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An Intuitionistic Fuzzy Consensus WASPAS Method for Assessment of Open-Source Software Learning Management Systems

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Abstract. Ineffective evaluation of open-source software learning management system (OSS-LMS) packages can negatively impact organizational effectiveness. Clients may struggle to select the best OSS-LMS package from a wide range of options, leading to a complex multi-criteria group decision-making (MCGDM) problem. This evaluates OSS-LMS packages based on several criteria like usability, functionality, e-learning standards, reliability, activity tracking, course development, assessment, backup and recovery, error reporting, efficiency, operating system compatibility, computer-managed instruction, authentication, authorization, troubleshooting, maintenance, upgrading, and scalability. Handling uncertain data is a vital aspect of OSS-LMS package evaluation. To tackle MCGDM issues, this study presents a consensus weighted sum product (c-WASPAS) method which is applied to an educational OSS-LMS package selection problem to evaluate four OSS-LMS packages, namely ATutor, eFront, Moodle, and Sakai. The findings indicate that the priority order of alternatives is Moodle > Sakai > eFront > ATutor and, therefore, MOODLE is the best OSS-LMS package for the case study. A sensitivity analysis of criteria weights is also conducted, as well as a comparative study, to demonstrate the effectiveness of the proposed method. It is essential to note that proper OSS-LMS package evaluation is crucial to avoid negative impacts on organizational performance. By addressing MCGDM issues and dealing with uncertain information, the c-WASPAS method presented in this study can assist clients in selecting the most appropriate OSS-LMS package from multiple alternatives. The findings of this study can benefit educational institutions and other organizations that rely on OSS-LMS packages to run their operations.

Key words: intuitionistic fuzzy set, cross entropy measure, consensus based WASPAS, OSS-LMS package selection.

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1. Introduction

The widespread implementation of the internet in recent times has resulted in the integration of Information and Communication Technology (ICT) into the everyday activities of educational institutions, research centres, organizations, government agencies, and individuals (Natarajan, 2015). The growth in ICT and the internet has enabled the development of new learning environments and techniques (Albarrak *et al.*, 2010), providing educational institutions with an innovative educational framework called e-learning. E-learning utilizes multimedia, such as audio, video, animations, and text illustrations, to deliver education and knowledge to students without any location barriers, thus offering an alternative to traditional classroom instruction. The most common form of e-learning is a software application called a learning management system (LMS). An LMS is a digital platform that provides a variety of tools and resources to facilitate and manage online learning. It allows instructors to create and deliver course content, track and assess student progress, and communicate with learners. Similarly, learners can access course materials, participate in discussions, complete assignments, and receive feedback (Ramesh and Ramanathan, 2013). LMSs are commonly used in educational institutions, corporations, and other organizations that offer training and development programs. However, the implementation of an LMS requires significant financial and institutional commitment (Edrees, 2013). According to Caminero *et al.* (2013), an LMS is also a software system comprised of various tools that support teaching and learning activities. Because of the rapid development of computer and internet-based technologies, LMS has become a critical component in the advancement of educational systems. As a result, many LMSs are now available online, including both authorized and free versions (Cavus, 2007). Many educational institutions spend a significant amount of time and money to implement LMSs (Edrees, 2013). Several LMSs have been presented as open-source software (OSS) licenses, including Moodle, Sakai, ATutor, Dokeos, and eFront, which are especially useful for e-learning (Awang and Darus, 2012). OSS is software that does not require a license and comes with the source code. It is intended to address the rising costs of campus-wide software while allowing the development of learner-centred structures (Abdullateef *et al.*, 2015, 2016b; van Rooij, 2011, 2012).

Selecting the wrong OSS-LMS package can have a negative impact on an organization's business processes and roles. If an organization selects the wrong OSS-LMS package, it may not meet its requirements and expectations, resulting in inadequate training, lower employee productivity, and decreased organizational performance. An unsuitable OSS-LMS package can result in increased costs and time associated with system modifications or replacements. It is thus crucial for organizations to carefully evaluate and select an appropriate OSS-LMS package that aligns with their specific needs and objectives to ensure efficient and effective management of their e-learning initiatives. However, due to the wide variety of available options, lack of user experience and knowledge, and constant development of information technology, the process of selecting the most suitable OSS-LMS has become increasingly complex (Jadav and Sonar, 2011; Zaidan *et al.*, 2015). Since multi-criteria decision-making (MCDM) methods have wide range of applications

(Ulutaš *et al.*, 2021; Semenas *et al.*, 2021; Filip, 2021; Krishankumar *et al.*, 2021; Ivanović *et al.*, 2022; Deveci *et al.*, 2022; Hezam *et al.*, 2023a; Deveci *et al.*, 2023; Gökmener *et al.*, 2023; Gokasar *et al.*, 2023a, 2023b; Petrovas *et al.*, 2023), MCDM methods can be used to assess and select the best OSS-LMS package by taking into account multiple conflicting criteria. MCDM methods consider multiple criteria and weigh their relative importance to arrive at a decision that best aligns with the organization's goals and objectives. The evaluation of OSS-LMS packages requires a thorough examination and investigation of various factors, such as usability, functionality, reliability, security, and compatibility with other systems. Organizations must carefully evaluate each criterion to ensure that the selected OSS-LMS package meets their specific needs and requirements. The application of MCDM methods enables organizations to streamline their decision-making process and make well-informed decisions regarding the selection of an OSS-LMS package.

Literature research has uncovered that various scholars have utilized diverse strategies for the assessment and determination of LMSs. The investigation carried out by Waynet Inc. (2007) depicted an overview style assessment of open-source LMSs aiming to suggest an LMS that could be applied by the Commonwealth of Learning. Hultin's (2007) studied LMSs and how to assess them, contingent upon the learning condition and the customers' needs. Graf and List (2005) introduced an appraisal of open-source e-learning stands by concentrating on the adaptation competences of the framework. Another assessment of LMSs was described by Wyles (2007). It was divided into two parts: 1st part portrayed the outcomes of an underlying assessment of open-source LMS software and the 2nd part described the assessment technique applied to choose the best LMS as a feature of the overall platform architecture. Kljun *et al.* (2007) aimed to assist the individuals who are engaged in e-learning to assess optimal LMS to suit them. The writers categorized the operators of LMSs into three clusters: learners, tutors, and administrators. Arh and Blazic (2007) devised an MCDM model that employs an expert structure to choose the most appropriate and effective LMS from Blackboard 6, Moodle 1.5.2, and CLIX 5.0. Machado and Tao (2007) examined the client experience of two competing LMSs, Moodle and Blackboard, based on their ease of use and viability. Çetin *et al.* (2010) used Analytical Hierarchy Process (AHP) method to address the problem of LMS evaluation using nine evaluation criteria. Albarrak *et al.* (2010) evaluated three OSS-LMSs: Jusur, Moodle, and Sakai. Srdevic *et al.* (2012) used AHP to select the most reasonable LMSs as well. Caminero *et al.* (2013) utilized a performance assessment technique for three OSS-LMSs, namely dotLRN, Moodle, and Sakai. Edrees (2013) assessed two LMSs, Blackboard, and Moodle, based on their readiness to support Web 2.0. Ramesh and Ramanathan (2013) developed a tool to assess LMSs based on six categories of criteria. Işik *et al.* (2015) applied fuzzy AHP for choosing the best LMS based on nine considered criteria. Hock *et al.* (2015) assessed three OSS-LMSs, namely Atutor, Ilias, and Moodle, based on the dependence on the convenience and utilized acknowledgment of the systems. Abdullateef *et al.* (2016a) introduced the assessment and determination of three OSS-LMSs based on the three directions, namely collection of available three OSS-LMSs, detail of the assessment criteria, and capability of the selection techniques. Karagöz *et al.* (2017) built up a mobile app for finding analogy of two open-source LMSs and two commercial LMS dependent

Table 1
Summary of existing works on LMS selection.

Reference	Primary focus
Waynet Inc. (2007)	Overview style assessment of open-source LMSs
Hultin's (2007)	Assessment of LMSs depending upon the learning condition and the customers' needs
Graf and List (2005)	Appraisal of open-source e-learning stands by concentrating on the adaptation competences of the framework
Wyles (2007)	LMS assessment based on OSS software and overall platform architecture
Kljun *et al.* (2007)	To assist the individuals who are engaged in e-learning
Arh and Blazic (2007)	Devised an MCDM model that employs an expert structure to choose the most appropriate and effective LMS from Blackboard 6, Moodle 1.5.2, and CLIX 5.0.
Machado and Tao (2007)	Examined the client experience of two competing LMSs, Moodle and Blackboard, based on their ease of use and viability
Cetin *et al.* (2010)	LMS evaluation using Analytical Hierarchy Process (AHP)
Albarrak *et al.* (2010)	Evaluated three OSS-LMSs: Jusur, Moodle, and Sakai.
Srdevic *et al.* (2012)	Selection of the most reasonable LMS using AHP tool
Caminero *et al.* (2013)	Performance assessment for three OSS-LMSs, namely dotLRN, Moodle, and Sakai.
Edrees (2013)	Assessment of two LMSs, Blackboard, and Moodle, based on their readiness to support Web 2.0
Işik *et al.* (2015)	LMS selection using fuzzy AHP
Hock *et al.* (2015)	Assessment of three OSS-LMSs, namely- Atutor, Ilias, and Moodle based on dependent on the convenience.
Abdullateef *et al.* (2016b)	Determination of the suitable LMS based on collection of available OSS packages, detail of the assessment criteria, and capability of the selection techniques
Karagöz *et al.* (2017)	Built up a mobile app for finding analogy of two open-source LMSs and two commercial LMS
Adewumi *et al.* (2019)	Evaluation of LMS software using experts opinions
Al Amoush and Sandhu (2020)	Focused on the instructor's perspective for evaluating LMS uses
Santiago *et al.* (2020)	Determination of the academic efficiency performance by evaluating different LMS systems
Alturki and Aldraiweesh (2021)	Determination of efficiency of LMS model during covid-19 period

on some specific criteria. Adewumi *et al.* (2019) tried to evaluate the LMS software selection using questionnaires for experts and their suggestions. Al Amoush and Sandhu (2020) has focused on the instructor's perspective for evaluating LMS uses. Santiago *et al.* (2020) tried to determine the academic efficiency performance by evaluating different LMS systems. Alturki and Aldraiweesh (2021) proposed a model which shows the efficiency of LMS model during covid-19 period. A summary of these works is presented below (see Table 1).

1.1. *Research Gaps and Our Contributions*

The idea of fuzzy sets (FSs) was developed by Zadeh (1965), primarily as a result of taking confusing human judgments into account while resolving practical issues. FS philosophy plays a crucial role in shaping the understanding and interpretation of reality based on computational observations. It acknowledges and embraces the presence of ambiguity, partial belongingness, and inaccuracy in real-world phenomena. By incorporating these aspects into the analysis and decision-making process, FS philosophy provides a more comprehensive and nuanced perspective on complex systems and their behaviours. This allows for a more realistic representation and modelling of uncertain and imprecise information, leading to improved insights and outcomes in various fields, such as artificial intelligence, data science, and decision science. Atanassov (1986) presented the Intuitionistic FS (IFS) as a generalization of FS to deal with situations with incomplete data by using a non-belongingness grade. Since its introduction, IFS has been used by many researchers for solving group decision-making issues. Unfortunately, none of the existing IF decision support models, namely IF-Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) (Rouyendegh *et al.*, 2020), IF-Multi-Objective Optimization on the basis of Ratio Analysis with multiplicative form (MULTIMOORA) (Garg and Rani, 2022), IF-Evaluation based on Distance from Average Solution (EDAS) (Mishra *et al.*, 2020), IF-COmplex PRoportional ASsessment (COPRAS) (Kumari and Mishra, 2020), and IF-measurement of alternatives and ranking according to compromise solution (MARCOS) (Deb *et al.*, 2022) don't deal with the "consensus-reaching process" for experts. Because of their knowledge and backgrounds, decision makers in multi-criteria group decision-making problems may have opinions that are very different from one another. As a result, a consensus-building process is required for the decision-makers to raise the level of unanimity (Liu and Huang, 2020). Although many consensus models (Herrera *et al.*, 1996; Dong *et al.*, 2010; Herrera-Viedma *et al.*, 2014; Gong *et al.*, 2015; Liao *et al.*, 2016; Wu and Xu, 2016; Zhang *et al.*, 2018; Wu and Liao, 2019) were developed earlier, no consensus model has been developed so far with IF numbers. Moreover, in the aforementioned studies on consensus process, the information was not adjusted before it was aggregated, which may have resulted in irrational decision results.

The selection of appropriate OSS-LMS packages is a significant and uncertain MCDM challenge that is primarily taken into account by many educational organizations due to faulty information, hazy human observation, and time constraints. Numerous academics have focused on the creation of novel MCDM approaches due to the setting's growing complexity and widespread variations. MCDM methods can be divided into two categories (Saha *et al.*, 2022): (i) utility-based models like COPRAS, Weighted Aggregated Sum Product Assessment (WASPAS), MARCOS, and MULTIMOORA, and (ii) outranking models like Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE), Elimination and Choice Translating Reality (ELECTRE) and Organization REgarding SYnthesis of the criteria for Rankings of TEchnical alternatives (ORESTE). Due to complicated computations, the outranking techniques have trouble managing numerous choices and criteria. The utility-based models are helpful in treating MCDM issues when there are many experts and criteria involved. WASPAS was developed by Zavadskas *et al.* (2012) as a unique utility degree-based MCDM method to deal with a variety of realistic decision-making concerns. The benefits of WASPAS are as follows: (a) it employs a straightforward method of calculation, (b) it can select the most preferred alternative by making use of AOs, (c) being a mixture of Weighted Sum Model (WSM) and Weighted Product Model (WPM), it has more accuracy, and (d) it allows us to estimate with the maximum amount of accuracy conceivable. WASPAS method has not been merged with consensus reaching to get a reasonable outcome in OSS-LMS package selection problem.

Motivated by the above facts, this present work is dedicated to address the ambiguity and vagueness that arise during the assessment of OSS-LMS packages. To achieve this, a robust and logical decision-making model has been proposed in this paper. The contributions can be summarized as follows:

- A consensus IF-WASPAS approach is developed to tackle group decision-making issues.
- To demonstrate the applicability of the consensus based IF-WASPAS technique, a real-world case study for the selection of OSS-LMS packages is explored.
- In order to verify the conclusions reached by the proposed method, a sensitivity investigation of criteria weights is also presented.
- In order to prove the superiority of the developed approach, a comparative analysis is presented.

1.2. *Arrangement of the Paper*

A brief review of the literature is provided in Section 2. Few essential concepts related to IF sets are introduced in Section 3. An IF consensus WASPAS (IF-c-WASPAS) strategy is designed in this section, where the criteria values are represented by IFNs. The proposed method is clarified using a case study of OSS-LMS package selection in Section 4. Sensitivity analysis of criteria weights and comparative analysis are covered in Section 5. Conclusions are drawn from the entire study, and a summary of the prospects for the future is provided in Section 6.

2. Literature Review

2.1. *IFSs*

IFS sets are an extension of FSs which introduce the concept of non-membership degree to represent the degree to which an element does not belong to a set. In an IFS, each element is associated with three values: membership degree, non-membership degree, and hesitation degree. Membership degree, non-membership degree, and hesitation degree are fundamental concepts in FS theory. These degrees are used to quantify the relationship between elements and FSs, taking into account uncertainty and imprecision. The membership degree indicates the degree to which an element belongs to a particular FS. It represents the extent of similarity or relevance of the element to the set. A membership degree of 1 indicates full membership, while a degree of 0 indicates no membership at all. The non-membership degree, on the other hand, represents the degree to which an element does not belong to a FS. It captures the degree of dissimilarity or rejection of the element from the set. A non-membership degree of 1 implies complete non-membership, while a degree of 0 suggests full membership. The hesitation degree reflects the level of uncertainty or hesitation in assigning the membership and non-membership degrees to an element. It accounts for situations where the degree of belongingness or non-belongingness is not clearly defined. A higher hesitation degree indicates greater ambiguity or lack of confidence in assigning the membership and non-membership degrees. These three degrees work together to provide a more nuanced and flexible representation of the relationship between elements and FSs, allowing for a more realistic modelling and analysis of complex and uncertain information. IFSs have found several applications in various fields. Mukherjee (2017) selected the best fuel technology for land transportation subject to multiple criteria resulting in a sustainable transportation system. Büyüközkan *et al.* (2018) evaluated different public bus technologies as urban transportation alternatives. Wang *et al.* (2018) assessed consumer satisfaction in urban rail travel. Mishra *et al.* (2019c) solved a multi-criteria IT personnel selection problem with IF measures and Additive Ratio Assessment (ARAS) method. Mishra *et al.* (2020) utilized IF-EDAS methodology for evaluation of health-care waste disposal technologies. Kumari and Mishra (2020) used IF-parametric measures and IF-COPRAS for selecting green suppliers. Rouyendegh *et al.* (2020) utilized IF-TOPSIS approach for green supplier choice. Rani *et al.* (2021) assessed the performance of telecom service providers using IF-grey relational analysis. Yuan and Yang (2021) developed a dynamic MCDM model based on IF data. Tugrul (2022) developed a IFS based decision-making methodology for evaluation of paper quality. Buran and Erçek (2022) presented a business model canvas framework for public transportation organizations. Yan *et al.* (2022) provided a framework to determine the priority of a rail transit system from the perspective of green and low carbon. Palanisami *et al.* (2022) developed a new approach of multi-modal medical image fusion using IF sets. Deb *et al.* (2022) developed a decision-making model for the selection of enterprise resource planning systems. Gohain *et al.* (2022) developed a symmetric distance formula and applied it to practical problems of decision-making, pattern recognition, and clustering problems. Rasoulzadeh *et al.* (2022) introduced a multi-objective approach to the portfolio selection problem. Hezam *et al.* (2022) developed a hybrid IF-method based on the removal effects of criteria (MEREC), ranking sum (RS), and double normalization-based multi-aggregation (DNMA) (MEREC-RS-DNMA) methodology for assessment of alternative fuel vehicles. Senapati *et al.* (2023) developed an advanced decision-support model for the prioritization of sustainable transportation-sharing practices. Çakır and Taş (2023) defined circular IFSs for solving supplier selection problem. Mishra *et al.* (2023) used IF fairly aggregation operators and ARAS based model for assessing sustainable industrial buildings. An IF entropy based methodology was proposed by Hezam *et al.* (2023b) for assessment of sustainable supplier.

2.2. *WASPAS method*

WASPAS is a weighted aggregation approach in which each criterion is assigned a weight that represents its relative importance in the decision-making process. The performance of each alternative is assessed by multiplying its evaluation score on each criterion by the corresponding weight, and then summing up the weighted scores across all criteria.

The alternative with the highest aggregated score is considered the best choice. WASPAS is widely used in various fields, including decision science, operation research, and engineering, to support decision-making processes that involve multiple criteria and alternatives. Deveci *et al.* (2018) developed interval type-2 FSs-based model with WASPAS and TOPSIS methods. Stanujkic and Karabasevic (2018) proposed IF-WASPAS method to survey the websites. Mishra and Rani (2018) assessed reservoir flood control management using interval-valued IF-WASPAS technique with information measures. Pamučar *et al.* (2019) identified safety advisors for hazardous material transportation using linguistic neutrosophic WASPAS. Mishra *et al.* (2019a) assessed the mobile phone service providers using IF-WASPAS. Mishra *et al.* (2019b) developed hesitant fuzzy-WASPAS method for green supplier selections. Kahraman *et al.* (2019) introduced Pythagorean fuzzy WASPAS model for the selection of the most reasonable administrators. Keshavarz-Ghorabaee *et al.* (2019) worked on the assessment of sustainable developed strategies using Type-2 fuzzy-based WASPAS and Sequential Elimination and Choice Translation (SECA) methods. Bid and Siddique (2019) assessed human hazards resultant combination of WASPAS and TOPSIS. Gundogdu and Kahraman (2019) investigated robot selection problem for the industry using WASPAS method with spherical fuzzy data. Krishankumar *et al.* (2019) worked on the selection of construction project risk technique statistical variance and WASPAS. Schitea *et al.* (2019) selected the best hydrogen mobility roll-up site utilizing integrated WASPAS, COPRAS, and EDAS under intuitionistic FSs. Dorfeshan and Mousavi (2020) assessed critical paths of aircraft maintenance planning using a coordinated MABAC and WASPAS under the interval type-2 fuzzy setting. To address the doctor recruitment issue, Sharma and Pradhan (2020) examined the machinability criteria for SUS-304L steel using WASPAS model for FSs. Mohagheghi and Mousavi (2020) resolved a sustainable project portfolio problem using WASPAS method with interval-valued Pythagorean FSs. Davoudabadi *et al.* (2020) addressed a supplier evaluation issue by utilizing a combined approach using TOmada de Decisao Interativa Multicriterio (TODIM), WASPAS, and TOPSIS methods under interval-valued IF setting. For assessing desirable alternative-fuel technology, Rani and Mishra (2020) used WASPAS with q-rung orthopair fuzzy data. Badalpur and Nurbakhsh (2021) investigated the negative impacts of risks on the project using WASPAS. Rudnik *et al.* (2021) worked on the selection of improvement projects with ordered fuzzy WASPAS method. Simić *et al.* (2021) solved the issue of selection of last-mile delivery mode using Picture fuzzy WASPAS method. The selection of eco-friendly vendors was done by Liu *et al.* (2022) under Bipolar complex fuzzy environment with Criteria Importance Through Intercriteria Correlation (CRITIC)-WASPAS model. Senapati and Chen (2022) utilized picture fuzzy WASPAS technique for solving MCDM issues. Handayani *et al.* (2023) used WASPAS method for selection of online English course. Assis *et al.* (2023) applied WASPAS tool to select appropriate helicopters for aerial activities. Arisantoso *et al.* (2023) used WASPAS method for webcam selection.

3. Preliminaries

Definition 1 (Atanassov, 1986). An IFS ζ on Γ is described by $\varphi = \{\langle y_i, \alpha(y_i), \beta(y_i)\rangle \mid y_i \in \Gamma\}$, $\alpha, \beta : \Gamma \rightarrow [0, 1]$ being the membership and non-membership functions respectively, satisfying $0 \leqslant \alpha(y_i) + \beta(y_i) \leqslant 1$. Also we use $\pi(y_i) = 1 - \alpha(y_i) - \beta(y_i)$. An IFS ζ transforms to an IF number (IFN) if Γ contains only one element and we write $\varphi = \langle \alpha, \beta \rangle$, for $\alpha, \beta \in [0, 1]$ and $0 \leqslant \alpha + \beta \leqslant 1$.

Definition 2 (Deb *et al.*, 2022). Consider an IFN $\varphi = \langle \alpha, \beta \rangle$. Then:

$$\begin{aligned} &s(\varphi) = \frac{1}{2}(1 + \alpha - \beta), \\ &a(\varphi) = \alpha + \beta \end{aligned} \tag{1}$$

are known as the accuracy and score values of φ, where $s(\varphi) \in [0, 1]$ and $a(\varphi) \in [0, 1]$. For the IFNs $\varphi_1 = \langle \alpha_1, \beta_1 \rangle$ and $\varphi_2 = \langle \alpha_2, \beta_2 \rangle$, a ranking rule is:

(i) $\varphi_1 \succ \varphi_2 \left| \begin{array}{l} s(\varphi_1) > s(\varphi_2), \\ s(\varphi_1) = s(\varphi_2),\ a(\varphi_1) > a(\varphi_2), \end{array} \right.$

(ii) $\zeta_1 = \zeta_2 \mid \mathbb{S}_{\zeta_1} = \mathbb{S}_{\zeta_2}, \mathbb{A}_{\zeta_1} = \mathbb{A}_{\zeta_2}$.

Definition 3 (Deb *et al.*, 2022). For the IFNs $\varphi_1 = \langle \alpha_1, \beta_1 \rangle$ and $\varphi_2 = \langle \alpha_2, \beta_2 \rangle$, the basic operations are:

(i) $\varphi_1^c = \langle \beta_1, \alpha_1 \rangle$,

(ii) $\varphi_1 \oplus \varphi_2 = \langle \alpha_1 + \alpha_2 - \alpha_1\alpha_2, \beta_1\beta_2 \rangle$,

(iii) $\varphi_1 \otimes \varphi_2 = \langle \alpha_1\alpha_2, \beta_1 + \beta_2 - \beta_1\beta_2 \rangle$,

(iv) $\lambda\varphi_1 = \langle 1 - (1 - \alpha_1)^\lambda, \beta_1^\lambda \rangle$ $(\lambda > 0)$,

(v) $\varphi_1^\lambda = \langle \alpha_1^\lambda, 1 - (1 - \beta_1)^\lambda \rangle$ $(\lambda > 0)$.

Definition 4 (Deb *et al.*, 2022). Assume $\varphi_t = \langle \alpha_t, \beta_t \rangle$, $t = 1, 2, \dots, l$ be IFNs. Then IFWA and IFWG operators are given respectively by

$$IFWA(\varphi_1, \varphi_2, \dots, \varphi_n) = \bigoplus_{t=1}^{l} w_t\varphi_t = \left\langle 1 - \prod_{t=1}^{l}(1 - \alpha_t)^{w_t}, \prod_{t=1}^{l} \beta_t^{w_t} \right\rangle, \tag{2}$$

$$IFWG(\varphi_1, \varphi_2, \dots, \varphi_n) = \bigotimes_{t=1}^{l} \zeta_t^{w_t} = \left\langle \prod_{t=1}^{l} \alpha_t^{w_t}, 1 - \prod_{t=1}^{l}(1 - \beta_t)^{w_t} \right\rangle, \tag{3}$$

where w_t is the weight of φ_t, with $\sum_{t=1}^{l} w_t = 1$, $w_t \in [0, 1]$.

4. Consensus WASPAS Method

The weighted sum model (WSM) and weighted product model (WPM) were combined by Zavadskas *et al.* (2012) to develop a unique utility degree-based MCDM method referred to as WASPAS. This methodology was designed to deal with a variety of realistic decision-making concerns. WASPAS allows decision-makers to flexibly assign weights to criteria based on their relative importance, reflecting the preferences and priorities of the decision-maker. It considers multiple criteria simultaneously, enabling a comprehensive assessment of alternatives based on different dimensions or factors. The method aggregates the performance scores using the weighted sum product approach, which takes into account the interdependencies among criteria and the performance of alternatives. WASPAS method provides a transparent decision-making process, as it allows decision-makers to clearly understand how the final scores are calculated and how each criterion contributes to the overall evaluation. Unfortunately, WASPAS model fails to deal with the "consensus-reaching process" for experts. To tackle this, we present a consensus WASPAS methodology with IF data. The procedural steps of the proposed consensus-based decision-making model are as follows:

Step 1: Construct the initial IF decision matrices.

Assume that m is the number of alternatives Q_k $(k = 1, 2, \dots, p)$ and n is the number of criteria T_t $(t = 1, 2, \dots, q)$ connected with a group decision-making issue in which each alternative is evaluated by the decision-makers E_r $(r = 1, 2, \dots, l)$ under the IF environment. Consider that the initial findings examined by the decision-makers are depicted as the IF decision matrices $M_r = [\varphi_r^{(kt)}]_{p\times q} = [\langle \alpha_r^{(kt)}, \beta_r^{(kt)} \rangle]_{p\times q}$.

Step 2: Obtain the aggregated IF decision matrix by employing the IFWA (or IFWG) operator.

The aggregated IF decision matrix is $[\varphi^{(kt)}]_{p\times q} = [\langle \alpha^{(kt)}, \beta^{(kt)} \rangle]_{p\times q}$, where:

$$\begin{aligned} &\varphi^{(kt)} = IFWA\big(\varphi_1^{(kt)}, \varphi_2^{(kt)}, \dots, \varphi_l^{(kt)}\big) = \bigoplus_{r=1}^{l}\big(\delta_r \varphi_r^{(kt)}\big) \\ \text{or}\quad &\varphi^{(kt)} = IFWG\big(\varphi_1^{(kt)}, \varphi_2^{(kt)}, \dots, \varphi_l^{(kt)}\big) = \bigotimes_{r=1}^{l}\big(\varphi_r^{(kt)}\big)^{\delta_r}, \end{aligned} \tag{4}$$

where δ_r is the weight of E_r.

Step 3: Find the consensus degree of each decision-maker.

Utilizing the fact that the correlation measure is capable of describing the similarity degree between various opinions, we define the correlation measure $\psi_t^{(r)}$ of the decision-maker E_r under the criterion T_t in this way:

$$\psi_t^{(r)} = \frac{\sum_{k=1}^{p}\left[\begin{array}{c}\left(\frac{Dist_{kt}^{(r)}}{Dist_t^{(r)}} - \frac{1}{m}\sum_{k=1}^{p}\frac{Dist_{kt}^{(r)}}{Dist_t^{(r)}}\right)\\ \times\left(\frac{Dist_{kt}}{Dist_t} - \frac{1}{m}\sum_{k=1}^{p}\frac{Dist_{kt}}{Dist_t}\right)\end{array}\right]}{\left(\begin{array}{c}\sqrt{\sum_{k=1}^{p}\left(\frac{Dist_{kt}^{(r)}}{Dist_t^{(r)}} - \frac{1}{m}\sum_{k=1}^{p}\frac{Dist_{kt}^{(r)}}{Dist_t^{(r)}}\right)^2}\\ \times\sqrt{\sum_{k=1}^{p}\left(\frac{Dist_{kt}}{Dist_t} - \frac{1}{m}\sum_{k=1}^{p}\frac{Dist_{kt}}{Dist_t}\right)^2}\end{array}\right)} \tag{5}$$

$(t = 1, 2, \dots, q;\ r = 1, 2, \dots, l)$, where

$$\varphi_r^{(kt)(+)} = \Big\langle \max_k \alpha_r^{(kt)}, \min_k \beta_r^{(kt)} \Big\rangle, \qquad \varphi_r^{(kt)(-)} = \Big\langle \min_k \alpha_r^{(kt)}, \max_k \beta_r^{(kt)} \Big\rangle,$$
$$\varphi^{(kt)(+)} = \Big\langle \max_k \alpha^{(kt)}, \min_k \beta^{(kt)} \Big\rangle, \qquad \varphi^{(kt)(-)} = \Big\langle \min_k \alpha^{(kt)}, \max_k \beta^{(kt)} \Big\rangle,$$
$$Dist_{kt}^{(r)} = Dist\big(\varphi_r^{(kt)}, \varphi_r^{(kt)(+)}\big), \qquad Dist_t^{(r)} = Dist\big(\varphi_r^{(kt)(+)}, \varphi_r^{(kt)(-)}\big),$$
$$Dist_{kt} = Dist\big(\varphi^{(kt)(+)}, \varphi^{(kt)}\big), \qquad Dist_t = Dist\big(\varphi^{(kt)(+)}, \varphi^{(kt)(-)}\big).$$

Next, the consensus degree $\rho^{(r)}$ of the decision-maker E_r can be defined as:

$$\rho^{(r)} = \frac{1}{q}\sum_{t=1}^{q} \psi_t^{(r)} \quad (r = 1, 2, \dots, l). \tag{6}$$

It can be verified that $-1 \leqslant \rho^{(r)} \leqslant 1$. The greater value $\rho^{(r)}$ means the stronger consensus degree of the decision-maker E_r in the group. If ρ denotes the minimum consensus degree, then $\rho^{(r)} \geqslant \rho$ needs to be attained. When $\rho^{(r)} < \rho$, the FF decision matrices from Step 1 should be modified until $\rho^{(r)} \geqslant \rho$ is obtained for all decision-makers.

Step 4: Normalize the aggregated IF decision matrix.

Suppose that the normalized aggregated IF decision matrix is $[\tilde{\varphi}^{(kt)}]_{p\times q} = [\langle \tilde{\alpha}^{(kt)}, \tilde{\beta}^{(kt)} \rangle]_{p\times q}$, where:

$$\tilde{\varphi}^{(kt)} = \begin{cases} \langle \alpha^{(kt)}, \beta^{(kt)} \rangle, & \text{if } C_t \text{ is beneficial criterion,} \\ \langle \beta^{(kt)}, \alpha^{(kt)} \rangle, & \text{if } C_t \text{ is non-beneficial criterion.} \end{cases} \tag{7}$$

Step 5: Estimate the IF "relative significance degree" (RSD) for every alternative.

Suppose ϑ_t is the weight of T_t $(t = 1, 2, \dots, q)$ with $\sum_{t=1}^{q} \vartheta_t = 1$ and $0 \leqslant \vartheta_t \leqslant 1$.

Step 5.1: The IF-RSD of Q_k using WSM is calculated as:

$$\overline{RSD}(Q_k) = \bigoplus_{t=1}^{q} \big(\vartheta_t \tilde{\varphi}^{(kt)}\big). \tag{8}$$

The IF-RSD of Q_k using WPM is calculated as:

$$\overline{\overline{RSD}}(Q_k) = \bigotimes_{t=1}^{q} \big(\tilde{\varphi}^{(kt)}\big)^{\vartheta_t}. \tag{9}$$

Step 5.2: The overall IF significance degree of Q_k is calculated by:

$$\eta_k = \big(w\overline{RSD}(Q_k)\big) \mathbin{\tilde{\oplus}} \big((1-w)\overline{\overline{RSD}}(Q_k)\big) \quad (k = 1, 2, \dots, p), \tag{10}$$

Table 2
Description of the OSS-LMS alternatives.

OSS-LMS	Depiction
ATutor (Q_1)	ATutor is an open-source LMS designed for flexibility and convenience. Administrators can easily install or update the software, customize templates for a unique look and feel, and extend functionality with innovative modules. (http://www.atutor.ca/).
MOODLE (Q_2)	Moodle is the most popular open-source LMS, offering teachers, administrators, and students a robust, secure, and integrated system for learning environments. (Moodle.org).
eFront (Q_3)	eFront LMS provides the best open-source solutions for e-learning, with a flexible, powerful, efficient, and fully functional structure. (http://www.efrontlearning.net/).
Sakai (Q_4)	Sakai is an open-source LMS that provides a flexible and versatile platform for teaching, training, research, and other collaborations. It is constantly evolving based on the needs of faculty, students, and organizations. (https://sakaiproject.org/).

or

$$\eta_k = \left(\widetilde{RSD}(Q_k)\right)^{w} \tilde{\otimes} \left(\overline{\widetilde{RSD}}(Q_k)\right)^{(1-w)} \quad (k = 1, 2, \ldots, p). \tag{11}$$

Here, $w \in [0, 1]$. For $w = 1$, and $w = 0$, WASPAS reduces to WSM and WPM, respectively.

Step 6: Compute the scores of the IFNs η_k $(k = 1, 2, \ldots, p)$.

Step 7: Generate the ranking order of alternatives and chose the best option.

5. Case Study & Solution

A. Problem Description

In order to avoid face-to-face interactions, the COVID-19 pandemic has forced many educational institutions to quickly move from traditional attendance-based education to online distance learning. Online distance learning can be either synchronous or asynchronous, depending on the mechanism of delivery. During any pandemic situation like Covid-19, it is very essential for an educational institution to select an appropriate OSS-LMS package to manage administration, monitoring, reporting of online classes and training programs, create a virtual classroom where teachers can interact with their students and conduct learning activities online. Suppose an educational institution wants to select an efficient OSS-LMS package out of four OSS-LMS packages: **ATutor (Q1)** (Graf and List, 2005; Abdullateef *et al.*, 2016a), **eFront (Q3)** (Abdullateef *et al.*, 2016b), **Moodle (Q2)** (Caminero *et al.*, 2013; van Rooij, 2011; Abdullateef *et al.*, 2016a, 2016b; Graf and List, 2005), and **Sakai (Q4)** (Caminero *et al.*, 2013; van Rooij, 2011; Abdullateef *et al.*, 2016a, 2016b; Graf and List, 2005). Their information is given in Table 2.

In this study, four OSS-LMS are being considered as alternatives and will be evaluated based on fifteen criteria. The criteria and their corresponding citations, arranged by publication year within each criterion, are as follows: **Activity Tracking (T1):** (Graf and List, 2005; Arh and Blazic, 2007; Srdevic *et al.*, 2012; Abdullateef *et al.*, 2016a); **Reliability (T2)**: (Jadav and Sonar, 2011; Srdevic *et al.*, 2012; Abdullateef *et al.*, 2016b);

Course Development (T3): (Graf and List, 2005; Arh and Blazic, 2007; Srdevic *et al.*, 2012; Abdullateef *et al.*, 2016a); **Assessment (T4):** (Arh and Blazic, 2007; Graf and List, 2005; Srdevic *et al.*, 2012; Abdullateef *et al.*, 2016a); **Backup and Recovery (T5):** (Arh and Blazic, 2007; Srdevic *et al.*, 2012; Abdullateef *et al.*, 2016a); **Error Reporting (T6)**: (Jadav and Sonar, 2011; Abdullateef *et al.*, 2016a); **Efficiency (T7)**: (Abdullateef *et al.*, 2016b); **DBMS standards (T8)** (Jadav and Sonar, 2011; Abdullateef *et al.*, 2016b); **OS compatibility (T9)** (Jadav and Sonar, 2011; Abdullateef *et al.*, 2016b); **IMS LIP (T10)** (Arh and Blazic, 2007; Srdevic *et al.*, 2012; Abdullateef *et al.*, 2016a); **AICC Computer managed Instruction (T11)** (Arh and Blazic, 2007; Srdevic *et al.*, 2012; Abdullateef *et al.*, 2016a); **Authentication (T12)** (Arh and Blazic, 2007; Graf and List, 2005; Srdevic *et al.*, 2012; Abdullateef *et al.*, 2016b); **Authorization (T13)** (Arh and Blazic, 2007; Srdevic *et al.*, 2012; Abdullateef *et al.*, 2016a); **Troubleshooting, maintenance and upgrading (T14)** (Caminero *et al.*, 2013; Abdullateef *et al.*, 2016b); and **Communication synchronous and asynchronous (T15)** (Arh and Blazic, 2007; Graf and List, 2005; Srdevic *et al.*, 2012; Abdullateef *et al.*, 2016a).

Details of the criteria based on which OSS-LMS packages are to be evaluated are:

1) Activity Tracking (T1):

Monitoring students' learning activities is a part of activity tracking in the classroom. The reports are meant to offer the instructor a sense of what occurs in a pedagogically important course. Progress reports are part of course analysis, which often also includes time stamps for the activities' occurrences. The handling level of the course and participants may be checked by the tutor. The first and last login dates and times are also visible to the course tutor. A tutor can view the amount of time spent on the course or other activities for specific pupils.

2) Reliability (T2):

The software can function continuously without crashing. Software package reliability refers to its capacity to operate consistently under particular circumstances without crashing. The degree of fault tolerance for the software is evaluated using consistency. The number of crashes during a certain task's execution can also be monitored to gauge dependability.

3) Course Development (T3):

The organization of the course using a web interface satisfies modifying the course outline, the curriculum, the inclusion of customization of the student tools, the communication tools, etc. The course's content and structure are both easily editable by the author. Content navigation tools are generated automatically by the system. A single zip package may be used to upload and download HTML pages, pictures, and Flash videos. Links must be built between content pages, between courses, and to student tools. The content and course format may both be readily changed by the instructor. The content navigation can be generated automatically by the system.

4) Assessment (T4:)

The test's questions and format may be simply created or modified by the tutor. The system enables the learner to evaluate themselves. This feature allows the student to evaluate themselves. The method offers online evaluation. The mechanism makes student transcripts available. A quiz editor is provided by the system. With assessment, the tutor has the option to put the student to the test in a variety of ways. several testable possibilities. The test's questions and content format may simply be edited by the author. Features automated evaluation of the reliability of the test questions and the capacity to import tests from other programs and systems.

5) Backup and recovery (T5):

The software package is capable of providing backup and recovery features. The DBMS backup and recovery subsystem is in charge of recovery. For example, if the computer system breaks in the middle of a complicated update transaction, the recovery subsystem is in charge of restoring the database to the condition it was in before the transaction began. The recovery time target is the maximum amount of time required to get your learning management system back up and running after a failure. When it comes to judging how secure your computer systems are, the RTO is by far the most disregarded criterion. "Are we backed up?" business owners frequently inquire. Usually, the response is "yes".

6) Error reporting (T6):

One of the most significant requirements is the software package's error reporting and messaging capability. Sometimes software suffers from various errors or flaws, and prompt reporting of those errors is critical for further resolution in the run time. Error reporting always makes a system possible for smooth processing, which is extremely important for an LMS system since at the time of online assessment, such reporting and rapid remedy are always useful for students and teachers.

7) Efficiency (T7):

Since everyone learns differently, an effective LMS should provide choices for configuring accessibility, display settings, and demonstrating methods in a reasonable period to meet a wide range of courses, learning styles, and accessibility demands. Keep an eye out for an LMS that can be easily utilized for training, learning, and evaluation all at once. The major factor enabling the software package to deliver results in a suitable time is data size.

8) DBMS standards (T8):

A learning management system (LMS) is software used to offer and administer educational courses. It is a client-server system that is often web-based and used to manage student enrollment, course content distribution, test and assignment administration, and associated record keeping. It keeps a record of all information pertaining to students, including their tuition and financial obligations, academic performance, use of school-provided transportation, and frequent attendance at libraries, labs, computer labs, and other facilities. Database applications that are often used include MS-Access, MS-SQL, MS-Excel, Oracle, DB2, Informix, Sybase, MySQL, and Ingrace.

9) OS compatibility (T9):

When using the LMS system, package compatibility with the operating systems MS Windows, Novell, Unix, Linux, and MAC is crucial. When switching from one OS to another, it is necessary to also switch modules, quizzes, courses, etc. OS compatibility is crucial in this circumstance.

10) IMS LIP (T10):

A specification for a common method of storing data on learners is the IMS Learner Information Package (LIP). LIP is made to make it possible to transfer learner data between different software programs, including their current progress and rewards. The Centre for Recording Achievement and CETIS have since modified the LIP standard for usage within the UK HE Sector, resulting in a mapping of the UK HE Transcript to LIP so that crucial student data may be transmitted electronically.

11) AICC Computer managed Instruction (T11):

"Computer Managed Instruction" is referred to as CMI. CMI is a general abbreviation that may be used to describe any type of computer-based learning in that environment. eLearning developers providing less support: AICC is still supported at a basic level by the majority, of course, authoring tools and learning management systems, although instructional designers and course developers are increasingly adopting more recent e-learning standards. The mobility of a course across different CMI learning environments and the communication between a lesson and the learning environment are all covered in the CMI standard.

12) Authentication (T12):

To prevent replay attacks, common security procedures concentrate on how login credentials and subsequent tokens are handled. Application security includes controls over user behaviour and data privacy. The controlling of verification credentials and successive tokens is the main focus of standard security procedures to stop replay attacks.

13) Authorization (T13):

Following successful authentication, authorization processes determine what the user is permitted to do. The majority of web application logging and monitoring is handled by the application framework. Systems that allow anonymous users must be strengthened to validate every user input.

14) Troubleshooting, maintenance and upgrading (T14):

Average independent code module sizes are usually advantageous. The level of module independence can be determined by specifying whether groups or sub-modules must be installed together, even if only a portion is required. The software package's maximum number of concurrent users it can support should also be noted. Additionally, the software should have the capability to divide into multiple application tiers that can be distributed across multiple servers, as well as the ability to distribute modules across these servers. The software's ability to be altered is referred to as maintainability, and modifications may include corrections, enhancements, or adaptations of the program to accommodate changes in the environment, requirements, and functional requirements. Measuring maintainability measures in a constrained experimental environment is challenging; they require extensive real-world testing.

Table 3
Linguistic ratings.

LVs	FFNs
Very Very High (VVH)	(0.9, 0.1)
Very High (VH)	(0.8, 0.15)
High (H)	(0.7, 0.25)
Medium (M)	(0.5, 0.45)
Low (L)	(0.4, 0.55)
Very Low (VL)	(0.2, 0.75)
Very Very Low (VVL)	(0.1, 0.9)

Table 4
IF initial assessment matrix.

	Expert 1				Expert 2				Expert 3				Expert 4			
Criteria	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
T1	VVH	VH	L	H	VVH	M	L	VVH	VH	H	H	M	M	M	VH	VH
T2	VH	VH	H	VVH	L	M	L	L	VH	H	H	VVH	H	VH	VH	M
T3	H	M	H	VL	M	VH	H	H	M	VVH	L	M	L	VVH	M	H
T4	VH	H	M	VVH	L	M	VVL	M	L	VVL	H	H	M	M	M	H
T5	M	M	H	M	VH	L	H	VH	M	M	VL	L	M	VH	H	H
T6	H	VH	L	H	VVL	M	VH	VVH	VVH	M	H	L	VVL	H	M	H
T7	VVL	VVH	M	M	L	VH	M	VH	L	VVL	M	VH	L	M	M	L
T8	VH	L	VVH	VVH	VL	M	M	L	H	M	L	VL	VVH	VVL	M	M
T9	H	M	M	VVL	H	VH	L	M	M	VH	VH	M	M	VL	VVH	VVH
T10	L	VVH	H	L	M	M	M	L	VL	M	M	L	M	L	VVH	VVH
T11	L	VH	VH	M	0.4	VH	VVH	L	H	L	VVH	M	H	H	VL	VVL
T12	H	L	M	L	H	M	M	L	L	VH	L	M	M	L	VL	VH
T13	H	L	VVH	VH	VH	H	VL	VVH	M	H	H	VH	H	VVH	L	VL
T14	M	M	M	L	M	H	L	H	M	M	M	H	H	M	H	L
T15	VVH	H	H	VH	VVH	VVH	M	H	VL	VVH	H	L	L	VH	M	VH

15) Communication synchronous and asynchronous (T15):

The LMS emphasizes asynchronous and synchronous communication, mostly in the form of chat rooms and threaded discussion boards. Discussion forums are the major threaders of asynchronous communication. Email communication is crucial in a learning setting. Creators can converse with and observe who is within. Students have access to several discussion platforms for information sharing. Chat rooms, audio conferences, and/or video conferencing are the principal uses of synchronized communications. Wherever uncertainty has to be cleared up or for any other reason, online dialogue between students and instructors is always a smart alternative. The technology allows for the download of all chatroom statistics. Through this device, audio and video conferencing are also possible.

B. Problem Solution

A team of four decision-making specialists was constituted to select the best option among the considered OSS-LMS packages. The linguistic variables and their accompanying IFNs were defined by experts in Table 3. Table 4 gives the IF linguistic decision matrix.

To obtain a reasonable result, we implement the proposed consensus-based IF-WASPAS model to prioritize the considered options. Assume that DMEs' weights are

Table 5
Aggregated matrix.

Criteria	Q1	Q2	Q3	Q4
T1	⟨0.8217, 0.1596⟩	⟨0.6429, 0.3028⟩	⟨0.6215, 0.3220⟩	⟨0.7632, 0.2070⟩
T2	⟨0.7046, 0.2396⟩	⟨0.7107, 0.2352⟩	⟨0.6705, 0.3824⟩	⟨0.7651, 0.2239⟩
T3	⟨0.5292, 0.4190⟩	⟨0.8336, 0.1507⟩	⟨0.5846, 0.3626⟩	⟨0.5745, 0.3715⟩
T4	⟨0.5381, 0.4050⟩	⟨0.4615, 0.4926⟩	⟨0.4973, 0.4549⟩	⟨0.7236, 0.2439⟩
T5	⟨0.6096, 0.3345⟩	⟨0.5746, 0.3690⟩	⟨0.5974, 0.3476⟩	⟨0.6333, 0.3103⟩
T6	⟨0.6263, 0.3603⟩	⟨0.6299, 0.3156⟩	⟨0.6526, 0.2919⟩	⟨0.7255, 0.2473⟩
T7	⟨0.3493, 0.6069⟩	⟨0.6625, 0.3048⟩	⟨0.5000, 0.4500⟩	⟨0.6907, 0.2519⟩
T8	⟨0.7200, 0.2460⟩	⟨0.4064, 0.5494⟩	⟨0.6172, 0.3538⟩	⟨0.5617, 0.4099⟩
T9	⟨0.6067, 0.3414⟩	⟨0.6696, 0.2706⟩	⟨0.7244, 0.2418⟩	⟨0.6116, 0.3657⟩
T10	⟨0.4029, 0.5460⟩	⟨0.6221, 0.3488⟩	⟨0.6882, 0.2831⟩	⟨0.6026, 0.3716⟩
T11	⟨0.5845, 0.3621⟩	⟨0.6947, 0.2491⟩	⟨0.8147, 0.1724⟩	⟨0.3987, 0.5572⟩
T12	⟨0.5846, 0.3626⟩	⟨0.5892, 0.3528⟩	⟨0.4116, 0.5375⟩	⟨0.5588, 0.3841⟩
T13	⟨0.6866, 0.2598⟩	⟨0.7323, 0.2371⟩	⟨0.6319, 0.3357⟩	⟨0.7718, 0.1947⟩
T14	⟨0.5554, 0.3931⟩	⟨0.5644, 0.3840⟩	⟨0.5330, 0.4150⟩	⟨0.5958, 0.3509⟩
T15	⟨0.7182, 0.2709⟩	⟨0.8539, 0.1319⟩	⟨0.6127, 0.3354⟩	⟨0.6898, 0.2543⟩

respectively 0.20, 0.27, 0.30, and 0.23. Then, the aggregated IF decision matrix (Table 5) is obtained by using the IFWA operator. Assume that the minimum consensus degree is $\rho = 0.25$. The consensus degree of each expert is calculated based on Eqs. (6) and (7) as: $\rho^{(1)} = 0.253$, $\rho^{(2)} = 0.496$, $\rho^{(3)} = 0.451$, and $\rho^{(4)} = 0.210$. Since $\rho^{(4)} < 0.25$, the initial assessments for 4th expert should be modified. In the revised assessment matrix, for the 4th expert, the updated entries are: (Q1, T1): **H**, (Q4, T1): **VVH**, (Q3, T12): **VVL**. Then, the revised aggregated IF decision matrix is constructed with the help of IFWA operator. The consensus degrees are recalculated with the help of Eqs. (5) and (6) as: $\rho^{(1)} = 0.252$, $\rho^{(2)} = 0.496$, $\rho^{(3)} = 0.446$, and $\rho^{(4)} = 0.260$. Since $\rho^{(r)} \geqslant 0.25$ $(r = 1, 2, 3, 4)$, desired consensus reaching process has been done.

Since all the considered criteria are of benefit type, normalization is not required. Suppose the weights of criteria are: $\vartheta_1 = 0.06$, $\vartheta_2 = 0.1$, $\vartheta_3 = 0.2$, $\vartheta_4 = 0.1$, $\vartheta_5 = 0.01$, $\vartheta_6 = 0.05$, $\vartheta_7 = 0.1$, $\vartheta_8 = 0.05$, $\vartheta_9 = 0.1$, $\vartheta_{10} = 0.05$, $\vartheta_{11} = 0.06$, $\vartheta_{12} = 0.05$, $\vartheta_{13} = 0.01$, $\vartheta_{14} = 0.05$, and $\vartheta_{15} = 0.01$. The IF-RSD of all alternatives using WSM and WPM are then calculated using Eqs. (8) and (9), respectively. The overall IF significance degrees of alternatives are calculated by Eq. (10) (taking $w = 0.5$) and are given as:

$$\eta_1 = \langle 0.8411, 0.1305\rangle, \quad \eta_2 = \langle 0.8900, 0.0887\rangle,$$
$$\eta_3 = \langle 0.8595, 0.1206\rangle, \quad \eta_4 = \langle 0.8787, 0.1012\rangle.$$

The scores of these FFNs are respectively 0.8553, 0.9006, 0.8695, 0.8887 according to which $Q_2 \succ Q_4 \succ Q_3 \succ Q_1$ ("$\succ$" means "superior to") as preference order with Q_2 as the most suitable option.

6. Discussions

The discussion section is divided into two parts: (A) sensitivity investigation of criteria weights, and (B) comparison of the suggested approach to currently used methods.

A. Sensitivity analysis of criteria weights

In this section, sensitivity analysis is used to assess the impact of a suitable criterion on the results of the model that has been provided. The term "most significant criterion" is used to denote a criterion with the highest weight value. Saha *et al.* (2021a, 2023a) used Eq. (12) to calculate the weight ratio.

$$\vartheta_c = (1 - \vartheta_s) \times \frac{\vartheta_c^0}{\Theta_c^0} = \vartheta_c^0 - \alpha_c \times \Delta x, \tag{12}$$

where ϑ_c – variation in criteria weights,

ϑ_s – weight of the most prominent criteria,

ϑ_c^0 – original values of criteria weights,

Θ_c^0 – sum of actual values of modified criteria weights,

α_c – weight coefficient of elasticity.

The relative significance of the various values of the criteria weights is demonstrated by α_c when we associate the variations with the most pertinent criterion weight. It is possible to calculate α_c (Kirkwood, 1997) using the following formula:

$$\alpha_c = \frac{\vartheta_c^0}{\Theta_c^0}. \tag{13}$$

Hypotheses of the adopted sensitivity analysis are as follows Kahraman (2002):

(1) α_s (an appropriate criterion weight coefficient of elasticity is provided); and
(2) The ratio of fluctuating weights remains constant during the SA procedure.

The fluctuation degree applied to a set of weight coefficients is given by a parameter Δx that is specified in terms of the corresponding weighted elastic coefficient, as indicated in Eq. (14). If the weight of the most important characteristic varies, a constraint should be in place. If this is not done, related weights may turn negative and the restrictions on proportionate weights may be broken. Positive and negative values of the parameter could signify an increase or reduction in the degree of importance, respectively. From the following, we may infer the limit values of Δx.

$$-\vartheta_s^0 \leqslant \Delta x \leqslant \min\left\{\frac{\vartheta_c^0}{\alpha_c}\right\}. \tag{14}$$

The boundaries and original weights of criteria are established and estimated using the pre-defined parameters. The values of a group of weight coefficients are determined by applying Eqs. (15) and (16):

$$\vartheta_s = \vartheta_s^0 + \alpha_s \times \Delta x, \tag{15}$$

$$\vartheta_c = \vartheta_c^0 - \alpha_c \times \Delta x, \tag{16}$$

where ϑ_s^0 – given weight of the most significant criteria,

ϑ_c^0 – given value of changeable weights.

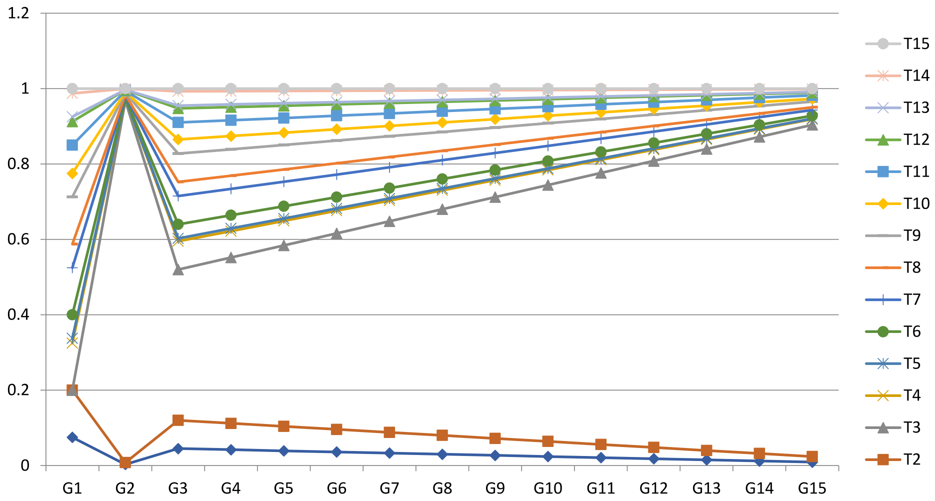

Fig. 1. Various criteria weights sets for sensitivity analysis.

It should be kept in mind that the revised criteria set mentioned above satisfies the equation $\sum \vartheta_s + \sum \vartheta_c = 1$, which is thought of as the fundamental requirement of the percentage of weight coefficients. The rankings of the alternatives are established taking into consideration the updated criteria weight values. T3 has the most significant weight coefficient, which was determined from the analysis, of $\vartheta_3 = 0.2$, making it one of the most significant criteria in this study. After that, the weight elasticity values are assessed, and it is found that the weight coefficient's (Δx) fluctuation bounds fall within the range of $-0.2 \leqslant \Delta x \leqslant 0.8$. Several criteria weight sets (G1, G2, ..., G15) are then formed based on restrictions for the change of weight coefficient values of criteria.

The weight sets are split into fifteen groups for the range $-0.2 \leqslant \Delta x \leqslant 0.8$. The weight coefficients are viewed from various perspectives for each set using Eqs. (15) and (16), and these values are shown in Fig. 1. As a result, several criteria weight sets are applied to determine the alternatives' final scores, which are shown in Fig. 2. The results of this study showed that alternative Q2 is the best choice. After that, we used the results from various weight sets taken into account by various criteria to determine the SRCC values (Saha *et al.*, 2021a). A "high correlation" between alternative ranks is observed, as indicated by the average SRCC value of 0.9 (Saha *et al.*, 2021b). Therefore, stability of the model is established.

B. Comparative Investigation

This part aims to provide a comparative analysis of the developed consensus-based IF decision support model with the existing IF decision-making methods, namely IF-TOPSIS (Rouyendegh *et al.*, 2020), IF-MULTIMOORA (Garg and Rani, 2022), IF-EDAS (Mishra *et al.*, 2020), IF-COPRAS (Kumari and Mishra, 2020), and IF-MARCOS (Deb *et al.*, 2022). These methods are applied to solve the addressed selection issue of OSS-LMS package selection. According to the comparison results, the ranking order obtained by

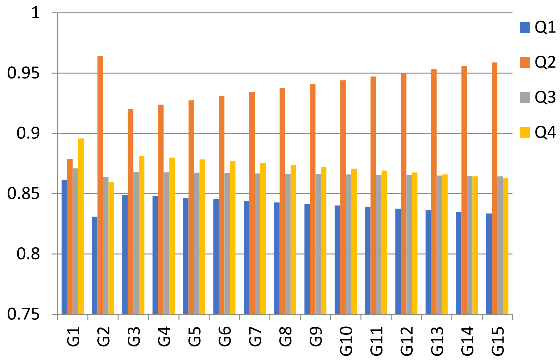

Fig. 2. Scores of the alternatives for various sets of criteria weights.

these existing methods is $Q_2 \succ Q_1 \succ Q_3 \succ Q_4$. On the other hand, the IF-c-WASPAS method generates the order $Q_2 \succ Q_1 \succ Q_3 \succ Q_4$ which is exactly the same.

Some advantages of IF-c-WASPAS are as follows:

1. The consensus-reaching process for decision-makers is integrated into the introduced model, while the available FF methods (Rouyendegh *et al.*, 2020; Garg and Rani, 2022; Mishra *et al.*, 2020; Kumari and Mishra, 2020; Deb *et al.*, 2022) are unable to rectify the consensus level of experts. As a result, our model lessens decision-making process biases, making the process more significant and logical.
2. The consensus-reaching process using WASPAS methods offers the following advantages: (i) estimation of values can be achieved with the highest degree of precision, (ii) surpasses WPM and WSM in terms of accuracy, (iii) enables the selection of the optimal choice through the utilization of AOs, unlike other methods that only allow for the selection of the option closest to the ideal answer.
3. The proposed model is useful for assessing and prioritizing OSS-LMS packages under real-life scenarios when there is a lack of quantitative input information.

7. Conclusions

Adaptive online educational practices are a constantly evolving area of study, notably in academic contexts. It is a unique way for people and organizations to acquire knowledge and to fulfill their demands. These demands can be reached by the use of LMSs that are elements of e-learning. LMSs are software-based applications that incorporate a package of schemes for learning and training online. This LMS has now enhanced a top priority and major projects in enterprises and educational organizations. The number of accessible OSS-LMSs is constantly booming and getting significant projection. OSS is enhancing a choice for every institution, as they are advantageous to users in enabling platforms to be transformed according to user specifications, and because of the minimum costs charged to get a more reliable service, compared to other software like commercial ones that need licensing fees to run, with an added subscription and also a maintenance fee to make the

LMS software up-to-date. In answer to mounting demands, software enterprises have been recommending a different types of software packages that can be adapted and fulfill the precise needs of an establishment as well as handmade. The evaluation and adoption of an improper OSS-LMS package unfavourably affect the marketing procedures and duties of the institution. This paper focuses on consensus based IF-WASPAS methodology to help a decision-maker or administrators in the education environment to compare and appraise the OSS-LMS packages and choose the suitable one over certain criteria. The comparison is presented between four OSS-LMSs, namely Moodle, Sakai, ATutor, and eFront. The outcomes show that MOODLE is best for the present study compared to other four OSS-LMSs. As potential future research directions, a combination of subjective and objective weights for expert weight determination can be utilized, taking into account assessments of expert similarity (Saha *et al.*, 2021a, 2021b). To enhance the significance of the model, incorporating measures such as dispersion, uncertainty, and cross-entropy can be explored (Saha *et al.*, 2023a, 2023b). The developed consensus approach can also be integrated with MULTIMOORA, MARCOS, DNMA, COPRAS, and VIKOR methodologies to develop novel techniques. Furthermore, the developed model can be extended to encompass dual hesitant fuzzy sets and probabilistic dual hesitant fuzzy sets.

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