision-making to address the mutual association among the judgements of the decision makers (DM), and applied it to hazard planning and emergency management.

There are alternative approaches for addressing uncertainty. Wu (2009) captured uncertainty in decision-making by applying the GRA and Demspster-Shafer theory for the supplier selection in single and group decision-making, respectively. Wu (2011) combined Herzberg's motivation–hygiene theory and the rough set theory for extracting and segmenting the perceived benefit of ERP users'. Their approach can analyse both qualitative and quantitative data using statistical assumptions. Although the fuzzy set theory was previously developed before the GST, Sun, Guan, Yi, and Zhou (2018) applied GRA to hesitant fuzzy set (HFS) to express the degree of closeness, and found greater accuracy and integrity compared to the traditional HFS. Abel, Cortés Ríos, Paton, Keane, and Fernandes (2020) proposed the target evidence collection approach for the reduction of uncertainty in addressing supplier selection problem. Rudnik, Bocewicz, Kucińska-Landwójtowicz, and Czabak-Górska (2020) proposed the hybrid MCDM evaluation method called order fuzzy number weighted aggregated sum product assessment (OFN-WASPAS) in the portfolio selection for a project and used the AHP in estimating the evaluation criteria weights. Luíza da Costa, Dias de Lima, and Barbosa (2021) attempted to stabilise the weight-based feature selection using artificial neural network weights by using a voting method to rank the level of importance.

Most studies use the AHP in software evaluation, which includes ERP systems. Although ERP software is usually modular, researchers have not focused on analysing and evaluating the HR module. Moreover, even though the AHP has the problem of an exponential increase in the comparison of evaluation criteria, it is still being used in solving MCDM problems such as the supplier selection problem (Dotoli, Epicoco, & Falagario, 2020). This paper fills the gap in the literature by focusing on HR management that is needed in all organisations, as well as the use of the simple PA method and FUCOM with the GST. The Grey-PA-FUCOM hybrid method requires just $n-1$ comparisons for n criteria, which is less the number of pairwise comparisons than the hybrid AHP methods that require $n(n-1)/2$ comparisons. Finally, among the numerous extensions of GST to classical MCDM evaluation methods, to the best of our knowledge, this is the first to use the regime method based on GST to address the uncertainties in decision-making and the selection of HRIS.

3. Methodology

3.1. Evaluation criteria

The evaluation criteria for an HRIS were mainly deduced from the literature, such as the evaluation of ERP software by Ayağs and Özdemİr (2007). The lessons developed by (Carvallo, Franch, & Quer, 2007) for determining the criteria for software components were also considered. The evaluation criteria consist of five first-level criteria and 27 second-level criteria, as shown in Fig. 1. The evaluation criteria are described as follows:

3.1.1. Human-resource management functions (C_1)

HRM is the primary role of an HRIS and is based on organisational needs. Staff Information Management (C_{1-1}): provides the database that keeps complete records of all employee data records, which begins from the first point of contact with the employee, and includes their supervisors' reports on them (Karaarslan & Gundogar, 2009). Organization Structure and Labour Management (C_{1-2}): the software ability to organize an employee and their skills in the company organogram, including both the hierarchy type of the organogram and the visualization of other kinds. Compensation and Benefits (C&B) with Budget Management (C_{1-3}): the finances and welfare that employees receive for their labour, which may be directly received at regular intervals in the form of wages, salaries, bonuses, and commissions, or indirectly in the form of career path/prospects, recognition, a pleasant work environment, and working conditions. Staff Training Management (C_{1-4}): a database of training courses for employees with their abilities, course attendance, testing and grading, and question management. Staff Recruiting Management (C_{1-5}): the software ability to provide applicant tracking and onboarding for candidates to join the company. This manages the job-analysis process, screening, selection of information, referral

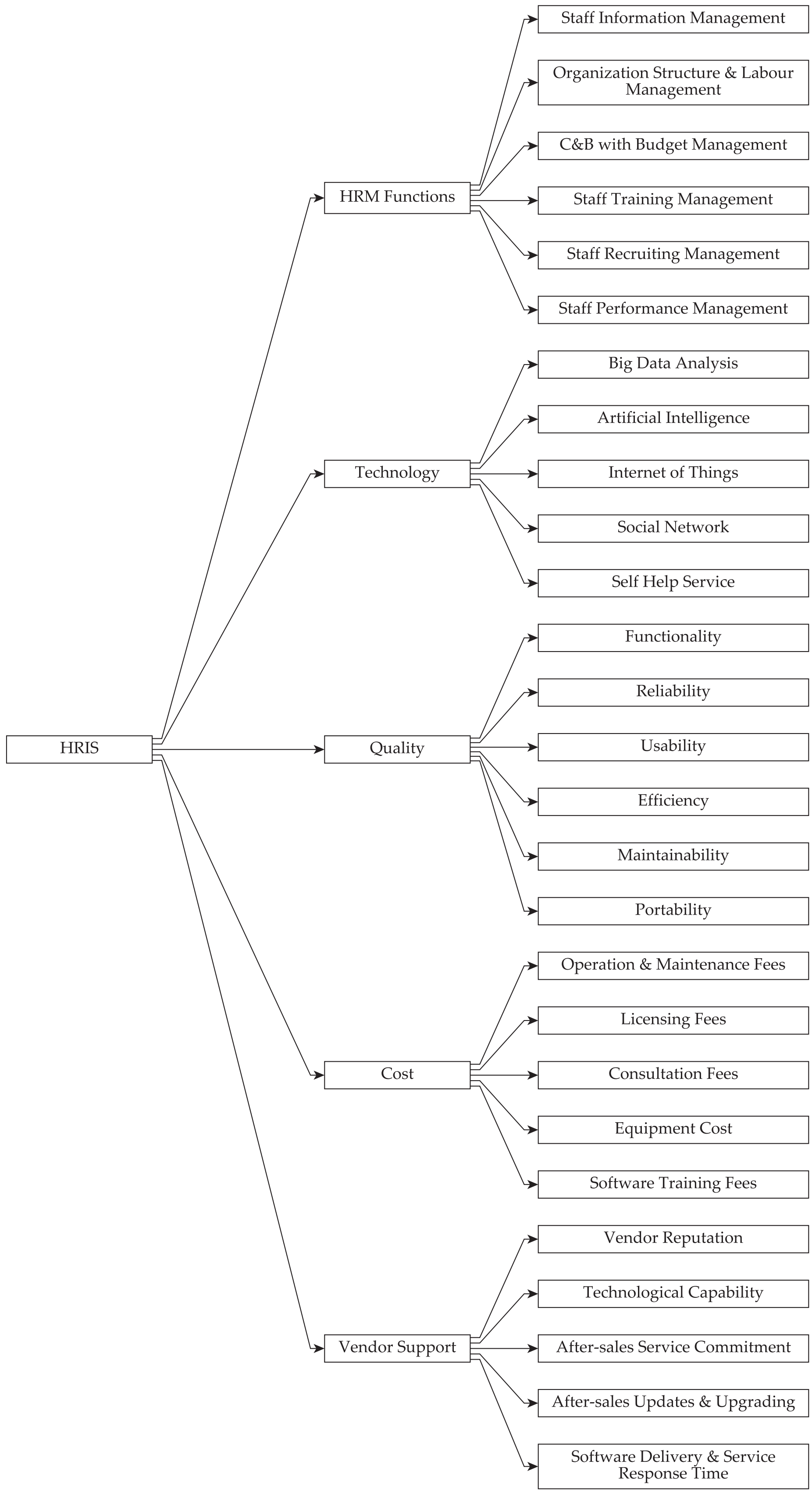

Fig. 1. Hierarchical diagram for evaluating human resource information systems (HRISs).

databases, and professional associations, as well as the application programming interface (API) for sourcing with recruitment advertising agencies. Staff Performance Management (C_{1-6}): tracks the organizational goals with task tracking, appraisal, work-hour tracking, reward and punishment tracking, documentation of performance plans, coaching and assessment of staff, and performance measurement reporting.

3.1.2. Technology (C_2)

Technology measures the software's ability to keep up with current information-technology trends and give the HRIS additional advantages. Big Data Analysis (C_{2-1}): the system ability to manage, organize, and analyse unstructured and complete organization information. Artificial Intelligence (C_{2-2}): beyond facial-recognition systems for entry into and exit from the organization, as well as logging in and out of computer systems, it should be able to analyse people's facial expressions and postures, and give recommendations for employees' appropriate roles. Internet of Things (IoT, C_{2-3}): the ability to provide sensors that can track and log employee activities with their tools using unique identifiers (UID) or radio-frequency identification (RFID), thus providing the organization with real-time analytical information. Social Network (C_{2-4}): provides a platform for employees to casually interact with each other and the outside world to improve business networking. This can directly provide an API for social-network platforms like WeChat, MicroBlog (Weibo), Facebook, and LinkedIn. Self-Help Service (C_{2-5}): provides the staff-information update system with minimal interaction with HR managers by providing automated responses to employee inquiries such as leave applications and extensions.

3.1.3. Software quality (C_3)

Software quality measures the relative standard that the software provides (Şen & Baraçlí, 2010; Zeng et al., 2017). Functionality (C_{3-1}): the extent to which the software meets the design requirements of the organisation. This aspect reflect the software's suitability (Carvallo et al., 2007; Efe, 2016). Reliability (C_{3-2}): the ability of the organisation to trust an employee and their organisational information on the software. This aspect includes the software's architecture (Ayağs & Özdemİr, 2007; Carvallo et al., 2007; Haas, 1995; Piengang, Beauregard, & Kenné, 2019). Usability (C_{3-3}): the ease of using software's graphic and web-user interfaces by limiting expert systems for HR managers at the back end and providing an intuitive-use front end (Ayağs & Özdemİr, 2007; Efe, 2016; Kahraman, Beskese, & Kaya, 2010; Piengang et al., 2019). Efficiency (C_{3-4}): the ability to reduce time to finish getting HR jobs, doing them very well, and improving the overall performance of the organisation (Carvallo et al., 2007; Kahraman et al., 2010). Maintainability (C_{3-5}): the ease of keeping the software up and running with reliable backup systems that can minimise downtime and unplanned data duplication (Ayağs & Özdemİr, 2007; Piengang et al., 2019). Portability (C_{3-6}): the availability of the company's complete HR data to be exported and imported to different software without data corruption (Ayağs & Özdemİr, 2007; Haas, 1995; Henningsson, Yetton, & Wynne, 2018; Kahraman et al., 2010).

3.1.4. Cost (C_4)

Cost is the total amount of money incurred to set up and run the software (Ayağs & Özdemİr, 2007; Azadeh, Shirkouhi, Samadi, & Shirkouhi, 2014). Operation and Maintenance Fees (C_{4-1}): the fees paid for continuously organizing HR processes using the software (Ayağs & Özdemİr, 2007; Efe, 2016; Kahraman et al., 2010; Zeng et al., 2017). Licensing Fees (C_{4-2}): the costs of obtaining official permission to use the software (Ayağs & Özdemİr, 2007; Azadeh, Shirkouhi, & Rezaie, 2010; Carvallo et al., 2007; Piengang et al., 2019; Zeng et al., 2017). Consultation Fees (C_{4-3}): the costs of having discussions about the software and organization goals for decision-making (Ayağs & Özdemİr, 2007; Efe, 2016; Kahraman et al., 2010; Piengang et al., 2019). Equipment Cost (C_{4-4}) (Ayağs & Özdemİr, 2007; Azadeh et al., 2010; Azadeh et al., 2014; Henningsson et al., 2018; Kahraman et al., 2010; Piengang et al., 2019): beyond computers, servers, laptops, and mobile phones, these include shared equipment such as facial-recognition terminals and cameras, proprietary wireless access points for taking staff attendance, and smart card-reading systems with access control and logging. Software Training Fees (C_{4-5}): costs of teaching employees, especially HR and IT managers, to obtain the required skills to fully utilize all software features (Kahraman et al., 2010; Piengang et al., 2019).

3.1.5. Vendor support (C_5)

Vendor support measures the assistance provided by the software provider (Ayağs & Özdemİr, 2007; Efe, 2016). Vendor Reputation (C_{5-1}): the general opinion of the software provider based on past performances with other clients (Ayağs & Özdemİr, 2007; Azadeh et al., 2010; Azadeh et al., 2014; Zeng et al., 2017). Technological Capability (C_{5-2}): the qualities that the companies possess to provide software solutions (Ayağs & Özdemİr, 2007; Azadeh et al., 2010; Haas, 1995; Zeng et al., 2017). After-Sales Service Commitment (C_{5-3}): the pledge given to the organization in the form of a guarantee (Efe, 2016; Zeng et al., 2017). After-Sales Update and Upgrade (C_{5-4}): the possibility of adding new packages, fixing bugs, patching security holes and vulnerabilities, and keeping up with recent technological changes (Efe, 2016; Piengang et al., 2019; Zeng et al., 2017). Software Delivery and Service Response Time (C_{5-5}): the period of implementation from planning through payment to deployment for organization use (Haas, 1995; Zeng et al., 2017; Piengang et al., 2019).

3.2. Weighting methods

The weighting methods indicate whether a criterion is more or less important than another. These are generally represented using ratios. First, we independently present the PA method and the FUCOM. Next, the Grey-PA-FUCOM weighting method is outlined, and used for evaluating HRIS.

3.2.1. Point-allocation method

PA directly scores the evaluation criteria, and then scales them to one unit to form the decision weight. Commonly, points, from 0 to 10, or percentage scores, from 0% to 100%, are given. Here, percentage scores (0%–100%) are used. The steps of the PA method are as follows.

Step 1. Obtain the percentage scores for the criteria. The DMs (v) directly rate the criteria from 0 to 100 points, which is a percentage score of 0%–100%.

Step 2. Scale the percentage scores. The percentage scores for each of the local weights are scaled to a unit value by using the following.

For the first-level criteria, Eq. (1) is used:

$$x_p^{'}(v) = \frac{x_p(v)}{\sum_{p=1}^{\rho} x_p(v)}, \tag{1}$$

where x is the criterion with an index of p, and ρ is the index for the last first-level criterion.

For the second-level criteria, Eq. (2) is used:

$$x_{p-q}^{'}(v) = \frac{x_{p-q}(v)}{\sum_{q=1}^{\sigma} x_{p-q}(v)}, \tag{2}$$

where x is the criterion with an index of q, and $\sigma$is the index for the last second-level criterion. Thus,

$\sum_{p=1}^{\rho} x_p^{'}(v) = 1$ and $\sum_{q=1}^{\sigma} x_{p-q}^{'}(v) = 1$.

Step 3. Compute the effective scaled weights. This is the product of the first- and second-level criteria weights, and is calculated using Eq. (3):

$$w_j^{'}\left(v\right) = x_p^{'}\left(v\right) \times x_{p-q}^{'}\left(v\right). \tag{3}$$

Thus, $\sum_{j=1}^{n} w_j^{'}(v) = 1$.

3.2.2. Full-Consistency MCDM Method

The FUCOM method begins with ranking the evaluation criteria, then pairwise comparing every criterion with its relative direct lower-ranked criterion, and finally determining the weights of the criteria using an objective function. The steps for determining the FUCOM weights are as follows.

Step 1. Rank the criteria. The DMs rank the evaluation criteria in descending order.

$$C_{j(1)}\left(v\right) > C_{j(2)}\left(v\right) > C_{j(3)}\left(v\right) > \ldots > C_{j(k)}\left(v\right) > C_{j(k+1)}\left(v\right) \tag{4}$$

Step 2. Obtain the comparative priorities of the criteria. An upper-ranked criterion $C_{j(k)}(v)$ is pairwise compared with its direct lower-ranked criterion, $C_{j(k+1)}(v)$, as expressed by the v^{th} DM.

$$\Phi(v) = \left(\varphi_{1/2}, \varphi_{2/3}, \ldots, \varphi_{k/(k+1)}\right)(v), \tag{5}$$

where $(\varphi_{k/(k+1)})(v)$ is the comparative priority of $C_{j(k)}(v)$ to $C_{j(k+1)}(v)$.

Step 3. Compute the weights. For each DM (v), the weights are the solution to the optimisation function that minimises the deviation from full consistency, $\chi(v)$, as in Eq. (6).

$$\begin{gathered}
\min \chi(v) \\
s.t. \\
\left|\frac{w_{j(k)}^{''}}{w_{j(k+1)}^{''}} - \varphi_{k/(k+1)}\right|\left(v\right) \leqslant \chi\left(v\right), \forall j \\
\left|\frac{w_{j(k)}^{''}}{w_{j(k+2)}^{''}} - \varphi_{k/(k+1)} \otimes \varphi_{(k+1)/(k+2)}\right|\left(v\right) \leqslant \chi\left(v\right), \forall j. \\
\sum_{j=1}^{n} w_j^{''}\left(v\right) = 1, \forall j \\
w_j^{''}\left(v\right) \geqslant 0, \forall j
\end{gathered} \tag{6}$$

where $w_j^{''}$is the weight for the j^{th} criterion.

The first constraint computes the weights. Next, mathematical transitivity is satisfied by the second constraint. Then, the third constraint maintains the weighting convention that all weights are fractions, and the sum of the weights is one. Lastly, the fourth constraint constrains the weights to being positive values. Please, see Pamučar et al. (2018).

Step 4. Compute the effective weights. These are the product of the first- and second-level criteria weights, as in Eq. (7).

$$w_j^{''}\left(v\right) = x_p^{''}\left(v\right) \times x_{p-q}^{''}\left(v\right) \tag{7}$$

Thus, $\sum_{j=1}^{n} w_j^{''}(v) = 1$.

3.2.3. Grey-PA-FUCOM method

The Grey-PA-FUCOM method is a representation of the weights obtained by both the PA and FUCOM methods in grey numbers. Then, the effective weights for the evaluation criteria are calculated. The steps for computing the Grey-PA-FUCOM weights are as follows.

Step 1. Compute the effective PA and FUCOM weights. The raw weights are obtained based on the PA computation in Section 3.2.1 and the FUCOM weights in Section 3.2.2.

Step 2. Represent the PA and FUCOM weights as grey numbers. The minimum and maximum weights obtained using the PA and FUCOM methods are scaled to obtain the Grey-PA-FUCOM weights for the first- and second-level criteria as $\otimes w_p^* = \left[\underline{w}_p^*, \overline{w}_p^*\right]$ and $\otimes w_{p-q}^* = \left[\underline{w}_{p-q}^*, \overline{w}_{p-q}^*\right]$, respectively. The lower and upper bounds of the grey numbers for the first-level criteria are computed using Eqs. (8) and (9), respectively.

$$\underline{w}_p^* = \frac{\min\limits_{1\leqslant v\leqslant \vartheta}\left(w_p^{'}(v), w_p^{''}(v)\right)}{\sum\limits_{p=1}^{\rho}\max\limits_{1\leqslant v\leqslant \vartheta}\left(w_p^{'}(v), w_p^{''}(v)\right)}, \tag{8}$$

$$\overline{w}_p^* = \frac{\max\limits_{1\leqslant v\leqslant \vartheta}\left(w_p^{'}(v), w_p^{''}(v)\right)}{\sum\limits_{p=1}^{\rho}\max\limits_{1\leqslant v\leqslant \vartheta}\left(w_p^{'}(v), w_p^{''}(v)\right)}, \tag{9}$$

where $w_p^{'}$ and $w_p^{''}$ are the PA and FUCOM weights, respectively, for the v^{th} DM.

Similarly, for the second-level criteria, the lower and upper bounds of the grey numbers are computed using Eqs. (10) and (11), respectively.

$$\underline{w}_{p-q}^* = \frac{\min\limits_{1\leqslant v\leqslant \vartheta}\left(w_{p-q}^{'}(v), w_{p-q}^{''}(v)\right)}{\sum\limits_{q=1}^{\sigma}\max\limits_{1\leqslant v\leqslant \vartheta}\left(w_{p-q}^{'}(v), w_{p-q}^{''}(v)\right)}, \tag{10}$$

$$\overline{w}_{p-q}^* = \frac{\max\limits_{1\leqslant v\leqslant \vartheta}\left(w_{p-q}^{'}(v), w_{p-q}^{''}(v)\right)}{\sum\limits_{q=1}^{\sigma}\max\limits_{1\leqslant v\leqslant \vartheta}\left(w_{p-q}^{'}(v), w_{p-q}^{''}(v)\right)}, \tag{11}$$

where $w_{p-q}^{'}$ and $w_{p-q}^{''}$ are the PA and FUCOM weights, respectively, for the v^{th} DM.

Step 3. Compute the effective weight. After obtaining the local weights of each second-level criteria, they are scaled using Eq. (12).

$$\otimes w_j = \otimes w_p^* \times \otimes w_{p-q}^*, \tag{12}$$

where $\otimes w_j = \left[\underline{w}_j, \overline{w}_j\right]$.

Therefore, for n criteria of the Grey-PA-FUCOM weights, W is given as

$$W = \begin{pmatrix} \otimes w_1 & \otimes w_2 & \cdots & \otimes w_n \end{pmatrix}^T, \tag{13}$$

where $\sum_{j=1}^{n} \underline{w}_j = 1$.

3.3. Evaluation methods

First, we present a basic operation of interval grey numbers. For two interval grey numbers, $\otimes a = \underline{a}, \overline{a}$and $\otimes b = \underline{b}, \overline{b}$, where $\underline{a} < \overline{a}$ and $\underline{b} < \overline{b}$, which are the basic operations of these grey numbers from Liu and Lin (2010) and Esangbedo and Bai (2019). Furthermore, the arbitrary distance between two interval numbers from $\otimes a = \underline{a}, \overline{a}$to $\otimes b = \underline{b}, \overline{b}$is calculated using Eq. (14) (Zhang, Wu, & Olson, 2005) as follows:

$$|\otimes a - \otimes b| = \max\left(\left|\underline{a} - \underline{b}\right|, \left|\overline{a} - \overline{b}\right|\right). \tag{14}$$

All evaluation methods used here share some preliminary commonalities: obtaining the raw data from the DMs and formulating a grey decision table. To begin, a scoresheet or questionnaire can be used to obtain the raw data from the DM. Then, a grey decision table is constructed, as shown in Table 1, where the performance values are represented as grey numbers obtained using Eq. (15):

$$\otimes d_{i,j} = \left[\underline{d}_{i,j}, \overline{d}_{i,j}\right] = \left[\min\limits_{1\leqslant v\leqslant \vartheta} d_{ij}\left(v\right), \max\limits_{1\leqslant v\leqslant \vartheta} d_{ij}\left(v\right)\right]. \tag{15}$$

Table 1
Grey decision table.

Criteria/Alternatives	A_1	…	A_i	…	A_m
c_1	$\otimes d_{1,1}$	…	$\otimes d_{i1}$	…	$\otimes d_{m1}$
⋮	⋮	⋱	⋮	⋱	⋮
c_j	$\otimes d_{1j}$	…	$\otimes d_{ij}$	…	$\otimes d_{mj}$
⋮	⋮	⋱	⋮	⋱	⋮
c_n	$\otimes d_{1n}$	…	$\otimes d_{i,n}$	…	$\otimes d_{mn}$

Here, $\underline{d}_{i,j}$ and $\overline{d}_{i,j}$ correspond to the upper and lower bounds of the element in the decision matrix for m alternatives and n criteria.

3.3.1. Regime method

The regime method was developed by Hinloopen et al. (1983) as a MCDM approach to evaluate alternatives using ordinal data the alternatives' relative impacts are already qualitatively established. The regime method begins with constructing a regime matrix, which is a pairwise comparison of the alternatives in the impact matrix. The impact matrix represents the measurement of the effect of the alternative on the evaluation criteria represented in ordinal values. Finally, the regime, i.e. each pairwise comparison of all alternative for the evaluation criteria, is used to determine the best alternative. An application of the regime method is given by Alinezhad and Khalili (2019).

3.3.2. Grey-regime method

In a stepwise form, the regime method is extended using GST to account for the uncertainties in both the measurement of the performance values of the alternatives and the pairwise comparisons. The steps of the grey-regime method are as follows.

Step 1. Construct the grey decision matrix, D. The grey decision matrix is directly obtained from Table 1 and written as in Eq. (16).

$$D = \begin{pmatrix} \otimes d_{1,1} & \otimes d_{1,2} & \cdots & \otimes d_{1,n} \\ \otimes d_{2,1} & \otimes d_{2,2} & \cdots & \otimes d_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ \otimes d_{m,1} & \otimes d_{m,2} & \cdots & \otimes d_{m,n} \end{pmatrix}, \tag{16}$$

where $\otimes d_{i,j} = \left[\underline{d}_{i,j}, \overline{d}_{i,j}\right] = \left[\min_{1 \leqslant v \leqslant \vartheta} d_{ij}(v), \max_{1 \leqslant v \leqslant \vartheta} d_{ij}(v)\right]$. $\underline{d}_{i,j}$ and $\overline{d}_{i,j}$ correspond to the upper and lower bounds of the element decision matrix for m number of alternatives and n number of criteria.

Step 2. Normalise the grey decision matrix. Decision matrix $D$is normalised to obtain a normalised grey decision matrix $\widehat{D}$. The benefit and cost preference scores are normalised using Eqs. (17) and (18), respectively.

$$\otimes d^*_{ij} = \left[\frac{\underline{d}_{ij} - \min\limits_{1 \leqslant i \leqslant m} \underline{d}_{ij}}{\max\limits_{1 \leqslant i \leqslant m} \overline{d}_{ij} - \min\limits_{1 \leqslant i \leqslant m} \underline{d}_{ij}}, \frac{\overline{d}_{ij} - \min\limits_{1 \leqslant i \leqslant m} \underline{d}_{ij}}{\max\limits_{1 \leqslant i \leqslant m} \overline{d}_{ij} - \min\limits_{1 \leqslant i \leqslant m} \underline{d}_{ij}}\right], \tag{17}$$

$$\otimes d^*_{ij} = \left[\frac{\max\limits_{1 \leqslant i \leqslant m} \overline{d}_{ij} - \overline{d}_{ij}}{\max\limits_{1 \leqslant i \leqslant m} \overline{d}_{ij} - \min\limits_{1 \leqslant i \leqslant m} \underline{d}_{ij}}, \frac{\max\limits_{1 \leqslant i \leqslant m} \overline{d}_{ij} - \underline{d}_{ij}}{\max\limits_{1 \leqslant i \leqslant m} \overline{d}_{ij} - \min\limits_{1 \leqslant i \leqslant m} \underline{d}_{ij}}\right]. \tag{18}$$

Then, the normalised decision matrix is given by Eq. (19):

$$\widehat{D} = \begin{pmatrix} \otimes\widehat{d}_{1,1} & \otimes\widehat{d}_{1,2} & \cdots & \otimes\widehat{d}_{1,n} \\ \otimes\widehat{d}_{2,1} & \otimes\widehat{d}_{2,2} & \cdots & \otimes\widehat{d}_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ \otimes\widehat{d}_{m,1} & \otimes\widehat{d}_{m,2} & \cdots & \otimes\widehat{d}_{m,n} \end{pmatrix}, \tag{19}$$

where $\otimes \widehat{d}_{ij} = \left[\underline{\widehat{d}}_{ij}, \overline{\widehat{d}}_{ij}\right] = \left[\min_{1 \leqslant v \leqslant \vartheta} d^*_{ij}(v), \max_{1 \leqslant v \leqslant \vartheta} d^*_{ij}(v)\right]$.

Step 3. Compute the Superiority index, $\widetilde{E}_{fl}$. These are the criteria where alternative A_f is better than alternative A_l. Since the performance values of the alternatives are uncertain and are represented using grey numbers, there are some possibilities where alternative A_f may be better or worse than alternative A_l.

Now, we denote the possibility of $f < l, f > l$, and $f = l$ as $p(f < l)$, $p(f > l)$, and $p(f = l)$, respectively. Then for grey numbers, the possibility of $\otimes\alpha = \left[\underline{\alpha}, \overline{\alpha}\right]$ being superior to $\otimes\beta = \left[\underline{\beta}, \overline{\beta}\right]$, i.e. $\otimes\alpha > \otimes\beta$, is defined as $p(\otimes\alpha \succ \otimes\beta)$ in Eq. (20). It should be noted that Zheng and Wang (2015) presented the possibility for interval numbers, and Chen and Esangbedo (2018) extended the inferior possibility to GST with seven cases. In this paper, the grey superior possibility is used.

$$p\left(\otimes\alpha \succ \otimes\beta\right) = \begin{cases} 1 & \underline{\beta} \leqslant \overline{\beta} < \underline{\alpha} \leqslant \overline{\alpha} \\ \dfrac{\underline{\beta} - \underline{\alpha}}{\overline{\alpha} - \underline{\alpha} + 1} + \dfrac{\overline{\alpha} - \underline{\beta} + 1}{\overline{\alpha} - \underline{\alpha} + 1}\left(0.5\dfrac{\overline{\alpha} - \underline{\beta} + 1}{\beta - \underline{\beta} + 1} + \dfrac{\overline{\beta} - \overline{\alpha}}{\overline{\beta} - \underline{\beta} + 1}\right) & \underline{\beta} \leqslant \underline{\alpha} \leqslant \overline{\beta} < \overline{\alpha} \\ \dfrac{\underline{\beta} - \underline{\alpha}}{\overline{\beta} - \underline{\alpha} + 1} + 0.5\dfrac{\overline{\beta} - \underline{\alpha} + 1}{\overline{\beta} - \underline{\alpha} + 1} & \underline{\beta} \leqslant \underline{\alpha} \leqslant \overline{\alpha} \leqslant \overline{\beta} \\ 0 & \underline{\beta} \leqslant \overline{\alpha} < \underline{\beta} \leqslant \overline{\beta} \\ 0.5\dfrac{\overline{\beta} - \underline{\alpha} + 1}{\overline{\alpha} - \underline{\alpha} + 1}\dfrac{\overline{\beta} - \underline{\alpha} + 1}{\overline{\beta} - \underline{\beta} + 1} & \underline{\alpha} \leqslant \underline{\beta} \leqslant \overline{\beta} < \overline{\alpha} \\ 0.5\dfrac{\overline{\beta} - \underline{\alpha} + 1}{\overline{\beta} - \underline{\beta} + 1}\dfrac{\overline{\beta} - \overline{\alpha}}{\overline{\beta} - \underline{\beta} + 1} & \underline{\alpha} \leqslant \underline{\beta} \leqslant \overline{\beta} \leqslant \overline{\alpha} \\ 0.5 & \underline{a} = \overline{a} = \underline{\beta} = \overline{\beta} \end{cases} \tag{20}$$

Step 4. Determine the superiority identifier, $\otimes \widehat{E}_{fl}$. This is the corresponding grey weight for the superiority index as given in Eq. 20,

$$\otimes\widehat{E}_{fl} = \sum_{\substack{j=1 \\ j\in \widetilde{E}_{fl}}}^{n} \otimes w_{j}. \tag{21}$$

Step 5. Construct the impact matrix. This is obtained by determining the ordinal values of the alternatives. Since the performance values are in grey numbers, the ordinal values are determined using the grey possibilities as given in Eq. 20.

Step 6. Construct the regime matrix. The regime matrix is built using the elements in Eq. 22,

$$E_{fl,j} = \begin{cases} -1 & \text{if} \quad r_{f,j} < r_{l,j} \quad \text{iff} \quad p\left(\otimes \widehat{d}_{fl} \prec \otimes \widehat{d}_{fl}\right) < 0.5 \\ 0 & \text{if} \quad r_{f,j} = r_{l,j} \quad \text{iff} \quad p\left(\otimes \widehat{d}_{fl} = \otimes \widehat{d}_{fl}\right) = 0.5 , \\ +1 & \text{if} \quad r_{f,j} > r_{l,j} \quad \text{iff} \quad p\left(\otimes \widehat{d}_{fl} \succ \otimes \widehat{d}_{fl}\right) > 0.5 \end{cases} \tag{22}$$

where $j = 1 \ldots n$.

Step 7. Determine the grey guide index, $\otimes E_{fl}^{'}$. This is the weighted regime matrix, which elements are computed using Eq. 23,

$$\otimes E_{fl}^{'} = \sum_{j=1}^{n} \otimes w_j E_{fl,j}; j = 1 \ldots n. \tag{23}$$

Step 8. Sort and Rank. This step arranges the alternatives sequentially from the highest possibility to the lowest. The alternative with the largest possibility is considered the best.

4. Results and analysis

An oil and gas company in China with over 7,000 employees needed to globally automate the majority of its HRM processes to improve efficiency. Further information about the company is withheld for anonymity. Using the literature, work experiences, and company needs, the evaluation criteria were selected and scored to obtain the criteria weights. The conventional method used by the HR department, the PA method, was applied to assign weights to the criteria as described in Section 3.2.1. Then, the global HR director with some HR managers performed background checks on HRIS providers. Five HRIS vendors made presentations that included a quick demonstration of their HRIS. The DMs were provided with opportunities to interact with the software and ask questions, as well as grade the vendors on a scoresheet based on the evaluation criteria. Next, these scores were ranked. Then, the customised questionnaires were designed for each DM to obtain their

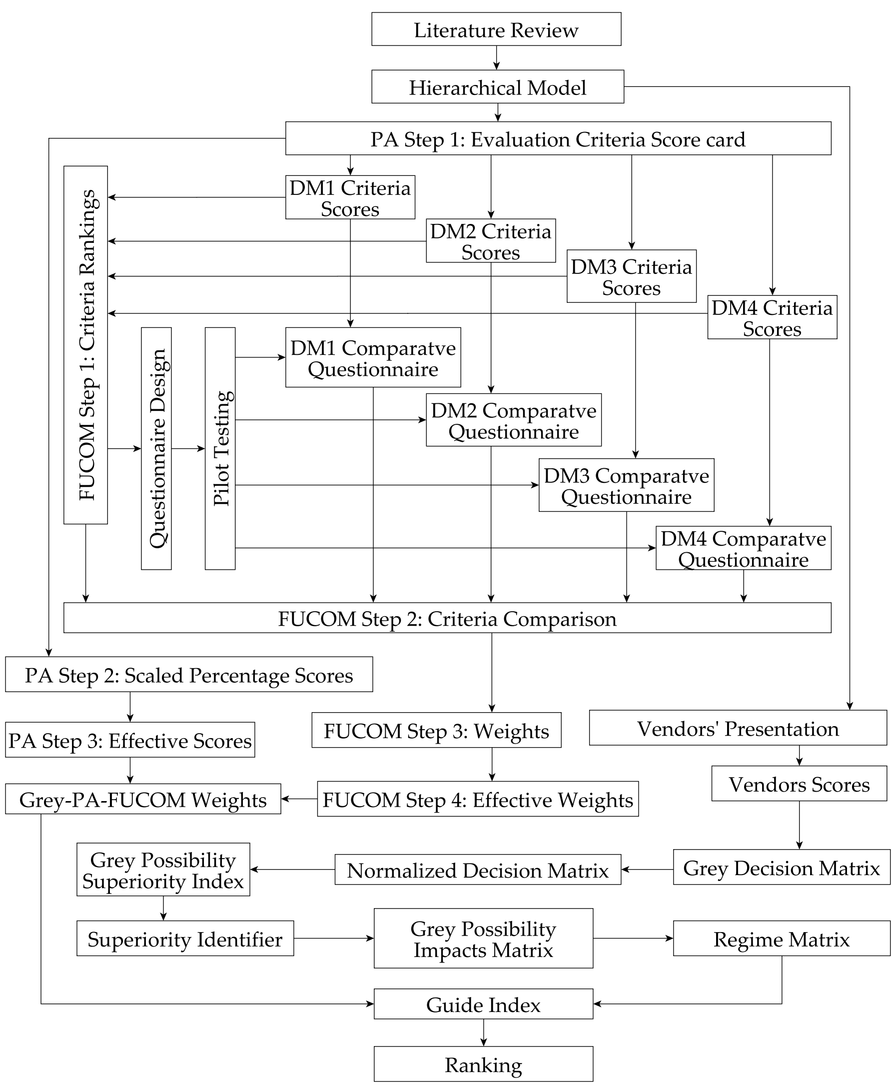

Fig. 2. Flowchart of HRIS evaluation.

comparative points for use in the FUCOM method. A flowchart of the evaluation process is presented in Fig. 2. The methods presented in Section 3 were applied here.

4.1. Application of the grey PA-FUCOM method

4.1.1. PA method

For this research, the percentage points assigned to the criteria were scored by four DMs, including an associate professor of HRM and three HR managers. The percentage scores were obtained and scaled. First, the DMs were asked to use the scoresheet to assign percentage scores to all criteria. Next, these scores were scaled to one. Then, the effective weights were computed. Based on Section 3.2.1, the steps are given as follows:

Step 1. Obtain percentage scores for the criteria. The percentage scores of all criteria were obtained from the four DMs. The DMs rated the criteria from 0% to 100%. These scores are given in Table 2.

Step 2. Scale the percentage ratings. The percentage rating for each of the local weights are scaled to one. The scaled first- and second-level criteria weight are obtained using Eqs. (1) and (2), respectively. The scaled PA weights for the DMs are given in Table 3.

Step 3. Compute the effective scaled weights. Effective scaled weights are computed as the product of the first- and second-level criteria weights as in Eq. (3), and are given in Table 4. Thus, $\sum_{j=1}^{27} w_j^{'}(v) = 1$.

Table 2
Raw data of decision makers' (DMs) rankings.

Indicators	DM_1	DM_2	DM_3	DM_4
HRM Functions (C_1)	100	98	85	90
Technology (C_2)	72	100	65	80
Software Quality (C_3)	83	100	65	90
Cost (C_4)	80	94	75	80
Vendor Support (C_5)	79	93	75	90
Staff Information Management (C_{1-1})	82	100	100	95
Organization Structure and Labour Management (C_{1-2})	57	84	95	100
Compensation and Benefits with Budget Management (C_{1-3})	81	98	85	75
Staff Training Management (C_{1-4})	86	85	70	80
Staff Recruiting Management (C_{1-5})	84	84	75	90
Staff Performance Management (C_{1-6})	80	100	50	99
Big Data Analysis (C_{2-1})	90	93	100	80
Artificial Intelligence (C_{2-2})	100	94	70	80
Internet of Things (C_{2-3})	91	100	85	95
Social Network (C_{2-4})	85	94	75	90
Self Help Service (C_{2-5})	86	93	40	80
Functionality (C_{3-1})	100	84	90	95
Reliability (C_{3-2})	84	91	90	90
Usability (C_{3-3})	86	96	75	80
Efficiency (C_{3-4})	91	92	60	95
Maintainability (C_{3-5})	100	96	85	80
Portability (C_{3-6})	87	93	70	80
Operation and Maintenance Fees (C_{4-1})	68	94	75	95
Licensing Fees (C_{4-2})	67	89	65	90
Consultation Fees (C_{4-3})	74	93	85	80
Equipment Cost (C_{4-4})	85	94	75	80
Software Training Fee (C_{4-5})	79	99	50	80
Vendor Reputation (C_{5-1})	86	93	95	80
Technological Capability (C_{5-2})	100	93	75	100
After-sales Service Commitment (C_{5-3})	100	100	95	100
After-sales Update and Upgrade (C_{5-4})	92	100	65	100
Software Delivery and Service Response Time (C_{5-5})	87	100	70	80

Table 3
Scaled point-allocation weights.

Criteria/ Decision makers	DM_1	DM_2	DM_3	DM_4
C_1	0.2415	0.2021	0.2329	0.2093
C_2	0.1739	0.2062	0.1781	0.186
C_3	0.2005	0.2062	0.1781	0.2093
C_4	0.1932	0.1938	0.2055	0.186
C_5	0.1908	0.1918	0.2055	0.2093
⋮	⋮	⋮	⋮	⋮
C_{5-1}	0.0353	0.0367	0.0488	0.0364
C_{5-2}	0.041	0.0367	0.0385	0.0455
C_{5-3}	0.041	0.0395	0.0488	0.0455
C_{5-4}	0.0378	0.0395	0.0334	0.0455
C_{5-5}	0.0357	0.0395	0.036	0.0364

4.1.2. FUCOM method

A questionnaire template for this paper was designed and pilot tested for the customised questionnaire for each DM. The steps used are the same as those presented in Section 3.2.2.

Step 1. Rank the criteria. The points given to various criteria, as in Table 2, represent DM preferences. These are converted to rankings from the most to the least important criterion. For DM_1, the rankings for the first-level criteria based on the points given is as follows:

$$C_1(1) > C_3(1) > C_4(1) > C_5(1) > C_2(1) \tag{24}$$

Similarly, for DM_4, the rankings for the fifth second-level criteria based on the point given is as follows:

$$C_{5-2}(4) = C_{5-3}(4) = C_{5-4}(4) > C_{5-1}(4) = C_{5-5}(4) \tag{25}$$

The other inequalities for the other DMs and criteria were omitted.

Step 2. Obtain the comparative priorities. Comparative priorities are the results obtained from the DMs by answering the questionnaire. The comparison-measurement scale employed in this research is the conventional scale used in the AHP, where equally important $=1$, weakly important $=3$, strongly important $=5$, very strongly important $=7$, and absolutely important $=9$, and the intermediate values between two adjacent judgements (Piengang et al., 2019). The comparative priorities are shown in Table 5.

Step 3. Compute the weights. The weights are calculated by minimising the deviation from full consistency (χ) in the optimisation Function (26). Based on the steps in Section 3.2.2 and objective Function (6), the first-level criteria by DM_1 is given as follows:

$$\begin{gathered}
\min \chi \\
s.t. \\
\left|\frac{w_1}{w_3} - \frac{4}{1}\right| \leqslant \chi, \left|\frac{w_3}{w_4} - \frac{7}{4}\right| \leqslant \chi, \left|\frac{w_4}{w_5} - \frac{3}{7}\right| \leqslant \chi, \left|\frac{w_5}{w_2} - \frac{3}{4}\right| \leqslant \chi, \\
\left|\frac{w_1}{w_4} - \frac{4}{1} \times \frac{7}{4}\right| \leqslant \chi, \left|\frac{w_3}{w_5} - \frac{7}{4} \times \frac{4}{7}\right| \leqslant \chi, \left|\frac{w_4}{w_2} - \frac{4}{7} \times \frac{3}{4}\right| \leqslant \chi, \\
w_1 + w_2 + w_3 + w_4 + w_5 = 1, \\
w_1, w_2, w_3, w_4, w_5 \geqslant 0.
\end{gathered} \tag{26}$$

The objective functions for the other criteria by the other DMs were omitted, but the results are given in Table 4. Just before computing the effective weight, a scatter plot of the local weights of each DM showing the distribution of the local weights of both PA and FUCOM method are given in Fig. 3. The dots and rings are the local weights based on the PA and FUCOM methods, respectively.

Step 4. Compute the effective weights. Effective FUCOM weights are computed using Eq. (7) for each DM based on the FUCOM method. The results are given in Table 4.

Table 4
Computed criteria ranking by DMs.

Indicators	Point allocation method				FUCOM method				Grey weights
	DM_1	DM_2	DM_3	DM_4	DM_1	DM_2	DM_3	DM_4	
C_1	0.2415	0.2021	0.2329	0.2093	0.506	0.3846	0.5932	0.3077	[0.1191, 0.3495]
C_2	0.1739	0.2062	0.1781	0.186	0.1687	0.0769	0.0847	0.0385	[0.0227, 0.1215]
C_3	0.2005	0.2062	0.1781	0.2093	0.1265	0.3846	0.0847	0.3077	[0.0499, 0.2266]
C_4	0.1932	0.1938	0.2055	0.186	0.0723	0.0769	0.1186	0.0385	[0.0227, 0.1211]
C_5	0.1908	0.1918	0.2055	0.2093	0.1265	0.0769	0.1186	0.3077	[0.0453, 0.1813]
C_{1-1}	0.0421	0.0367	0.049	0.0369	0.0148	0.1374	0.2665	0.0259	[0.0069, 0.1248]
C_{1-2}	0.0293	0.0308	0.0466	0.0388	0.1186	0.0275	0.0666	0.1295	[0.0129, 0.0607]
C_{1-3}	0.0416	0.0359	0.0417	0.0291	0.1186	0.0275	0.0888	0.0647	[0.0129, 0.0556]
C_{1-4}	0.0442	0.0312	0.0343	0.0311	0.1186	0.0275	0.0666	0.0432	[0.0129, 0.0556]
C_{1-5}	0.0432	0.0308	0.0368	0.0349	0.1186	0.0275	0.0381	0.0185	[0.0087, 0.0556]
C_{1-6}	0.0411	0.0367	0.0245	0.0384	0.0169	0.1374	0.0666	0.0259	[0.0079, 0.0644]
C_{2-1}	0.0346	0.0405	0.0481	0.035	0.012	0.0444	0.0569	0.0586	[0.0056, 0.0275]
C_{2-2}	0.0385	0.0409	0.0337	0.035	0.0361	0.037	0.0095	0.0586	[0.0045, 0.0275]
C_{2-3}	0.035	0.0435	0.0409	0.0416	0.0361	0.2219	0.0142	0.1172	[0.0067, 0.1039]
C_{2-4}	0.0327	0.0409	0.0361	0.0394	0.0361	0.037	0.019	0.0147	[0.0069, 0.0192]
C_{2-5}	0.0331	0.0405	0.0193	0.035	0.006	0.0444	0.019	0.0586	[0.0028, 0.0275]
C_{3-1}	0.0366	0.0314	0.0341	0.0382	0.0202	0.0055	0.0533	0.1295	[0.0026, 0.0607]
C_{3-2}	0.0307	0.034	0.0341	0.0362	0.0101	0.0055	0.0133	0.0259	[0.0026, 0.017]
C_{3-3}	0.0315	0.0359	0.0284	0.0322	0.0101	0.0275	0.0076	0.0185	[0.0036, 0.0168]
C_{3-4}	0.0333	0.0344	0.0227	0.0382	0.0067	0.0055	0.0133	0.0259	[0.0026, 0.0179]
C_{3-5}	0.0366	0.0359	0.0322	0.0322	0.0202	0.0275	0.0178	0.0432	[0.0083, 0.0202]
C_{3-6}	0.0318	0.0347	0.0265	0.0322	0.005	0.0055	0.0133	0.0647	[0.0023, 0.0303]
C_{4-1}	0.0352	0.0388	0.044	0.0416	0.0187	0.0431	0.007	0.0234	[0.0033, 0.0206]
C_{4-2}	0.0347	0.0368	0.0382	0.0394	0.0187	0.0108	0.0098	0.0033	[0.0015, 0.0185]
C_{4-3}	0.0383	0.0384	0.0499	0.035	0.0187	0.0072	0.0488	0.0039	[0.0018, 0.0234]
C_{4-4}	0.044	0.0388	0.044	0.035	0.0562	0.0072	0.007	0.0039	[0.0018, 0.0263]
C_{4-5}	0.0409	0.0409	0.0294	0.035	0.0141	0.0086	0.0122	0.0039	[0.0018, 0.0192]
C_{5-1}	0.0353	0.0367	0.0488	0.0364	0.0402	0.0183	0.0246	0.0013	[0.0006, 0.0229]
C_{5-2}	0.041	0.0367	0.0385	0.0455	0.0402	0.0183	0.0246	0.0119	[0.0056, 0.0213]
C_{5-3}	0.041	0.0395	0.0488	0.0455	0.0402	0.0183	0.0246	0.0119	[0.0056, 0.0229]
C_{5-4}	0.0378	0.0395	0.0334	0.0455	0.008	0.0183	0.0049	0.0119	[0.0023, 0.0213]
C_{5-5}	0.0357	0.0395	0.036	0.0364	0.0402	0.0037	0.0061	0.0013	[0.0006, 0.0188]

4.1.3. *Grey PA-FUCOM method*

The Grey-PA-FUCOM is a representation of the various weights obtained using the PA and FUCOM methods. Based on the procedure for the Grey-PA-FUCOM weighting method, as described in Section 3.2.3, the grey weights for HRIS evaluation are calculated as follows.

Step 1. Obtain the PA and FUCOM weights. These weights are computed in Sections 4.1.1 and 4.1.2.

Step 2. Represent the PA and FUCOM weights as grey numbers. The minimum and maximum weights by both methods are scaled to obtain the Grey-PA-FUCOM weights for the first- and second-level criteria. Eqs. (8) and (9) were used for the first-level indicators, where $w_p^{'}$ and $w_p^{''}$ are the PA and FUCOM weights for the DMs, respectively. Similarly, for the second-level criteria, the grey weights were computed using Eqs. (10) and (11), where $w_{p-q}^{'}$ and $w_{p-q}^{''}$ are the PA and FUCOM weights, respectively, for the DMs. The local weights are as follows:

$$w_1^* = \begin{pmatrix} [0.2021, 0.5932] \\ [0.0385, 0.2062] \\ [0.0847, 0.3846] \\ [0.0385, 0.2055] \\ [0.0769, 0.3077] \end{pmatrix}, \ldots, \quad w_{5-q}^* = \begin{pmatrix} [0.0013, 0.0488] \\ [0.0119, 0.0455] \\ [0.0119, 0.0488] \\ [0.0049, 0.0455] \\ [0.0013, 0.0402] \end{pmatrix}. \tag{27}$$

Step 3. Compute the effective weight. The weights were scaled to obtain the effective weights using Eq. (12). This amounted to the weights given in Eq. (28). The sum of the upper bounds is a unit value. Please see the last column W of Table 6 for the complete column matrix. Fig. 4 also shows a bar graph of the grey weights.

$$W = \begin{pmatrix} [0.0069, 0.1248] \\ [0.0129, 0.0607] \\ [0.0129, 0.0556] \\ \vdots \\ [0.0006, 0.0188] \end{pmatrix} \tag{28}$$

4.2. *Grey-REGIME method for HRIS evaluation*

After obtaining the criteria weights, the five HRIS' provided by the vendors were evaluated using the grey-regime methods as described in Section 3.3.2. First, the scores for the alternatives were obtained from the DMs. The raw data were obtained from the scoresheets of the DMs. Based on Eq. (15), the grey performance values for the alternatives are given in Table 6. The HRIS provided by the five vendors were evaluated based on the steps given in Section 3.3.2.

Step 1. Formulate the grey decision matrix. The ratings of the 4 DMs for the first vendor A_1 regarding the staff information management criterion (C_{1-1}) are 59, 65, 75, and60, respectively. These are converted to a grey preference as $\otimes d_{1,1} = [59, 75]$. Similarly, the ratings by the 4 DMs for the fifth vendor A_2 for software delivery & service response time criterion (C_{5-5}) are 70,80,85, and 70, respectively. These result in a grey

Table 5
Raw comparison data.

Indicators	Rankings	DM_1	DM_2	DM_3	DM_4
First-level Indicators	1st	-	-	-	-
	2nd	4	-	5	-
	3rd	7	5	5*	-
	4th	4	5	7	8
	5th	3	5	7*	8
HRM Functions(C_1)	1st	-	-	-	-
	2nd	1	-*	4	5
	3rd	8	5	3	5
	4th	1	5	7	7
	5th	7	5	4	3
	6th	1	5*	4	2
Technology (C_2)	1st	-	-	-	-
	2nd	1	6	6	8
	3rd	3	6	4	2
	4th	6	5	3	2*
	5th	1	5	3	2*
Software Quality (C_3)	1st	-	-	-	-
	2nd	-*	-*	-*	-*
	3rd	3	5	7	1
	4th	4	5	4	6
	5th	2	5	7	6*
	6th	2	5	4	6*
Cost (C_4)	1st	-	-	-	-
	2nd	4	6	5	7
	3rd	3	6*	5*	6
	4th	3	4	7	6*
	5th	3	5	4	6*
Vendor Support (C_5)	1st	-	-	-	-
	2nd	-*	-*	-*	-*
	3rd	5	-*	7	-*
	4th	1	4	6	9
	5th	1	5	4	9*

* = Criteria with equal ranking to the preceding criterion.

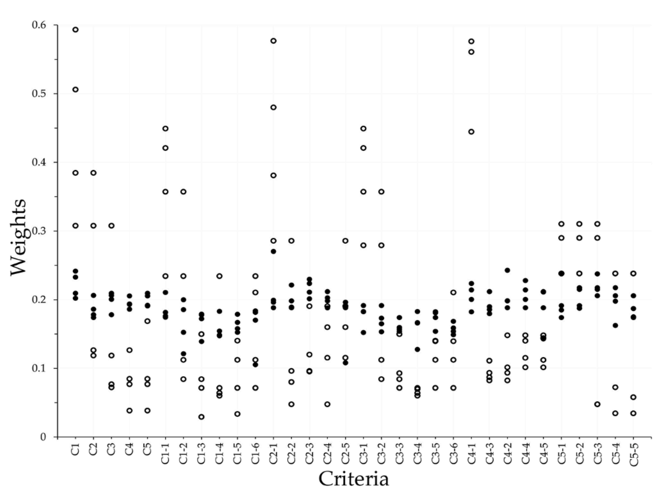

Fig. 3. Scatter Graph of the distribution of the DM weights.

preference of $\otimes d_{5,27} = [70, 85]$. The other grey preferences are given in Table 6and are used to construct the grey decision matrix based on Eq. (16).

The grey decision matrix is

$$D = \begin{pmatrix} [59,75] & [60,70] & \dots & [70,85] \\ [60,80] & [65,90] & \dots & [70,80] \\ [80,90] & [60,85] & \dots & [70,90] \\ [70,95] & [65,90] & \dots & [80,90] \\ [60,85] & [70,80] & \dots & [70,85] \end{pmatrix}, \tag{29}$$

where, $\otimes d_{ij} = \left[\underline{d}_{ij}, \overline{d}_{ij}\right] = \left[\min_{1\leqslant v\leqslant 4} d_{ij}(v), \max_{1\leqslant v\leqslant 4} d_{ij}(v)\right]$.

Step 2. Normalise the grey decision matrix.

$$\widehat{D} = \begin{pmatrix} [0.1429, 0.6556] & [0.2857, 0.6667] & \dots & [0.5714, 0.8182] \\ [0.4545, 0.6667] & [0.7222, 0.9091] & \dots & [0.5714, 0.8571] \\ [0.7273, 0.8889] & [0.2857, 0.8333] & \dots & [0.5714, 0.9091] \\ [0.5714, 1.0000] & [0.5714, 0.8571] & \dots & [0.5714, 0.9091] \\ [0.2857, 0.7143] & [0.4286, 0.8333] & \dots & [0.5714, 0.8182] \end{pmatrix}, \tag{30}$$

where, $\otimes \widehat{d}_{ij} = \left[\widehat{\underline{d}}_{ij}, \widehat{\overline{d}}_{ij}\right] = \left[\min_{1\leqslant v\leqslant 4} \widehat{d}_{ij}(v), \max_{1\leqslant v\leqslant 4} \widehat{d}_{ij}(v)\right]$.

Step 3. Compute the Superiority index, $\widetilde{E}_{fl}$. This is based on the grey superior possibility given in Eq. (20) as follows:

$$\begin{gathered} \widetilde{E}_{12} = C_{1-4}, C_{1-6}, C_{2-5}, C_{3-5}, C_{3-6}, C_{4-4}, C_{5-2}; \\ \widetilde{E}_{13} = C_{3-4}, C_{5-2}; \\ \widetilde{E}_{14} = C_{3-5}, C_{3-6}, C_{5-2}, C_{5-4}; \\ \widetilde{E}_{15} = C_{3-3}, C_{3-4}, C_{3-5}, C_{3-6}, C_{4-3}, C_{5-2}; \\ \vdots \\ \widetilde{E}_{54} = C_{1-3}, C_{1-4}, C_{1-5}, C_{1-6}, C_{2-1}, C_{2-4}, C_{3-2}, C_{3-5}, C_{4-1}, C_{4-2}, C_{4-4}, C_{5-1}, C_{5-4}. \end{gathered}$$

Step 4. Determine the Superiority identifier, $\widehat{E}_{fl}$.

$\widehat{E}_{12} = [0.0805, 0.2369]$ $\widehat{E}_{13} = [0.0383, 0.0405]$ $\widehat{E}_{14} = [0.0431, 0.1123]$ $\widehat{E}_{15} = [0.0531, 0.1333]$ $\widehat{E}_{21} = [0.0962, 0.4304]$ $\widehat{E}_{23} = [0.0386, 0.1359]$ $\widehat{E}_{24} = [0.0654, 0.2236]$ $\widehat{E}_{25} = [0.0768, 0.2777]$ $\widehat{E}_{31} = [0.1231, 0.7237]$ $\widehat{E}_{32} = [0.1073, 0.718]$ $\widehat{E}_{34} = [0.1054, 0.5881]$ $\widehat{E}_{35} = [0.107, 0.7121]$ $\widehat{E}_{41} = [0.1102, 0.7383]$ $\widehat{E}_{42} = [0.0877, 0.6652]$ $\widehat{E}_{43} = [0.0552, 0.2418]$ $\widehat{E}_{45} = [0.0844, 0.6311]$ $\widehat{E}_{51} = [0.1117, 0.5883]$ $\widehat{E}_{52} = [0.0913, 0.4867]$ $\widehat{E}_{53} = [0.0397, 0.1473]$ $\widehat{E}_{54} = [0.0687, 0.2599]$.

Step 5. Construct the Impact matrix, I

$$I = \begin{array}{c} \begin{array}{cccccc} C_1 & C_2 & C_3 & C_4 & \dots & C_{27} \end{array} \\ \begin{pmatrix} 5 & 5 & 5 & 4 & \dots & 3 \\ 4 & 1 & 2 & 5 & \dots & 5 \\ 1 & 4 & 1 & 1 & \dots & 2 \\ 2 & 1 & 4 & 2 & \dots & 1 \\ 3 & 3 & 3 & 3 & \dots & 3 \end{pmatrix} \end{array} \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ A_4 \\ A_5 \end{array} \tag{31}$$

Step 6. Construct the regime matrix (R), as shown in Eq. 22 below,

$$\begin{gathered} E_{1-2} = -1, -1, -1, 1, \dots -1; \\ E_{1-3} = -1, -1, -1, -1, \dots -1; \\ E_{1-4} = -1, -1, -1, -1, \dots -1; \\ E_{1-5} = -1, -1, -1, -1, \dots 1; \\ \vdots \\ E_{5-4} = -1, -1, 1, 1, \dots -1. \end{gathered}$$

which is

Table 6
Grey decision table.

Criteria/ Alternatives	Index (j)	A_1	A_2	A_3	A_4	A_5	W
C_{1-1}	1	[59, 75]	[60, 80]	[80, 90]	[70, 95]	[60, 85]	[0.0069, 0.1248]
C_{1-2}	2	[60, 70]	[65, 90]	[60, 85]	[65, 90]	[70, 80]	[0.0129, 0.0607]
C_{1-3}	3	[58, 80]	[70, 85]	[70, 95]	[60, 86]	[60, 90]	[0.0129, 0.0556]
C_{1-4}	4	[60, 70]	[60, 60]	[70, 90]	[70, 85]	[65, 90]	[0.0129, 0.0556]
C_{1-5}	5	[60, 75]	[60, 80]	[65, 90]	[60, 75]	[60, 90]	[0.0087, 0.0556]
C_{1-6}	6	[60, 70]	[58, 70]	[67, 90]	[68, 80]	[60, 85]	[0.0079, 0.0644]
C_{2-1}	7	[0, 60]	[0, 60]	[60, 70]	[58, 70]	[80, 80]	[0.0056, 0.0275]
C_{2-2}	8	[0, 60]	[0, 60]	[80, 80]	[70, 90]	[0, 60]	[0.0045, 0.0275]
C_{2-3}	9	[0, 60]	[0, 60]	[0, 60]	[60, 70]	[0, 60]	[0.0067, 0.1039]
C_{2-4}	10	[60, 80]	[60, 80]	[60, 75]	[60, 75]	[60, 80]	[0.0069, 0.0192]
C_{2-5}	11	[55, 85]	[60, 80]	[70, 90]	[60, 80]	[60, 80]	[0.0028, 0.0275]
C_{3-1}	12	[60, 80]	[60, 90]	[75, 80]	[70, 85]	[60, 85]	[0.0026, 0.0607]
C_{3-2}	13	[60, 85]	[60, 90]	[70, 85]	[60, 85]	[70, 90]	[0.0026, 0.017]
C_{3-3}	14	[60, 80]	[70, 85]	[60, 90]	[60, 90]	[65, 70]	[0.0036, 0.0168]
C_{3-4}	15	[60, 85]	[70, 85]	[60, 85]	[60, 90]	[65, 80]	[0.0026, 0.0179]
C_{3-5}	16	[70, 90]	[60, 85]	[75, 85]	[60, 80]	[60, 85]	[0.0083, 0.0202]
C_{3-6}	17	[70, 95]	[0, 70]	[75, 90]	[70, 90]	[60, 80]	[0.0023, 0.0303]
C_{4-1}	18	[60, 80]	[60, 80]	[70, 90]	[60, 85]	[70, 80]	[0.0033, 0.0206]
C_{4-2}	19	[50, 90]	[50, 90]	[65, 85]	[60, 85]	[60, 80]	[0.0015, 0.0185]
C_{4-3}	20	[60, 90]	[60, 90]	[65, 85]	[60, 90]	[60, 80]	[0.0018, 0.0234]
C_{4-5}	21	[60, 85]	[50, 90]	[70, 85]	[65, 80]	[65, 80]	[0.0018, 0.0263]
C_{4-5}	22	[70, 90]	[70, 90]	[65, 95]	[70, 95]	[70, 90]	[0.0018, 0.0192]
C_{5-1}	23	[70, 85]	[70, 85]	[80, 90]	[75, 85]	[85, 90]	[0.0006, 0.0229]
C_{5-2}	24	[70, 90]	[0, 70]	[65, 80]	[70, 85]	[0, 60]	[0.0056, 0.0213]
C_{5-3}	25	[60, 80]	[60, 80]	[70, 90]	[70, 90]	[70, 85]	[0.0056, 0.0229]
C_{5-4}	26	[70, 85]	[70, 90]	[70, 85]	[60, 80]	[60, 90]	[0.0023, 0.0213]
C_{5-5}	27	[70, 85]	[70, 80]	[70, 90]	[80, 90]	[70, 85]	[0.0006, 0.0188]

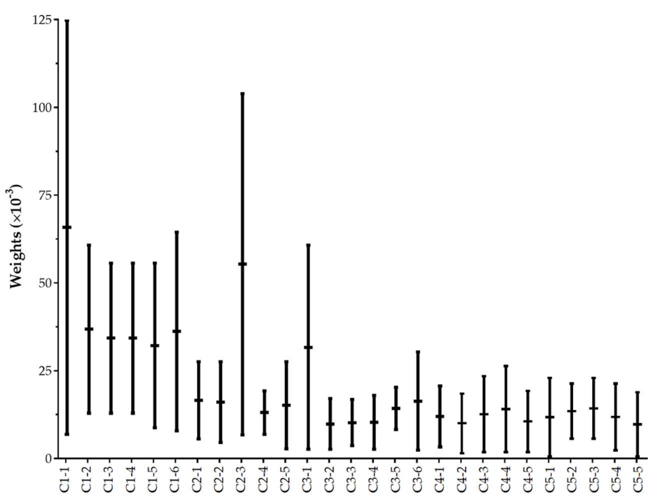

Fig. 4. Grey point allocation of the full-consistency multicriteria (FUCOM) weights.

$$R = \begin{array}{c} \\ \\ \\ \\ \\ \\ \\ \end{array}\begin{array}{cccccc} c_1 & c_2 & c_3 & c_4 & \cdots & c_{27} \\ \end{array}$$

$$R = \begin{pmatrix} -1 & -1 & -1 & 1 & \cdots & -1 \\ -1 & -1 & -1 & -1 & \cdots & -1 \\ -1 & -1 & -1 & -1 & \cdots & -1 \\ -1 & -1 & -1 & -1 & \cdots & 1 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ -1 & -1 & 1 & 1 & \cdots & -1 \end{pmatrix} \begin{array}{c} E_{1-2} \\ E_{1-3} \\ E_{1-4} \\ E_{1-5} \\ \vdots \\ E_{5-4} \end{array} \tag{32}$$

Step 7. Calculate the grey guiding index.

$\otimes E'_{1-2} = [0.0254, 0.1396]$, $\otimes E'_{1-3} = [-0.6332, -0.0874]$, $\otimes E'_{1-4} = [-0.4762, -0.0494]$, $\otimes E'_{1-5} = [-0.1762, -0.0294]$, $\otimes E'_{2-1} = [0.0512, 0.4716]$, $\otimes E'_{2-3} = [-0.5208, -0.0656]$, $\otimes E'_{2-4} = [-0.33, -0.0048]$, $\otimes E'_{2-5} = [-0.0134, 0.0014]$, $\otimes E'_{3-1} = [0.1106, 0.9194]$, $\otimes E'_{3-2} = [0.079, 0.7286]$, $\otimes E'_{3-4} = [0.0752, 0.5168]$, $\otimes E'_{3-5} = [0.0784, 0.7058]$, $\otimes E'_{4-1} = [0.0756, 0.6682]$, $\otimes E'_{4-2} = [0.0398, 0.5532]$, $\otimes E'_{4-3} = [-0.344, -0.034]$, $\otimes E'_{4-5} = [0.0332, 0.4806]$, $\otimes E'_{5-1} = [0.0704, 0.5534]$, $\otimes E'_{5-2} = [0.044, 0.408]$, $\otimes E'_{5-3} = [-0.498, -0.065]$, $\otimes E'_{5-4} = [-0.373, -0.024]$.

Step 8. Sort and Rank the alternatives. The HRIS' are ranked by summing the grey guiding index of each alternative compared to others. The alternative with the highest cumulative grey guiding index is the best. $E_{1-i} = [-0.1408, -1.146]$, $E_{2-i} = [-0.0178, -0.3926]$, $E_{3-i} = [0.3432, 2.8706]$, $E_{4-i} = [0.1146, 1.358]$, and $E_{5-i} = [0.0254, 0.0904]$.A plot of the cumulative grey guiding index for the five HRIS' is given in Fig. 5. As shown, the third alternative (A_3) is the best, i.e. $A_3 > A_4 > A_5 > A_2 > A_1$.

4.3. Rankings confirmation and study validation

To certify the rankings presented in this research, some confirmatory analysis was conducted using classical MCDM methods that have been extended to grey numbers. The MCDM methods presented by Kou et al. (2020), like the weighted sum model (WSM), GRA, and TOPSIS, are the classical methods that use crisp values. Conversely, GRA with grey numbers, the grey weighted sum model (GWSM), and TOPSIS with grey numbers are used to validate this research result.

4.3.1. Grey relational analysis with grey numbers

The classical GRA proposed by Deng (1989) was extended to grey

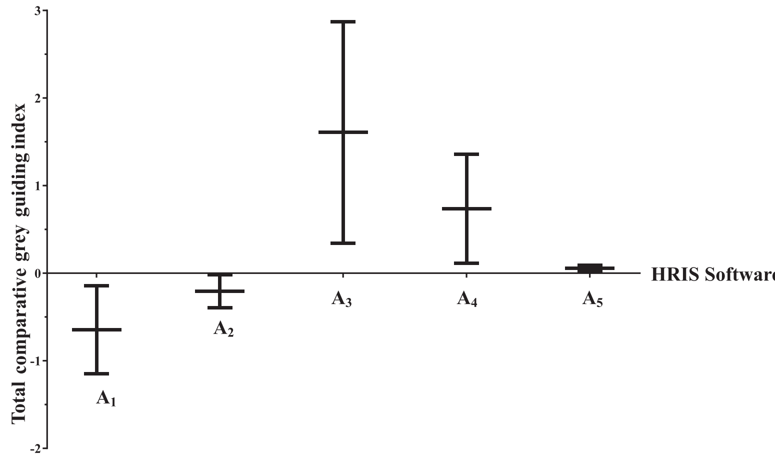

Fig. 5. Cumulative grey guiding index of alternatives.

numbers by Esangbedo and Che (2016a). The rankings are based on the grey relational grades.

Step 1. Construct the grey decision matrix. The grey decision matrix is given in Eq. (29) and derived from Table 6.

Step 2. Normalise the grey decision matrix. The grey decision matrix was normalised using Eq. (19), which is as follows:

$$\widehat{D} = \begin{pmatrix} [0, 0.4444] & [0, 0.3333] & [0, 0.5946] & \dots & [0, 0.75] \\ [0.0278, 0.5833] & [0.1667, 1] & [0.3243, 0.7297] & \dots & [0, 0.5] \\ [0.5833, 0.8611] & [0, 0.8333] & [0.3243, 1] & \dots & [0, 1] \\ [0.3056, 1] & [0.1667, 1] & [0.0541, 0.7568] & \dots & [0.5, 1] \\ [0.0278, 0.7222] & [0.3333, 0.6667] & [0.0541, 0.8649] & \dots & [0, 0.75] \end{pmatrix} \tag{33}$$

where

$$\otimes d^*_{ij} = \left[\frac{\underline{d}_{ij} - \min\limits_{1\leqslant i\leqslant m} \underline{d}_{ij}}{\max\limits_{1\leqslant i\leqslant 5} \overline{d}_{ij} - \min\limits_{1\leqslant i\leqslant 5} \underline{d}_{ij}}, \frac{\overline{d}_{ij} - \min\limits_{1\leqslant i\leqslant 5} \underline{d}_{ij}}{\max\limits_{1\leqslant i\leqslant 5} \overline{d}_{ij} - \min\limits_{1\leqslant i\leqslant 5} \underline{d}_{ij}} \right]. \tag{34}$$

Since percentage scores used, all preferences are beneficial preferences.

Step 3. Compute the weighted decision matrix. The weights are given in Eq. (28) were computed using Eq. (35), and the weighted–normalised decision matrix is as follows:

$$D^* = \begin{pmatrix} \otimes d^*_{1,1} & \otimes d^*_{1,2} & \otimes d^*_{1,3} & \cdots & \otimes d^*_{1,27} \\ \otimes d^*_{2,1} & \otimes d^*_{2,2} & \otimes d^*_{2,3} & \cdots & \otimes d^*_{2,27} \\ \otimes d^*_{3,1} & \otimes d^*_{3,2} & \otimes d^*_{3,3} & \cdots & \otimes d^*_{3,27} \\ \vdots & \vdots & \ddots & \vdots & \\ \otimes d^*_{5,1} & \otimes d^*_{5,2} & \otimes d^*_{5,3} & \cdots & \otimes d^*_{5,27} \end{pmatrix}, \tag{35}$$

where $\otimes d^*_{ij} = d'_{ij} \times \otimes w_{ij}$. In vector form, the series are as follows:

$$\begin{gathered} D^*_1 = \{[0, 0.0555][0, 0.0202][0, 0.0331]\dots, [0, 0.0141]\} \\ D^*_2 = \{[0.0002, 0.0728][0.0022, 0.0607][0.0042, 0.0406]\dots, [0, 0.0094]\} \\ D^*_3 = \{[0.004, 0.1075][0, 0.0506][0.0042, 0.0556]\dots, [0, 0.0188]\} \\ D^*_4 = \{[0.0021, 0.1248][0.0022, 0.0607][0.0007, 0.0421]\dots, [0.0003, 0.0188]\} \\ D^*_5 = \{[0.0002, 0.0901][0.0043, 0.0405][0.0007, 0.0481]\dots, [0, 0.0141]\} \end{gathered}.$$

Step 4. Determine the reference alternative. This is the optimal or ideal HRIS for all criteria.

$$D^*_0 = \{[0.5833, 1][0.3333, 1][0.3243, 1]\dots, [0.5, 1]\}, \tag{36}$$

where $\otimes d^*_{0j} = \left[\max_{1\leqslant i\leqslant 5} \underline{d}^*_{ij}, \max_{1\leqslant i\leqslant 5} \overline{d}^*_{ij} \right]$.

Step 5. Determine the distance from the reference alternative to the other alternative. This distance is computed as follows:

$$\Delta = \begin{pmatrix} \delta_{1,1} & \delta_{1,2} & \cdots & \delta_{1,n} \\ \delta_{2,1} & \delta_{2,2} & \cdots & \delta_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ \delta_{m,1} & \delta_{m,2} & \cdots & \delta_{m,n} \end{pmatrix} = \begin{pmatrix} 0.0693 & 0.0405 & 0.0225 & \dots & 0.0047 \\ 0.052 & 0.0022 & 0.015 & \dots & 0.0094 \\ 0.0173 & 0.0101 & 0 & \dots & 0.0003 \\ 0.0019 & 0.0022 & 0.0135 & \dots & 0 \\ 0.0347 & 0.0202 & 0.0075 & \dots & 0.0047 \end{pmatrix}, \tag{37}$$

where $\delta_{ij} = \left| \otimes d^*_{0j} - \otimes d^*_{ij} \right| = \max\left(\left| \underline{d}^*_{0j} - \underline{d}^*_{ij} \right|, \left| \overline{d}^*_{0j} - \overline{d}^*_{ij} \right| \right)$.

Step 6. Calculate the grey relational grade. The overall performance of the HRIS is determined using Eq. (38):

$$r_i = \frac{1}{n} \sum_{j=1}^{n} \gamma_{ij} = \frac{1}{27} \sum_{j=1}^{27} \gamma_{ij}, \tag{38}$$

where the grey relational coefficient $\gamma_{ij} = \frac{\min_{1\leqslant i\leqslant m} \min_{1\leqslant j\leqslant n} \delta_{ij} + \zeta \max_{1\leqslant i\leqslant m} \max_{1\leqslant j\leqslant n} \delta_{ij}}{\delta_{ij} + \zeta \max_{1\leqslant i\leqslant m} \max_{1\leqslant j\leqslant n} \delta_{ij}}$, and the grey distinguishing coefficient is $\zeta \in [0, 1]$. The transpose of the column matrix is as follows:

$$\begin{aligned} r_i &= (0.8728 \quad 0.8913 \quad 0.9527 \quad 0.9358 \quad 0.9148)^T \\ &\approx (5^{th} \quad 4^{th} \quad 1^{st} \quad 2^{nd} \quad 3^{rd})^T. \end{aligned} \tag{39}$$

Step 7. Rank the alternatives. This sorts the HRIS' from best to worst, where A_3 is the best HRIS provided by the third vendor.

4.3.2. Grey weighted sum model

This is the classical simple additive weighting method based on grey numbers. After obtaining the grey normalised weighted decision matrix, the white values, and the boundary distances, the rankings of the alternatives are computed., The steps presented by Esangbedo and Che (2016b) should be used.

Step 1. Construct the grey decision matrix, D, using Eq. (29).

Step 2. Normalise the grey decision matrix, D^*, using Eq. (43).

Step 3. Determine the criteria weights, W, using Eq. (28).

Step 4. Aggregate the weighted normalised decision matrix. $Y = W \times D^*$.

Step 5. Compute the white values of the alternatives, V_i.

$$V_i = y_i(1-\lambda) + y_i\lambda = (0.3362 \quad 0.3678 \quad 0.4720 \quad 0.4510 \quad 0.4189)^T, \tag{40}$$

where the whitening coefficient used is $\lambda = 0.5$.

Step 6. Determine the boundary distance of the alternatives. For the Euclidean distance,

$$S_i = \sqrt{\overline{y}^2 - \underline{y}^2} = (0.5031 \quad 0.5648 \quad 0.5479 \quad 0.5488 \quad 0.5702)^T. \tag{41}$$

Step 7. Rank the alternatives. The rank score is $z_i = V_i(1-S_i)$.

$$z_i = (0.1671 \quad 0.1601 \quad 0.2134 \quad 0.2035 \quad 0.1801)^T \approx (5^{th} \quad 4^{th} \quad 1^{st} \quad 2^{nd} \quad 3^{rd})^T. \tag{42}$$

4.3.3. *TOPSIS with grey numbers*

The TOPSIS method was developed by Hwang and Yoon (1981) and was extended to the GST by Zavadskas, Vilutienė, Turskis, and Tamosaitienė (2010).

Step 1. Construct the grey decision matrix using Eq. (29).

Step 2. Normalise the grey decision matrix.

$$\widetilde{D} = \begin{pmatrix} [0.6211, 0.7895] & [0.6667, 0.7778] & [0.6105, 0.8421] & \dots[0.7778, 0.9444] \\ [0.6316, 0.8421] & [0.7222, 1] & [0.7368, 0.8947] & \dots[0.7778, 0.8889] \\ [0.8421, 0.9474] & [0.6667, 0.9444] & [0.7368, 1] & \dots[0.7778, 1] \\ [0.7368, 1] & [0.7222, 1] & [0.6316, 0.9053] & \dots[0.8889, 1] \\ [0.6316, 0.8947] & [0.7778, 0.8889] & [0.6316, 0.9474] & \dots[0.7778, 0.9444] \end{pmatrix}, \tag{43}$$

where $\otimes d_{ij}^* = \frac{\otimes d_{ij}^*}{\max_{1\leqslant i\leqslant 5}\overline{d}_{ij}}$.

Step 3. Weighted normalise the grey decision matrix. ($\otimes d_{ij}^* = d_{ij}' \times \otimes w_{ij}$).

Step 4. Compute the positive and negative ideal solutions.

1. The positive ideal solution is

$$\begin{aligned} D^+ &= \{\otimes d_1^+, \otimes d_2^+, \dots, \otimes d_{27}^+\} \\ &= \{[0.0058, 0.1248], [0.01, 0.0607], [0.0095, 0.0556], \dots[0.0005, 0.0188]\}, \end{aligned} \tag{44}$$

where $\otimes d_j^+ = \left[\max_{1\leqslant i\leqslant 5}\underline{d_{ij}^*}, \max_{1\leqslant i\leqslant 5}\overline{d_{ij}^*}\right]$, and

2. The negative ideal solution is

$$\begin{aligned} D^- &= \{\otimes d_1^-, \otimes d_2^-, \dots, \otimes d_{27}^-\} \\ &= [0.0043, 0.0985], [0.0086, 0.0472], [0.0079, 0.0468], \dots[0.0005, 0.0167]\}, \end{aligned} \tag{45}$$

where $\otimes d_j^* = \left[\min_{1\leqslant i\leqslant 5}\underline{d_{ij}^*}, \min_{1\leqslant i\leqslant 5}\overline{\widetilde{d}_{ij}^*}\right]$.

Step 5. Compute the separation from the ideal solution. Both positive and negative distances are obtained.

1. The positive ideal points are

$$\begin{aligned} D^+ &= (D_1^+ \quad D_2^+ \quad D_3^+ \quad D_4^+ \quad D_5^+)^T \\ &= (0.2862 \quad 0.2912 \quad 0.2998 \quad 0.3026 \quad 0.2965)^T, \end{aligned} \tag{46}$$

where $D_i^+ = \left(\frac{1}{2}\sum_{i=1}^n\left(\otimes d_{ij}^* - \otimes d_j^+\right)^\mu\right)^{\frac{1}{\mu}}$ and μ is the type of distance. The Euclidean distance ($\mu = 2$) is usually used.

2. The negative ideal points are

$$\begin{aligned} D^- &= (D_1^- \quad D_2^- \quad D_3^- \quad D_4^- \quad D_5^-)^T \\ &= (0.2588 \quad 0.2642 \quad 0.2749 \quad 0.2785 \quad 0.2707)^T, \end{aligned} \tag{47}$$

where $D_i^- = \left(\frac{1}{2}\sum_{i=1}^n\left(\otimes d_{ij}^* - \otimes d_j^-\right)^\mu\right)^{\frac{1}{\mu}}$.

Step 6. Calculate the similarities to the positive ideal solution. The similarities of the HRIS software to the positive ideal software are calculated using Eq. (48)

$$T = (0.4749 \quad 0.4757 \quad 0.4783 \quad 0.4792 \quad 0.4772) \approx (5^{th} \quad 4^{th} \quad 2^{nd} \quad 1^{st} \quad 3^{rd})^T, \tag{48}$$

where $T_i = \frac{D_i^-}{D_i^- + D_i^+}$.

Based on the ranks given by the evaluation methods, Spearman's correlation is computed. While the rankings of the grey-regime method, GRA, and GWSM are perfectly correlated, the grey-regime method and TOPSIS-G have a Spearman's correlation of 0.9. Therefore, based on the proposed grey-regime, GRA, GWSM, and TOPSIS-G methods, $A_3 > A_4 > A_5 > A_2 > A_1$. Based on the DMs' preferences, the HRIS provided by the third vendor (A_3) is the most preferred, and the one provided by the first vendor (A_1) is the least preferred.

4.4. *Discussion*

The direct percentage scores of the DMs were clustered in the 3rd and 4th percentiles, as shown in Fig. 4. The skewness may partly be because the DMs were Chinese, and they all experienced the Chinese education grading system, in which the cut-off mark between failing and passing an examination is 60%. In some other cultures, the cut-off mark between pass and fail could be the midpoint in the percentage scale, which is 50%. Some other regions may also have their own subjective opinions and use 40%. The subjective perspective is first addressed by scaling, and then the DM ratings are normalised.

Evidently, the PA and FUCOM methods resulted in different weights, as shown in Fig. 3. However, the PA weights were less dispersed with a standard deviation of 0.0266 than the FUCOM weights with a standard deviation of 0.1392. From Fig. 4, Quality (C_3) based on Maintainability (C_{3-5}) was the weight with the shortest bar, indicating that the DMs relatively agreed about the weight, but there was no perfect agreement. However, Technology (C_2) based on IoT (C_{2-3}) had the longest bar. This indicates that DMs had diverging opinions about the advantages that IoT could have for HRM. Therefore, it was the weight with the highest uncertainty. Only one vendor's HRIS had IoT-related services, as shown in Table 6, i.e. C_{2-3} for A_1, A_2, A_3, and A_5 was zero. Although the fifth vendor (A_5) had the least level of uncertainty as indicated by the shortest bar in Fig. 5, the low bound of the best vendor (A_3) is greater than its upper bound.

Undoubtedly, one evidence of a poor decision is not considering uncertainty, which includes uncertainty in group decision-making, computational methods, and performance values. For instance, the installation of an HRIS system could introduce a new problem in the organisation. In turn, this may require change management to reduce the risk involved in using the new technology. Not considering uncertainty is where the classical regime method falls short. Another gap in the classical regime method is that it was not designed for group decision-making. Both in–house organisation experts and theoretical experts, such as an HR professor, can be involved in a group decision-making method. This paper has addressed these problems by capturing uncertainty, using GST, by applying the proposed grey-PA-FUCOM and grey-regime methods.

The computational complexity of the proposed methods is further investigated here. The PA method for group decision making, which is the average point used as weight, has a linear time complexity, $O(mkn)$, where k is the level of hierarchy for m number of DMs and n number of criteria in each level. Similarly, the complexity of the FUCOM method is also $O(mkn)$. Then, the equivalent complexity for the grey-PA-FUCOM method is also $O(mkn)$. This is less complex in comparison to the AHP in group decision making, $O(mkn^4)$, for m number of DMs and n number of decision matrix with k-levels of hierarchy (Tung, 1998). However, note that Tung (1998) did not account for uncertainties, such as fuzzy and grey derivatives of the AHP. In other words, it is reasonable to consider the grey-regime method as an alternative pairwise comparison MCDM method for group decision-making under uncertainty since it has lower time complexity.

5. Managerial implication

The results show that researchers and practitioners have different preferences both in assigning points to evaluation criteria and MCDM methods. While researchers may give high priority to accuracy, HR managers in organisations may be comfortable with a less cumbersome approach for estimating the weights of evaluation criteria. Of course, MCDM advancements made by researchers present a real benefit to HR practitioners. However, many people, including HR managers, may not have the skills to read, understand, and apply newly developed MCDM methods in the literature. That is, today's advanced MCDM methods that are published and available to the public may still remain a black box to HR managers if they cannot understand it. A clear example of this is that it is uncommon to see HR managers using IBM CPLEX, LINGO and MATLAB in making day to day decisions in the workplace, like engineering jobs that require complex computation. In practice, staff from another department may be needed to handle the complex computations needed for advanced MCDM methods. Thus, it would be beneficial for academia to take the additional step to provide an easy interface, in the form of a computer program, as inputs to the model that will provide an intuitive output.

Furthermore, since successfully running an enterprise and its survival is associated with HRM, selecting an HRIS to support the effective operations of the company should be taken seriously by applying improved evaluation approaches developed in the literature. In addition, softwares are, in the end, a tool. Deploying HRIS should follow industry guides to avoid failure during implementation. Moreover, it should not be forgotten that HRIS consist of HRM and MIS i.e. the HR and IT departments work together. The managerial implication is that HRM practices must be maintained along with enforcement of IT practices. This may be done by directly transferring a well-rounded IT specialist to the HR department who would be fully responsible for maintaining the system. For instance, the IT department may be responsible for a fault-tolerance HRIS server, which may be redundancy in the system. At the same time, the HR department should be fully responsible for independently creating and testing regular backups of its departmental data. This is because a company's strategies depend on the HR department, and the loss of employees' records is an avoidable company disaster. To reiterate, fault tolerance is not a backup; the HR department should take full responsibility for backing-up and safely storing backed-up information, while the IT department can be responsible for keeping the system up and running with no interruption.

HRIS also provides the benefit of accurate record-keeping in a centralised location. On the one hand, it may be appropriate to install HRIS in the company's premises with remote accessibility through a virtual private network. On the other hand, HRIS as a cloud-based service can be deployed. HRIS deployed in the cloud brings the benefit of easy updates and little effort to manage the IT infrastructure supporting the company's software. The risk of both approaches must be evaluated. It should not be forgotten that employee information and business strategies are company secrets. Deploying the company's critical data on the cloud implies that the core aspects of the company's business are managed on another company's computer. In this case, HRIS data should maintain data integrity. Furthermore, storing data on the cloud that cannot be imported locally in a test server is not advisable.

Undoubtedly, organisational goals should drive the configuration of a HRIS that can affect the company's operational and organisational effectiveness. The managerial implication is that standard approaches in change management cannot be neglected. Even after selecting the best software, not following the best practices in change management, such as monitoring the software during implementation and fine-tuning, can derail the HRIS from being a profitable investment in the company. It may be best to concurrently use both old and new systems during the transitional period. In addition, employees should be mandatorily trained on the usage of the software. In fact, this training should be included in the on-boarding process, and can increase the use of self-service HR. Moreover, the training should go beyond the employees and include training the trainers. This is because the trainers in the organisation have the primary role of imparting knowledge. Thus, a trainer's in-depth knowledge about the factors affecting software deployment cannot be understated.

Nevertheless, despite the benefits and efficiency HRIS brings, it may be a double-edged sword. If the company does not grow to justify the number of staff in the HR department, it may lead to downsizing of the HR departments since more work can be done with fewer people. The managerial implication is that there should be a strategic plan in handling a smooth downsizing process in the HR department as the need arises. This may include transferring staff to other departments and suspending further recruitment of new HR staff whose duties have been automated. Overall, employees who are rigid with their old orientation and are using the HRIS partially may have to be relieved of their jobs in the company.

Finally, as much as HRIS speeds up business decision-making, the company's internal data may not be sufficient to make acceptable probabilistic and statistical decisions. In this case, the methods in GST for uncertainty decision-making can be applied since the GST primarily addresses decision problems with less information. The simplicity of the point allocation method for making on the spot assessment of a decision means that it may remain in use in the foreseeable future. However, MCDM weighting methods, such as FUCOM, are less computationally intensive than the decade's old traditional AHP. Thus, the managerial implication is that while top management may use PA for a quick decision, it is imperative for the HR department to consider uncertainty in decision-making. In this case, the grey-regime is among the grey hybrid MCDM methods that provides a pairwise comparison of the decision alternatives.

6. Conclusion

Decision-making is the process of making a judgement based on the circumstances before us. For companies to be innovative, they should be able to attract and retain the right talent, and appropriately reward employees. Beyond simple HRM processes such as leave applications and time records that an HRIS can provide, an HRIS could support HR expert-level jobs that include succession planning, the follow-ups of intern talent pools, and reviews. In MCDM, the main required components to reach any decision are alternatives, evaluation criteria, and the performance value of each alternative based on various criteria. Moreover, to improve the components of a decision outcome, other aspects should be considered, such as the weights of the criteria and the uncertainty in the group decision-making environment.

This paper uses GST to bridge the gap between the typical weight-assessment methods used by HR managers in the industry and the cutting-edge weight-assessment methods proposed by academics. A new hybrid that combines the PA and FUCOM methods with the GST, namely, the Grey-PA-FUCOM, is proposed. The Grey-PA-FUCOM weights were combined with the proposed grey-regime method to evaluate five HRIS' provided by different vendors. All rankings given by the four evaluation methods are highly correlated, thus increasing the DM confidence that the HRIS supplied by the third vendor (A_3) was the best.

This paper also has limitations. One limitation is that as the number of DMs increase, it may be cumbersome to customise a questionnaire for obtaining comparison priorities. Although a straightforward and advanced weight method has been developed, the workload of applying it in a corporate environment is almost as much as that of solely applying the advanced methods that academia uses in solving MCDM problems. Future studies can highlight the benefits of IoT for HRM and the approaches for using it to improve HRM practices. Finally, setting up a repository of software packages for MCDM methods to be easily installed as plug-ins or add-ins for data-processing suites, such as Microsoft Excel, would encourage HR managers to use these functions to solve decision-making problems using advanced methods.

CRediT authorship contribution statement

Moses Olabhele Esangbedo: Conceptualization, Methodology, Writing - original draft, Writing - review & editing. **Sijun Bai:** Supervision, Project administration. **Seyedali Mirjalili:** Validation, Writing - review & editing. **Zonghan Wang:** Data curation.

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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