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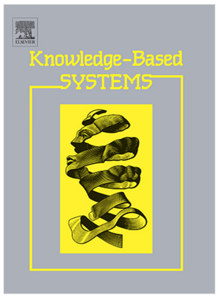

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Title Page

A Comparative Study of Evaluating and Benchmarking Sign Language Recognition System-based Wearable Sensory Devices Using a Single Fuzzy Set

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A Comparative Study of Evaluating and Benchmarking Sign Language Recognition System-based Wearable Sensory Devices Using a Single Fuzzy Set

Abstract

Recent research has focused on developing real-time sign language recognition systems (SLRSs) based on gesture recognition to classify hand motions into their equivalent meaning in spoken language, but no comprehensive system with all desirable features has been presented. The existence of different systems has hindered the process of selecting the most preferred system. Therefore, many researchers have compared and evaluated several recognition systems to identify the best one using multicriteria decision-making methods. These studies extended the fuzzy decision by opinion score method (FDOSM) using a single Likert scale under the Pythagorean fuzzy set (PFS) or one of its extensions. However, no comparative study has examined the influence of using multiple Likert scales with a single fuzzy set. Furthermore, the effect of employing multiple Likert scales on benchmarking results is a challenging task. Therefore, this paper examines the three Likert scales (five-, seven- and ten-point) under the same fuzzy environment. This paper extends FDOSM into PFSs based on the power Bonferroni mean (PBM) operator (named PFDOSM-PBM) to benchmark the real-time SLRS. The decision matrix is constructed based on 30 real-time SLRS-based wearable sensory devices and the 11 evaluation criteria. The results reveal that the five-point Likert scale is superior to other scales (i.e., seven- and ten-point) as it is flexible, easy to use and generates more accurate findings on the basis of uncertainty compared to other scales. Systematic ranking and comparative analysis are conducted to validate and evaluate the proposed method.

Keywords: FDOSM, Likert scale, Multicriteria decision-making, Pythagorean fuzzy sets, Sign language recognition systems.

Abbreviations			
SL	Sign language	IHAM	Interactive hybrid arithmetic mean
SLRSs	Sign language recognition systems	IPFWA	Interval-valued Pythagorean fuzzy weighted average
MCDM	Multicriteria decision-making	FWZIC	Fuzzy-weighted zero-inconsistency
FDOSM	Fuzzy decision by opinion score method	CPFWA	Cubic Pythagorean fuzzy weighted averaging
FFSs	Pythagorean fuzzy sets	PMPFWA	Pythagorean m-polar fuzzy weighted average mean

1 Introduction

Approximately 9.1 billion individuals worldwide are deaf and mute [1]. Deafness is a disability that impairs individuals' hearing and renders them unable to hear [2], whereas muteness is a disability that impairs individuals' ability to speak and renders them unable to talk [3]. Owing to birth abnormalities and other challenges, the population of deaf-mute victims has increased in recent years. According to the World Health Organization, approximately 5% of the global population or 466 million individuals suffer from hearing impairment. Deaf-mute individuals are impaired in hearing and/or speaking, but they are still capable of performing many other tasks. Communication is the single thing that divides them from normal people. If normal and deaf-mute people can communicate, they can easily lead normal lives. The only means of communication available to them is sign language (SL) [4,5].

SL evolved similarly to spoken languages. It is utilized by deaf-mute individuals for daily communication. It is considered the native language of those with hearing/specking impairments. No global standardization of SLs for deaf-mute individuals is available. Similar to spoken languages, SLs are not uniformly the same; they vary from location to another. Obtaining trained, experienced translators on demand is also impossible [6]. In contrast, a computer can be designed to convert SL into text, reducing the gap between normal people and the deaf-mute community. Recent research has focused on developing real-time sign language recognition systems (SLRSs) based on gesture recognition to classify hand motions into their equivalent meaning in spoken language [7]. Typically, a sensor- or vision-based technique is utilized for hand gesture recognition [8]. The primary benefit of sensor-based systems over vision-based systems is the decreased need to transform raw data into useful values [9]. Vision-based systems do not require sensors to be installed. Nonetheless, earlier research has highlighted a number of shortcomings in vision-based SLR systems [7]. The most significant issues, such as high processing costs [10], the limited field of vision of the capturing device, and the necessity for several cameras to achieve sufficient findings, are caused by enormous storage space, a complicated environment, imprecise gesture capture and fluctuating illumination [11].

In contrast, the adoption of wearable sensing devices provides numerous advantages, such as simplified data processing [12], supplying the recognition system with direct information regarding finger-bend data and wrist orientation, considering voltage values [13], lack of movement restrictions (e.g., sitting behind a desk/chair), and adaptability to various surroundings (e.g., background conditions have little effect on hand shape recognition) [14], and SLR-based glove devices are portable, lightweight, and comfortable [15]. Thus, sensor-based wearable systems (also known as wearable sensory devices) are convenient for capturing SL motions without environmental constraints.

Various types of sensors, including optical [16], flex [17], touch, tilt, and Hall effect magnetic sensors [18], have been built into wearable sensory systems. The finger's tilt angle was measured with the help of these sensors. Nonetheless, a great number of publications utilize the flex sensor to gather finger bend information. The sensor also collects data regarding motion tracking and hand orientation. For hand motion detection/orientation, a 3-axis accelerometer [19], 6-axis inertial measurement unit [20], and 9-axis inertial measurement unit [21] were used. Data gloves are used to detect hand gestures. Commercial and noncommercial gloves exist. Commercial examples include the DG5-V hand glove with 5-flex sensors and a 3-accelerometer [22], the 5DT Data Glove with 5-fiber-optic sensors [23], and the Cyberglove™ with 22-flexible sensors [24]. A noncommercial example includes an electronic glove with an accelerometer, 5-contact sensors, and 5-flex sensors [25].

There are several studies on SL in various languages, such as Arabic SL [26], Indian SL [27], Chinese SL [28], Thai SL [29], Bangle SL [30], English SL [31], and American SL [32] [33]. These examples show an increasing amount of research devoted to SLRS-based wearable sensory devices. In addition, distinct differences in the development of SLRS-based wearable sensory devices have been noted. Multiple studies that have focused on the number of sensors [34], data channels [35], signs [36], signers [18] as well as a complete set for full fingers [18], wrist [37], forearm joint analysis [38], gesture repetitions per signer [36] and SLRS cost [39] have demonstrated these distinctions. Moreover, the investigation has shown a connection between system effectiveness and whether sensory data are processed online or offline based on wearable sensory devices [13]. Despite the presence of a large number of SLRS-based wearable sensory devices, no comprehensive system with all desirable features has been presented. The existence of different systems has hindered the process of selecting the most preferred system [40]. Therefore, many researchers have compared and evaluated several recognition systems to identify the best one.

The layout of this paper is organized as follows: Section 2 reviews the recent studies evaluating real-time SLRS-based wearable sensory devices and the existing multicriteria decision-making (MCDM) solutions. Section 3 provides the methodology used to evaluate and benchmark real-time SLRS-based wearable sensory devices. Section 4 presents the results and discussions of PFDOSM-PBM. Section 5 introduces the evaluation of the findings of the proposed methodology. Section 6 outlines the conclusion, limitations and directions for future research.

2 Literature Review

Recently, [7] presented a ‘state of the art’ review of real-time SLRS-based wearable sensory devices from 2007 to 2017. Later, [41] proposed 30 American SLRS-based wearable sensory devices selected from [7] and updated them to cover the years 2018 through 2020. They chose American SL for the richness of its literature and as a proof of concept in their research. The 30 SLRS-based wearable sensory devices were evaluated by six evaluation criteria based on the perspectives of hand gesture recognition. The first criterion ‘Dataset’ included seven sub criteria, Number, Alphabet, Word/phrases, Gesture number, Participants, Repetitions and size; the second criterion ‘Gesture type’ included two sub criteria, Static and Dynamic; the third criterion ‘Sign type’ included two sub criteria, Isolated and Continuous; the fourth criterion ‘Solving misclassification error’ included six sub criteria, Cluster 1, Cluster 2, Cluster 3, Cluster 4, Cluster 5 and Cluster 6; the fifth criterion ‘Recognition systems’ included two sub criteria, Online and Offline; and the sixth and last criterion ‘Communication’ included two sub criteria, One way and Two ways. As stated by [7], the evaluation and benchmarking of real-time SLRS-based wearable sensory devices is an MCDM problem. Therefore, they extended the new MCDM ranking method, fuzzy decision by opinion score method [42], also known as FDOSM under Pythagorean fuzzy sets (FFSs) [43]. The fuzzy opinion matrices were aggregated using the interactive hybrid arithmetic mean (IHAM) operator for individual benchmarking, whereas the arithmetic mean was employed for group benchmarking. In addition, a five-point Likert scale was used to identify the difference degree between the ideal solution and the remaining values under a certain criterion. The robustness of their method was verified using a systematic ranking and comparative analysis.

Recently, [44] took 30 SLRS-based wearable sensory devices from [41] as alternatives and evaluated them using 11 criteria based on two main perspectives: hand gesture recognition and sensor glove systems. In addition to the six hand gesture recognition criteria [41], the five criteria of the sensor glove system included system cost, data channels, number of hands with two subcriteria (one hand and two hands), finger movements with three subcriteria (adduction–abduction [AA], flexion–extension [FE] and finger-pointing [FP]) and hand movement with two subcriteria (orientation and position). The authors introduced a new extension of the FDOSM for evaluating and benchmarking real-time SLRS-based wearable sensory devices under interval-valued PFSs. The fuzzy opinion matrices were aggregated using the interval-valued Pythagorean fuzzy weighted average (IPFWA) operator for individual benchmarking, whereas the arithmetic mean was employed for group benchmarking. In addition, a seven-point Likert scale was employed to determine the degree of difference between the ideal solution and the remaining values under certain criteria. Their method’s robustness was evaluated utilizing systematic ranking and comparison analysis.

To evaluate and benchmark real-time SLRS-based wearable sensory devices, a more recent study [45] adopted and evaluated 30 SLRS-based wearable sensory device alternatives based on 11 evaluation criteria [41,44]. They employed the fuzzy-weighted zero-inconsistency (FWZIC) [46] method to estimate the importance level of evaluation criteria and integrated it with FDOSM to benchmark real-time SLRS-based wearable sensory devices under cubic PFSs. The fuzzy opinion matrices were aggregated using the cubic Pythagorean fuzzy weighted averaging (CPFWA) operator for individual benchmarking, whereas the arithmetic mean was employed for group benchmarking. A ten-point Likert scale was employed to determine the degree of difference between the ideal solution and the remaining values under certain criteria. They evaluated the robustness of their method using systematic ranking and sensitivity analysis.

Additionally, [47] integrated FWZIC and FDOSM to evaluate and benchmark real-time SLRSs under Pythagorean m-polar fuzzy sets. They adopted 30 SLRS-based wearable sensory device alternatives and 11 evaluation criteria [41,44]. The fuzzy opinion matrices were aggregated using the Pythagorean m-polar fuzzy weighted average mean (PMPFWA) operator for individual benchmarking, whereas the arithmetic mean was employed for group benchmarking. In this paper, a ten-point Likert scale was used to measure the degree of difference between the ideal solution and the remaining values. The robustness of their method was evaluated using systematic ranking, sensitivity analysis and comparison analysis.

Table 1 compares the four aforementioned studies [41], [44], [45], and [47] in terms of differences and consensus about the group's benchmarking results, fuzzy sets, aggregation operator, and Likert scale. Comparing the group's benchmarking results of [41] and [44], the rankings of 24 SLRS-based wearable sensory devices, representing 80%, were distinct, whereas the rankings of 6 SLRS-based wearable sensory devices, representing 20%, were similar. The comparison of the group's benchmarking results of [41] and [45] yielded similar findings. Comparing the benchmarking findings of [41] and [47] revealed that the rankings of 25 SLRS-based wearable sensory devices, representing 83.3%, were distinct, but the rankings of 5 SLRSs, representing 16.7%, were similar. When the group benchmarking findings of [44] and [45] are compared, the same results were achieved. Furthermore, the comparison of the group benchmarking results of [44] and [47] showed that 26 SLRS-based wearable sensory devices, representing 86.7%, were different, but the rankings of 4 SLRS-based wearable sensory devices, representing 13.3%, were similar. Finally, comparing the group's benchmarking results of [45] and [47], the rankings of 9 SLRS-based wearable sensory devices, representing 30%, were distinct, whereas the rankings of 21 SLRS-based wearable sensory devices, representing 70%, were similar. Overall, comparing the group benchmarking findings of [41], [44], [45], and [47] revealed that the rankings of 29 SLRS-based wearable sensory devices, representing 96.7%, were distinct, but the rankings of only one SLRS-based wearable sensory device, representing 3.3%, were similar.

Table 1

Comparison Points Among the State of Art SLR$_S$-based Wearable Sensory Device Studies.

Group's benchmarking results Differences	[41]	[44]	[45]	[47]
[41]	-	24 (80%)	24 (80%)	25 (83.3%)
[44]	-	-	25 (83.3%)	26 (86.7%)
[45]	-	-	-	9 (30%)
[47]	-	-	-	-
Overall differences		29 (96.7%)		
Group's benchmarking results consensus	**[41]**	**[44]**	**[45]**	**[47]**
[41]	-	6 (20%)	6 (20%)	5 (16.7%)
[44]	-	-	5 (16.7%)	4 (13.3%)
[45]	-	-	-	21 (70%)
[47]	-	-	-	-
Overall consensus		1 (3.3%)		
Other comparison points	**[41]**	**[44]**	**[45]**	**[47]**
Fuzzy sets	PFSs	Interval-valued PFSs	Cubic PFSs	Pythagorean m-polar fuzzy sets
Aggregation operator	IHAM operator	IPFWA operator	CPFWA operator	PMPFWA operator
Likert scale	five-point	seven-point	ten-point	ten-point

As proven by the preceding studies, the evaluation and benchmarking of real-time SLRSs have gained a great amount of attention in recent years. Many fuzzy sets have been employed, such as PFSs, interval-valued PFSs, cubic PFSs and Pythagorean m-polar fuzzy sets, to handle the hesitancy and uncertainty of decision-makers. Furthermore, in individual benchmarking, fuzzy opinion matrices were aggregated using the IHAM, IPFWA, CPFWA and PMPFWA operators. In addition, five-, seven- and ten-point Likert scales were utilized with these fuzzy sets (see Table 1). However, no study has explored the influence of changing the Likert scale with a single fuzzy set, which is considered a research gap and challenging task due to the effect of employing multiple Likert scales on benchmarking results [41,44,45,47]. Therefore, the main objective of this paper is to answer the following question: Which of the three Likert scales—five-point, seven-point, and ten-point—is flexible, easy to use by experts in data gathering, and produces more accurate findings based on expert certainty in same fuzzy environment?. FDOSM was used by [41,44,45,47] to evaluate and benchmark real-time SLRSs. Thus, FDOSM is applied in the present paper to identify the differences in the ranking results across the three Likert scales with a single fuzzy set and fill the identified research gap.

To overcome the limitation of the traditional operational laws of Pythagorean fuzzy numbers (PFNs), minimize the negative effect of unreasonable evaluations on aggregating results, capture heterogeneous interrelationships among attributes and consider the interactions between the grades of membership and nonmembership, many aggregation operators were utilized with PFNs (i.e., *IHAM*, *IPFWA*, *CPFWA* and *PMPFWA* operators). Recently, [48] extended the power Bonferroni mean (PBM) operator to incorporate PFNs based on PFS to capture the interactions between the grades of membership and nonmembership while retaining the key advantages of PBM operators (Wang L. et al., 2021). The motivation of this work is to extend FDOSM into a PFS based on the PBM operator, namely, PFDOSM-PBM, to take advantage of previous characteristics. Through the evaluation and benchmarking of real-time SLRS-based wearable sensory devices as a comparative study, this extension is utilized to fill the previously described gap.

The novelty and main contribution of this paper is to examine the primary differences between three Likert scales (five-, seven- and ten-point) under the same fuzzy environment. This paper extends FDOSM into PFSs using a PBM operator (named PFDOSM-PBM) to evaluate and benchmark real-time SLRS-based wearable sensory devices and achieve the objective of this research.

3 Methodology

The methodology applied in the present research is shown in Fig.1. The adaptation and formulation of the real-time SLRS decision matrix is presented in Section 3.1. The formulation and development of PFDOSM-PBM, which is used to evaluate and benchmark the real-time SLRS alternatives, is presented in Section 3.2.

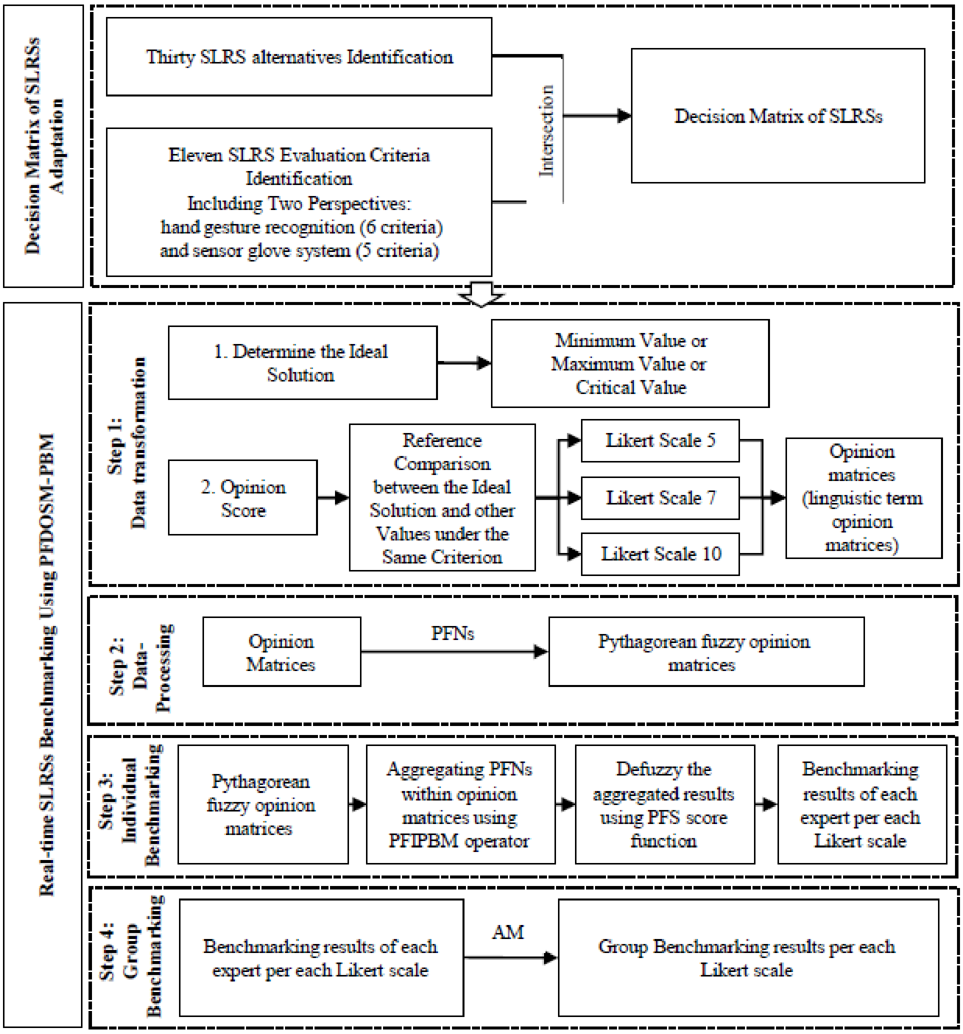

Fig. 1. Research methodology.

3.1 Real-time SLRS Decision Matrix Adaptation

This section presents the adaptation and formulation of the real-time SLRS decision matrix that consists of three steps. The first step identifies the real-time SLRS alternatives, the second step identifies the evaluation criteria of the real-time SLRS, and the third step intersects the real-time SLRS alternative and the evaluation criteria to construct the decision matrix.

Step 1: Identify real-time SLRS alternatives

Following [44,45,47], 30 real-time American SLRS-based wearable sensory devices were adopted from [41]. These SLRS-based wearable sensory devices were selected for evaluation and benchmarking using PFDOSM-PBM considering three Likert scales (i.e., five-, seven- and ten-point). The proposed method is unaffected by an increase in the number of selected systems. Moreover, the evaluation and benchmarking method can be used for other real-time SLRS-based wearable sensory devices in a range of other languages [13]. Nevertheless, following the study presented by [41], American SLRS-based wearable sensory devices were chosen as a proof of concept for this paper due to the extensiveness of their literature.

Step 2: Identify the evaluation criteria of real-time SLRS-based wearable sensory devices

In previous research, SLRS-based wearable sensory devices have been evaluated based on two perspectives: hand gesture recognition and sensor glove systems. As mentioned in the Introduction Section, [41] considered hand gesture recognition criteria, whereas [44] considered sensor glove system criteria with hand gesture recognition criteria. Both [45] and [47] adopted the two sets of criteria from [44]. Therefore, the present paper adopted the six evaluation criteria under hand gesture recognition (Dataset [C1], Gesture type [C2], Sign type [C3], Solving misclassification error [C4], Recognition systems [C5] and Communication [C6]) and the five evaluation criteria under the sensor glove system (System cost [C7], Data channels [C8], Number of hands [C9], Finger movements [C10] and Hand movement [C11]). Refs. [44,45,47] provided detailed definitions of the 11 evaluation criteria.

Step 3: Intersect real-time SLRS alternatives and evaluation criteria

This step describes the formulation of the decision matrix for real-time SLRS. The decision matrix was constructed based on the intersection between the 30 real-time SLRS-based wearable sensory devices and the 11 evaluation criteria. Table 2 presents the formulated real-time SLRS decision matrix. Depending on the criteria, the evaluation of real-time SLRS-based wearable sensory devices may be undertaken objectively or subjectively. The objective criteria were determined as factual, quantitative or measurable information. The criteria measured based on the objective values were C1 (including Gesture number [C1-4], Participants [C1-5], Reparation [C1-6] and Size [C1-7]), C7 and C8. In contrast, the subjective criteria were evaluated based on their presence in a given system. The criteria measured subjectively were C1 (including Number [C1-1], Alphabet [C1-2] and Word/phrases [C1-3]), C2 (including Static [C2-1] and Dynamic [C2-2]), C3 (including Isolated [C3-1] and Continuous [C3-2]), C4 (Cluster 1 [C4-1], Cluster 2 [C4-2], Cluster 3 [C4-3], Cluster 4 [C4-4], Cluster 5 [C4-5] and Cluster 6 [C4-6]), C5 (Online [C5-1] and Offline [C5-2]), C6 (One way [C6-1] and Two ways [C6-2]), C9 (One hand [C9-1] and Two hands [C9-2]), C10 (FE [C10-1], AA [C10-2] and Pointing [C10-3]) and C11 (Orientation [C11-1] and Position [C11-2]).

Table 2

Real-time SLRS decision matrix.

SLRSs based wearable sensory devices/ Criteria	Hand gesture recognition																						Sensor glove system							
	C1							C2		C3		C4						C5		C6		C7	C8	C9		C10			C11	
	C1-1	C1-2	C1-3	C1-4	C1-5	C1-6	C1-7	C2-1	C2-2	C3-1	C3-2	C4-1	C4-2	C4-3	C4-4	C4-5	C4-6	C5-1	C5-2	C6-1	C6-2			C9-1	C9-2	C10-1	C10-2	C10-3	C11-1	C11-2
SLRS1	C1-1/SLRS1	C1-2/SLRS1	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	C11-2/ SLRS1
SLRS2	C1-1/SLRS2	C1-2/SLRS2	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	C11-2/ SLRS2
SLRS3	C1-1/SLRS3	C1-2/SLRS3	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	C11-2/ SLRS3
⋮	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..
SLRS30	C1-1/SLRS30	C1-2/SLRS30	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	C11-2/ SLRS30

The evaluation criteria for the two perspectives, hand gesture recognition and sensor glove system, fall under multiple principles: cost, benefit and binomial criteria. All objective criteria are beneficial (a higher value is desired) except for (C7), which is a cost criterion (a higher value is undesired). All subjective criteria are binomial and evaluated by either Yes or No, indicating the presence or dearth of the criteria in a particular SLRS. The evaluation and benchmarking of real-time SLRS is hindered by three MCDM issues: the presence of various evaluation criteria, the importance of the criteria and their conflict [41,44,45,47]. To address this issue and compare the different ranking outcomes based on a single fuzzy set and multiple Likert scales in terms of logic and reality, constructing an MCDM solution is essential based on the proposed PFDOSM-PBM method, as described in the next section.

3.2 Real-time SLRS Benchmarking Using PFDOSM-PBM

The PFDOSM-PBM method is a new extension of FDOSM [42] under the PFS environment. The PFDOSM-PBM was developed to benchmark real-time SLRS-based wearable sensory devices based on three Likert scales (five-point, seven-point and ten-point). It consists of four main steps: data transformation unit, data-processing unit, individual benchmarking and group benchmarking, as shown in Fig. 1 and explained below.

Step 1: Data transformation unit

The decision matrix was converted into an opinion matrix:

i. The ideal solution for each criterion in the real-time SLRS-based wearable sensory device decision matrix was selected. The selection of ideal solutions was determined by the preferences of experts. At least three experts with a minimum of seven years of expertise in sensor-based recognition systems should be recruited for this purpose. The ideal solution is defined in Eq. (1):

$$A^* = \left\{\left[\left(\max_i v_{ij} \,\middle|\, j \in J\right), \left(\min_i v_{ij} \,\middle|\, j \in J\right), (Op_{ij} \in I.J) | i = 1.2.3. \dots .m\right]\right\}, \quad (1)$$

where max and min represent the benefit and cost criteria, respectively, and Op_{ij} represents the critical value that lies between the max and min values and is determined based on the expert's opinion. Notably, no critical value was selected for real-time SLRS benchmarking.

ii. The ideal solution for each criterion was compared with the values of all alternatives in terms of differences. Three Likert scales were used in the comparison (five- [49], seven-point [50] and ten-point [49]). Table 3 presents the linguistic expressions used with each Likert scale. Eq. (2) expresses the comparisons performed in this step.

$$Op_{Lang} = \left\{\left(\left(v_{ij} \geqq A_j{}^* \middle| j \in J\right). \middle| i = 1.2.3. \dots .m\right)\right\}, \quad (2)$$

where ≧ refers to the comparison conducted between the ideal solution and the values of all real-time SLRS alternatives under a certain criterion.

The final results of this step are the opinion matrices of three experts with each Likert scale used, as represented in Eq. (3).

$$Op\_Lang = \begin{array}{c} A_1 \\ \vdots \\ A_m \end{array} \begin{bmatrix} op_{11} & \cdots & op_{1n} \\ \vdots & \ddots & \vdots \\ op_{m1} & \cdots & op_{mn} \end{bmatrix}. \tag{3}$$

Step 2: Data-processing unit

The opinion matrices for each Likert scale were transformed into fuzzy matrices. The linguistic expressions within the opinion matrices were replaced with PFNs, as shown in Table 3. According to [51–54], PFSs, PFNs and their operational laws are defined as follows:

Definition 1 [51,55]. Let X be a universal set, and a PFS P is defined as

$$P = \{\langle x, (\mu_P(x), v_P(x))\rangle \mid x \in X\}, \tag{4}$$

where $\mu_P(x)$ *and* $v_P(x)$ represent the grades of membership and nonmembership of the element $x \in X$ to the set P, respectively. The functions $\mu_P(x), v_P(x): X \to [0,1]$ meet the condition $0 \le (\mu_P(x))^2 + (v_P(x))^2 \le 1$. The indeterminacy grade is $\pi_P(x) = \sqrt{1-(\mu_P(x))^2-(v_P(x))^2}$. For ease of presentation [53], PFN is represented by $\alpha = (\mu_\alpha, v_\alpha)$ a PFN, where $\mu_\alpha \in [0,1], v_\alpha \in [0,1]$ and $0 \le \mu_\alpha^2 + v_\alpha^2 \le 1$.

Definition 2 [51,53]. Let $\alpha = (\mu_\alpha, v_\alpha), \alpha_1 = (\mu_{\alpha_1}, v_{\alpha_1})$ and $\alpha_2 = (\mu_{\alpha_2}, v_{\alpha_2})$ be three PFNs, and their operational laws are shown as follows:

i. $\alpha^c = (v_\alpha, \mu_\alpha)$;

ii. $\alpha_1 \oplus \alpha_2 = \left(\sqrt{(\mu_{\alpha_1})^2 + (\mu_{\alpha_2})^2 - (\mu_{\alpha_1})^2(\mu_{\alpha_2})^2}, v_{\alpha_1}v_{\alpha_2}\right)$;

iii. $\alpha_1 \otimes \alpha_2 = \left(\mu_{\alpha_1}\mu_{\alpha_2}, \sqrt{(v_{\alpha_1})^2 + (v_{\alpha_2})^2 - (v_{\alpha_1})^2(v_{\alpha_2})^2}\right)$;

iv. $\lambda\alpha = \left(\sqrt{1-(1-(\mu_\alpha)^2)^\lambda}, (v_\alpha)^\lambda\right), \lambda > 0$;

v. $\alpha^\lambda = \left((\mu_\alpha)^\lambda, \sqrt{1-(1-(v_\alpha)^2)^\lambda}\right), \lambda > 0$.

Table 3

Likert scale linguistic expressions and their associated PFNs.

Linguistic expressions		Numerical scale	PFNs μ	PFNs v
Five-point Likert scale [49]				
No Difference (Equal)	ND	1	0.05	0.9
Slight Difference	SD	2	0.2	0.75
Difference	D	3	0.4	0.50
Big Difference	BD	4	0.6	0.25
Huge Difference	HD	5	0.8	0.1
Seven-point Likert scale [50]				
Linguistic expressions		Numerical scale	PFNs μ	PFNs v
Very No Difference (Equal)	VND	1	0.95	0.05
No Difference	ND	2	0.75	0.15
Slight Difference	SD	3	0.65	0.25
Difference	D	4	0.50	0.35
Big Difference	BD	5	0.35	0.55
Huge Difference	HD	6	0.15	0.75
Very Huge Difference	VHD	7	0.05	0.95
Ten-point Likert scale [49]				
Linguistic expressions		Numerical scale	PFNs μ	PFNs v
Extremely No Difference (Equal)	END	0	0.9999	0.0001
Very No Difference	VND	1	0.9	0.2
No Difference	ND	2	0.8	0.25
Slight Difference	SD	3	0.7	0.35
Difference	D	4	0.6	0.5
Big Difference	BD	5	0.5	0.6
Huge Difference	HD	6	0.45	0.7
Very Huge Difference	VHD	7	0.4	0.75
Extremely Huge Difference	EHD	8	0.2	0.8
Extremely very Huge Difference	EVHD	9	0.1	0.9

The three scales were selected due to their frequent use in the context of decision-making in the literature; thus, these scales were used based on their frequency and importance [49,50]. The final results of this step were the fuzzy opinion matrices of three experts with each Likert scale used.

Step 3: Individual benchmarking

The PFNs within three fuzzy opinion matrices of each expert per Likert scale were aggregated using the Pythagorean fuzzy interaction PBM (PFIPBM) operator. Let $\alpha_i = (\mu_{\alpha_i}, v_{\alpha_1})(i = 1,2, \dots, n)$ be the set of PFNs and $p, q \geq 0$. The PFIPBM operator is defined [48] as follows:

$$PFIPBM^{p,q}(\alpha_1,\alpha_2,\dots,\alpha_n)=$$

$$\left\{\begin{array}{l}
\left\{\left\{\begin{array}{l}
\left\{1-\left\{\prod_{i,j=1,i\neq j}^{n}\left\{\begin{array}{l}1-(1-\left(1-(\mu_{\alpha_i})^2\right)^{n\varphi_i}\right)+(1-\left((\mu_{\alpha_i})^2+(\nu_{\alpha_i})^2\right))^{n\varphi_i})^{p}\\(1-\left(1-(\mu_{\alpha_j})^2\right)^{n\varphi_j}\right)+(1-\left((\mu_{\alpha_j})^2+(\nu_{\alpha_j})^2\right))^{n\varphi_j})^{q}+\\(1-\left((\mu_{\alpha_i})^2+(\nu_{\alpha_i})^2\right))^{n\varphi_i p}(1-\left((\mu_{\alpha_j})^2+(\nu_{\alpha_j})^2\right))^{n\varphi_j q}\end{array}\right\}\right\}^{\frac{1}{n(n-1)}}\right.\\
\quad\left.+\left\{\prod_{i,j=1,i\neq j}^{n}\left((1-\left((\mu_{\alpha_i})^2+(\nu_{\alpha_i})^2\right))^{n\varphi_i p}(1-\left((\mu_{\alpha_j})^2+(\nu_{\alpha_j})^2\right))^{n\varphi_j q}\right)\right\}^{\frac{1}{n(n-1)}}\right\}\\
\quad-\left\{\left\{\prod_{i,j=1,i\neq j}^{n}\left((1-\left((\mu_{\alpha_i})^2+(\nu_{\alpha_i})^2\right))^{n\varphi_i p}(1-\left((\mu_{\alpha_j})^2+(\nu_{\alpha_j})^2\right))^{n\varphi_j q}\right)\right\}^{\frac{1}{n(n-1)}}\right\}^{\frac{1}{p+q}}
\end{array}\right\}^{\frac{1}{p+q}}\right\}^{\frac{1}{2}}\\
\left\{1-\left\{\left\{\begin{array}{l}1-\left\{\prod_{i,j=1,i\neq j}^{n}\left\{\begin{array}{l}1-(1-\left(1-(\mu_{\alpha_i})^2\right)^{n\varphi_i}\right)+(1-\left((\mu_{\alpha_i})^2+(\nu_{\alpha_i})^2\right))^{n\varphi_i})^{p}\\(1-\left(1-(\mu_{\alpha_j})^2\right)^{n\varphi_j}\right)+(1-\left((\mu_{\alpha_j})^2+(\nu_{\alpha_j})^2\right))^{n\varphi_j})^{q}+\\(1-\left((\mu_{\alpha_i})^2+(\nu_{\alpha_i})^2\right))^{n\varphi_i p}(1-\left((\mu_{\alpha_j})^2+(\nu_{\alpha_j})^2\right))^{n\varphi_j q}\end{array}\right\}\right\}^{\frac{1}{n(n-1)}}\\
\quad+\left\{\prod_{i,j=1,i\neq j}^{n}\left((1-\left((\mu_{\alpha_i})^2+(\nu_{\alpha_i})^2\right))^{n\varphi_i p}(1-\left((\mu_{\alpha_j})^2+(\nu_{\alpha_j})^2\right))^{n\varphi_j q}\right)\right\}^{\frac{1}{n(n-1)}}\end{array}\right\}^{\frac{1}{p+q}}\right\}^{\frac{1}{2}}\right\}
\end{array}\right\} \tag{5}$$

where

$$\varphi_i=\frac{(1+T(\alpha_i))}{\sum_{i=1}^{n}(1+T(\alpha_i))}, \tag{6}$$

$$T(\alpha_i)=\sum_{j=1,j\neq i}^{n}Sup(\alpha_i,\alpha_j),(i=1,2,\dots,n), \tag{7}$$

$$Sup(\alpha_i,\alpha_j)=\left(1-d(\alpha_i,\alpha_j)+\left|{\nu_{\alpha_i}}^2-{\nu_{\alpha_j}}^2\right|+\left|{\pi_{\alpha_i}}^2-{\pi_{\alpha_j}}^2\right|\right), \tag{8}$$

$$d(\alpha_i,\alpha_j)=\frac{1}{2}(\left|{\mu_{\alpha_i}}^2-{\mu_{\alpha_j}}^2\right|, \tag{9}$$

$$\pi_{\alpha_i}=\sqrt{1-{\mu_{\alpha_i}}^2-{\nu_{\alpha_i}}^2}. \ (10)$$

The aggregated results were defuzzied using the PFS score function [48] and transformed into crisp values according to Eq. (11). The crisp values represent the score values for each real-time SLRS.

$$s(\alpha)={\mu_\alpha}^2-{\upsilon_\alpha}^2 \tag{11}$$

These scores were sorted in descending order, that is, the finest real-time SLRS with the greatest score was ranked first, and vice versa.

Step 4: Group benchmarking

Group benchmarking was performed to unify the ranking results of the three recruited experts. Thus, the scores of the real-time SLRS of the three experts for each Likert scale were aggregated using the arithmetic mean shown in Eq. (12). The resulting score values were the final benchmarking results of the real-time SLRS-based wearable sensory devices. Notably, the real-time SLRS with the greatest score value was the best and ranked first, and vice versa.

$$Group\ benchmarking = \oplus R^* \tag{12}$$

where $\oplus$ represents the arithmetic mean, and R^* represents the final rank for each expert.

4 Results and Discussion

This section presents and examines the findings of the extended PFDOSM-PBM approach developed for real-time SLRS evaluation and benchmarking. The real-time SLRS decision matrix result is reported in Section 4.1. The real-time SLRS opinion matrices, real-time SLRS fuzzy opinion matrices, and individual and group benchmarking are discussed in Section 4.2.

4.1 Real-Time SLRS Decision Matrix Results

This section reports the results of the real-time SLRS decision matrix. The recruited experts (the same experts whose opinions were collected in Section 3.2 Step 1) evaluated 30 real-time SLRS-based wearable sensory devices (Section 3.1). The evaluation findings of the SLRS decision matrix were constructed based on the intersection between the set of SLRS alternatives and criteria. Table 4 summarizes the final evaluation result of the real-time SLRS decision matrix.

Table 4
Real-time SLRS decision matrix results.

alternatives	Hand gesture recognition																						Sensor glove system							
	C1							C2		C3		C4						C5		C6				C9		C10			11	
	C1-1	C1-2	C1-3	C1-4	C1-5	C1-6	C1-7	C2-1	C2-2	C3-1	C3-2	C4-1	C4-2	C4-3	C4-4	C4-5	C4-6	C5-1	C5-2	C6-1	C6-2	C7	C8	C9-1	C9-2	C10-1	C10-2	C10-3	C11-1	C11-2
SLRS1	No	No	Yes	6	1	1	6	Yes	No	Yes	No	Yes	Yes	No	No	No	No	Yes	No	Yes	No	150	5	Yes	No	Yes	No	No	No	No
SLRS2	No	No	Yes	5	1	1	5	Yes	No	Yes	No	Yes	Yes	No	No	No	No	No	Yes	Yes	No	112	10	Yes	No	Yes	No	No	No	No
SLRS3	No	No	Yes	26	N/A	N/A	N/A	Yes	No	Yes	No	Yes	Yes	No	No	No	No	Yes	No	Yes	No	72	5	Yes	No	Yes	No	No	No	No
SLRS4	No	Yes	No	10	1	1	10	Yes	No	Yes	No	Yes	Yes	No	No	No	No	No	Yes	Yes	No	63	5	Yes	No	Yes	No	No	No	No
SLRS5	No	No	Yes	4	1	2	8	Yes	No	Yes	No	Yes	No	No	No	No	No	Yes	No	Yes	No	47	5	Yes	No	Yes	No	No	No	No
SLRS6	No	Yes	No	N/A	N/A	N/A	N/A	Yes	No	Yes	No	No	No	No	No	No	No	Yes	No	Yes	No	50	5	Yes	No	Yes	No	No	No	No
SLRS7	Yes	Yes	No	36	N/A	30	1080	Yes	No	Yes	No	Yes	Yes	Yes	No	No	No	Yes	No	Yes	No	66	8	Yes	No	Yes	Yes	Yes	No	No
SLRS8	Yes	No	No	10	1	20	200	Yes	No	Yes	No	Yes	Yes	No	No	No	No	Yes	No	Yes	No	50	8	Yes	No	Yes	No	No	Yes	No
SLRS9	No	Yes	Yes	N/A	7	5	N/A	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	No	No	No	Yes	Yes	No	87	13	Yes	No	Yes	Yes	No	Yes	No
SLRS10	No	Yes	Yes	25	5	40	200	Yes	No	Yes	No	Yes	Yes	Yes	No	No	No	Yes	No	Yes	No	60	30	Yes	No	Yes	Yes	Yes	Yes	No
SLRS11	No	Yes	No	24	9	1	N/A	Yes	No	Yes	No	Yes	Yes	No	No	No	No	Yes	No	Yes	No	130	18	Yes	No	Yes	No	No	Yes	No
SLRS12	No	Yes	No	26	1	10	260	Yes	Yes	Yes	No	Yes	No	Yes	No	Yes	No	No	Yes	Yes	No	75	12	Yes	No	Yes	Yes	No	Yes	No
SLRS13	No	Yes	No	8	1	10	80	Yes	No	Yes	No	Yes	Yes	Yes	No	No	No	No	No	Yes	No	65	13	Yes	No	Yes	Yes	No	Yes	No
SLRS14	No	Yes	No	26	1	10	260	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	No	No	Yes	No	Yes	No	60	13	Yes	No	Yes	Yes	No	Yes	No
SLRS15	No	No	Yes	4	1	N/A	N/A	Yes	Yes	Yes	No	Yes	Yes	No	No	No	No	Yes	No	Yes	No	55	8	Yes	No	Yes	No	No	Yes	No
SLRS16	No	Yes	No	26	1	1	26	Yes	No	Yes	No	Yes	Yes	Yes	No	No	No	No	No	Yes	No	87	6	Yes	No	No	No	No	Yes	No
SLRS17	No	Yes	Yes	36	N/A	N/A	120	Yes	No	Yes	No	No	No	No	No	No	No	Yes	No	Yes	No	30	5	Yes	No	Yes	No	No	No	No
SLRS18	Yes	Yes	No	26	N/A	N/A	256	Yes	No	Yes	No	Yes	Yes	No	No	No	No	Yes	No	Yes	No	55	8	Yes	No	Yes	Yes	No	Yes	No
SLRS19	No	Yes	No	7	1	1	7	Yes	No	Yes	No	Yes	No	No	No	No	No	Yes	No	Yes	No	34	2	Yes	No	Yes	No	No	No	No
SLRS20	No	Yes	No	5	1	1	5	Yes	Yes	Yes	No	Yes	No	Yes	No	No	No	No	Yes	Yes	No	65	30	Yes	No	Yes	No	No	No	No
SLRS21	No	No	Yes	32	1	1	32	Yes	No	Yes	No	Yes	Yes	Yes	No	No	No	Yes	No	Yes	No	85	5	No	Yes	Yes	No	No	No	No
SLRS22	No	Yes	No	26	2	1	32	Yes	No	Yes	No	Yes	Yes	Yes	No	No	No	Yes	No	Yes	No	50	5	Yes	No	Yes	No	No	Yes	No
SLRS23	No	Yes	Yes	28	10	5	N/A	Yes	No	Yes	No	Yes	Yes	No	No	No	No	Yes	No	Yes	No	50	8	Yes	No	Yes	No	No	Yes	No
SLRS24	No	Yes	Yes	8	1	10	80	Yes	No	Yes	No	Yes	Yes	No	No	No	No	No	Yes	Yes	No	120	13	Yes	No	Yes	Yes	No	Yes	No
SLRS25	No	No	Yes	60	3	10	1800	Yes	Yes	No	Yes	Yes	Yes	Yes	No	Yes	No	Yes	No	Yes	No	120	4	No	Yes	Yes	No	No	Yes	No
SLRS26	No	Yes	No	N/A	57	5	6270	Yes	No	Yes	No	Yes	Yes	Yes	Yes	Yes	No	No	Yes	Yes	No	125	30	Yes	No	Yes	No	Yes	Yes	No
SLRS27	No	Yes	Yes	N/A	1	4	N/A	Yes	No	Yes	No	Yes	Yes	Yes	No	No	No	No	Yes	Yes	No	70	11	Yes	No	Yes	Yes	No	No	No
SLRS28	No	Yes	No	26	1	100	2600	Yes	Yes	Yes	No	Yes	Yes	Yes	No	No	No	No	Yes	Yes	No	20	8	Yes	No	Yes	Yes	No	No	No
SLRS29	Yes	Yes	No	36	N/A	30	1080	Yes	Yes	Yes	No	Yes	Yes	Yes	No	No	No	Yes	No	Yes	No	97	8	Yes	Yes	Yes	Yes	No	No	No
SLRS30	Yes	No	No	10	10	No	N/A	Yes	No	Yes	No	Yes	No	Yes	No	No	No	No	Yes	Yes	No	43	5	Yes	No	Yes	No	No	No	No

As stated in Section 3.1, each real-time SLRS within the decision matrix is evaluated either subjectively or objectively, depending on the evaluation criteria. With subjective criteria, each real-time SLRS is given a Yes or No reflecting the existence or the nonexistence of each criterion in the selected system. For instance, C5-1=Yes in SLRS1 indicates that the online recognition system is available, whereas C6-2=No indicates that two-way communication is absent in the same system. Experts looked for the measurable information of the objective criteria in the selected articles and wrote the values in the decision matrix. If the article did not mention the values of the criteria, the expert wrote 'N/A' (not available) into the decision matrix to indicate the absence of information. Selecting the most suitable real-time SLRS based on a particular criterion was simple. Based on the cost criterion, the SLRS28 system was the best alternative, whereas SLRS10, SLRS20, and SLRS26 were the best alternatives based on the data channel criterion. In the same scenario, SLRS1 was the worst alternative based on the cost criterion, whereas SLRS19 was the worst alternative based on the data channel criterion. However, identifying the best suited system while simultaneously taking into account all the listed criteria was a challenging task. Following [41,44,45,47], the decision matrix was fed to the benchmarking method (PFDOSM-PBM) to address this difficulty and examine the influence of changing the Likert scale with a single fuzzy set on the ranking results.

4.2 Real-time SLRS benchmarking results

In this section, the results of four PFDOSM-PBM formulation steps are reported.

First, the real-time SLRS decision matrix was transformed into the real-time SLRS opinion matrix, as explained in Section 3.2 Step 1. Three opinion matrices were created based on the opinion of the recruited experts for each Likert scale.

Second, each real-time SLRS opinion matrix was transformed into a real-time SLRS fuzzy opinion matrix using PFNs, as explained in Section 3.2 Step 2. Accordingly, three fuzzy opinion matrices were generated for each expert across each Likert scale.

Third, the PFNs within three fuzzy opinion matrices of each expert for each Likert scale were aggregated using the PFIPBM operator and defuzzied to find the score of each alternative, as explained in Section 3.2 Step 3. The alternatives of real-time SLRS were ranked based on the calculated scores of each expert across the three Likert scales, as given in Table 5. The experiment included certain values of p and q.

Table 5

Benchmarking results of three experts across three Likert scales ($p = 0\ and\ q = 1$).

Systems	Expert 1						Expert 2						Expert 3					
	Five-point Likert Scale		Seven-point Likert Scale		Ten-point Likert Scale		Five-point Likert Scale		Seven-point Likert Scale		Ten-point Likert Scale		Five-point Likert Scale		Seven-point Likert Scale		Ten-point Likert Scale	
	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank
SLRS1	0.1365	28	**-0.1351**	**30**	-0.1125	27	**0.1740**	**29**	-0.2840	28	-0.2663	26	0.1363	27	-0.0037	28	0.0013	27
SLRS2	0.1554	26	-0.0711	28	-0.1012	26	**0.1740**	**29**	-0.2040	26	-0.2736	28	0.1554	26	0.0141	26	0.0423	26
SLRS3	0.2294	21	0.0187	23	-0.0376	23	0.2638	22	-0.0676	23	-0.1809	22	0.2114	22	0.0541	23	0.0736	23
SLRS4	0.2073	23	0.0130	24	-0.0714	25	0.2073	25	-0.0823	24	-0.2173	24	0.1695	25	0.0483	24	0.0733	24
SLRS5	**0.1233**	**30**	-0.0460	26	-0.1393	29	0.1924	27	-0.2840	28	-0.2663	26	0.1363	27	0.0214	25	-0.0227	29
SLRS6	0.1421	27	-0.0512	27	**-0.2186**	**30**	0.1957	26	**-0.3875**	**30**	**-0.4002**	**30**	0.1233	29	**-0.1105**	**30**	**-0.0572**	**30**
SLRS7	0.5138	3	0.3538	10	0.4121	4	0.4776	8	0.4729	6	0.2983	7	0.5171	4	0.4195	6	0.4679	6
SLRS8	0.3314	16	0.2396	14	0.1541	15	0.3314	17	0.2130	13	0.0162	15	0.3171	14	0.1459	19	0.2488	15
SLRS9	0.4523	6	0.4785	2	0.3778	7	0.5075	4	0.5112	3	0.3190	5	0.4951	6	0.5284	2	0.4959	3
SLRS10	**0.5606**	**1**	**0.5368**	**1**	**0.5076**	**1**	**0.5741**	**1**	**0.6141**	**1**	**0.4802**	**1**	**0.5429**	**1**	0.5147	3	**0.5376**	**1**
SLRS11	0.3121	17	0.2394	15	0.0386	18	0.3517	15	0.1454	16	-0.0917	18	0.3023	18	0.0805	20	0.2060	18
SLRS12	0.4520	7	0.3990	6	0.3390	9	0.4786	7	0.4478	7	0.2140	8	0.4152	9	0.3976	9	0.4171	9
SLRS13	0.3657	11	0.1070	21	0.1970	12	0.3813	12	0.2831	12	0.0500	13	0.3687	12	0.2148	16	0.2852	13
SLRS14	0.5404	2	0.4383	5	0.4616	2	0.5511	2	0.5972	2	0.3824	2	0.5242	3	0.4790	5	0.4882	4
SLRS15	0.2953	18	0.1161	20	0.0012	20	0.3281	19	0.0126	19	-0.1501	19	0.3147	15	0.1567	18	0.1148	21
SLRS16	0.1931	24	-0.0926	29	-0.0175	22	0.2114	24	-0.0059	21	-0.1553	20	0.1931	23	0.0028	27	0.1068	22
SLRS17	0.1924	25	0.1924	16	-0.0171	21	0.2801	21	-0.1953	25	-0.2537	25	0.1748	24	0.0735	21	0.0699	25
SLRS18	0.4478	8	0.3657	8	0.2253	10	0.4610	10	0.3312	10	0.1044	11	0.4000	10	0.2780	12	0.3259	11
SLRS19	0.1237	29	0.0130	24	-0.1264	28	0.1789	28	-0.2142	27	-0.3532	29	**0.1231**	**30**	-0.0037	28	-0.0114	28
SLRS20	0.2950	19	0.1259	19	0.0079	19	0.3127	20	-0.0285	22	-0.1925	23	0.2767	19	0.1723	17	0.1686	19
SLRS21	0.2416	20	0.0431	22	0.1240	17	0.3299	18	0.1094	17	0.0041	16	0.2579	20	0.2460	14	0.2172	16
SLRS22	0.3493	14	0.2714	13	0.1656	14	0.3657	14	0.3310	11	0.0482	14	0.3146	16	0.2239	15	0.2814	14
SLRS23	0.3657	11	0.4390	4	0.2130	11	0.4283	11	0.1466	15	0.1354	9	0.3848	11	0.2831	11	0.3575	10
SLRS24	0.3657	11	0.2994	12	0.1929	13	0.3813	13	0.2122	14	0.0649	12	0.3146	16	0.2773	13	0.3045	12
SLRS25	0.3988	10	0.3557	9	0.3884	6	0.4639	9	0.3391	9	0.3121	6	0.4493	7	0.4823	4	0.4535	7
SLRS26	0.5005	4	0.3838	7	0.3901	5	0.4830	5	0.4897	5	0.3325	3	0.5284	2	0.3997	8	0.4820	5
SLRS27	0.3323	15	0.1561	17	0.1249	16	0.3465	16	0.0006	20	-0.0135	17	0.3323	13	0.3107	10	0.2130	17
SLRS28	0.4340	9	0.3538	10	0.3530	8	0.4804	6	0.3933	8	0.1164	10	0.4304	8	0.4133	7	0.4195	8
SLRS29	0.4966	5	0.4448	3	0.4551	3	0.5097	3	0.5103	4	0.3252	4	0.5001	5	0.5629	1	0.5164	2
SLRS30	0.2294	21	0.1434	18	-0.0505	24	0.2631	23	0.0578	18	-0.1667	21	0.2451	21	0.0731	22	0.1248	20

The benchmarking findings of the real-time SLRS when $p = 0\ and\ q = 1$ are given in Table 5, which explains the importance of the experts' opinions for each criterion from their different perspectives. Notably, the real-time SLRS with the greatest score was the best, whereas the real-time SLRS with the lowest score was the worst. According to Table 5, SLRS10 earned the first ranking results across the three experts for each Likert scale, with the exception of the third expert's seven-point scale, where SLRS29 ranked first. The first and second experts ranked SLRS14 the second best alternative across the three Likert scales, and except for the seven-point scale of the first expert, SLRS9 ranked first. However, the third expert's ranking results of the second-best alternative varied across the three Likert scales. SLRS26, SLRS9 and SLRS29 were ranked second by the third expert when five-, seven- and ten-point Likert scales were used, respectively. The third best alternative was SLRS7 with a five-point Likert scale and SLRS29 across the seven- and ten-point Likert scales of the first expert. The third best alternative was varied across the three Likert scales of the second and third experts. Furthermore, the first expert ranked SLRS5, SLRS1 and SLRS6 thirty across five-, seven- and ten-point Likert scales, respectively, as the worst alternative. The second expert ranked SLRS1 and SLRS2 worst with a five-point Likert scale and SLRS6 with the remaining scales. Finally, the third expert ranked SLRS19 worst with a five-point Likert scale and SLRS6 with the remaining scales.

These results reveal that different experts have varied ranks based on distinct scales. This situation necessitated the use of the differences and consensus indicator tests to determine the distinctions and matches by calculating the ranking differences and similarities for the same expert using different scales. This test was undertaken to determine the differences between the ranks. Table 6 presents the results of the difference indicator test for each expert when $p = 0\ and\ q = 1$.

Table 6

Difference indicator test for each expert results ($p = 0\ and\ q = 1$).

Experts	Expert 1				Expert 2				Expert 3			
Scales	Difference	%	Consensus	%	Difference	%	Consensus	%	Difference	%	Consensus	%
Five-Seven Scales	26	86.7%	4	13.3%	22	73.3%	8	26.7%	27	90%	3	10%
Five-Ten Scales	24	80%	6	20%	25	83.3%	5	16.7%	22	73.3%	8	26.7%
Seven-Ten Scales	26	86.7%	4	13.3%	23	76.7%	7	23.3%	23	76.7%	7	23.3%

Three experts with their between-scale differences were discussed based on the table results. The following three comparisons were established: (i) five-seven scales, (ii) five-ten scales and (iii) seven-ten scales. A total of (n = 26/30) that represents 86.7% differences were identified for the first expert, and the remaining (n = 4) that represents 13.3% were consistent for the first scale and similar alternatives (i.e., SLRS6, SLRS10, SLRS18 and SLRS20). The scale comparisons revealed fewer differences (80%) compared with the first (n = 24/30), leaving six alternatives (20%) in the rank with the same position (i.e., SLRS2, SLRS10, SLRS14, SLRS20, SLRS22 and SLRS23). The last scale comparison resulted in (n = 26/30) that represented 86.7% differences in ranking and only four (13.3%) consistent ones (i.e., SLRS3, SLRS10, SLRS15 and SLRS20).

The result for the second expert started with a total of (n = 22/30) that represented 73.3% differences for the first scale comparison, leaving eight alternatives that represent 26.7% with the same rank (i.e., SLRS10, SLRS12, SLRS13, SLRS14, SLRS15, SLRS18, SLRS25 and SLRS26). The subsequent comparison between five and ten scales identified additional differences (n = 25/30) that represented 83.3% with five (16.7%) identical ranking alternatives (i.e., SLRS3, SLRS10, SLRS14, SLRS15 and SLRS22). The third and last comparison for the second expert identified a total of (n = 23/30) that represented 76.7% rank differences, and the seven (23.3%) remaining unchanged ranks were attributed to SLRS4, SLRS6, SLRS10, SLRS14, SLRS15, SLRS17 and SLRS29.

The third and last expert results started with a total of (n = 27/30) that represented 90% rank differences and three (10%) consistent rankings for SLRS2, SLRS12 and SLRS23. Afterward, the second comparison between five and ten scales identified (n = 22/30) differences that represented 73.3% with eight (26.7%) identical ranking alternatives (SLRS1, SLRS2, SLRS10, SLRS11, SLRS12, SLRS20, SLRS25 and SLRS28). The third and final comparison for the third expert revealed a total of (n = 23/30) rank differences, representing 76.7%, and the remaining seven (23.3%) unaltered ranks were attributed to SLRS2, SLRS3, SLRS4, SLRS6, SLRS7, SLRS12 and SLRS19. Notably, some alternatives with consistent ranking were found across the three different scales for the third expert, including SLRS2 and SLRS12 between the three scales. Such an occurrence revealed the clarity of rank differences and similarities using each of the scales and across each of the experts. Using different scales can result in varying rankings, which affect the ranking in the MCDM approach. The visual representation of the benchmarking differences and consensus among three experts within the same Likert scale is shown in Fig. 2.

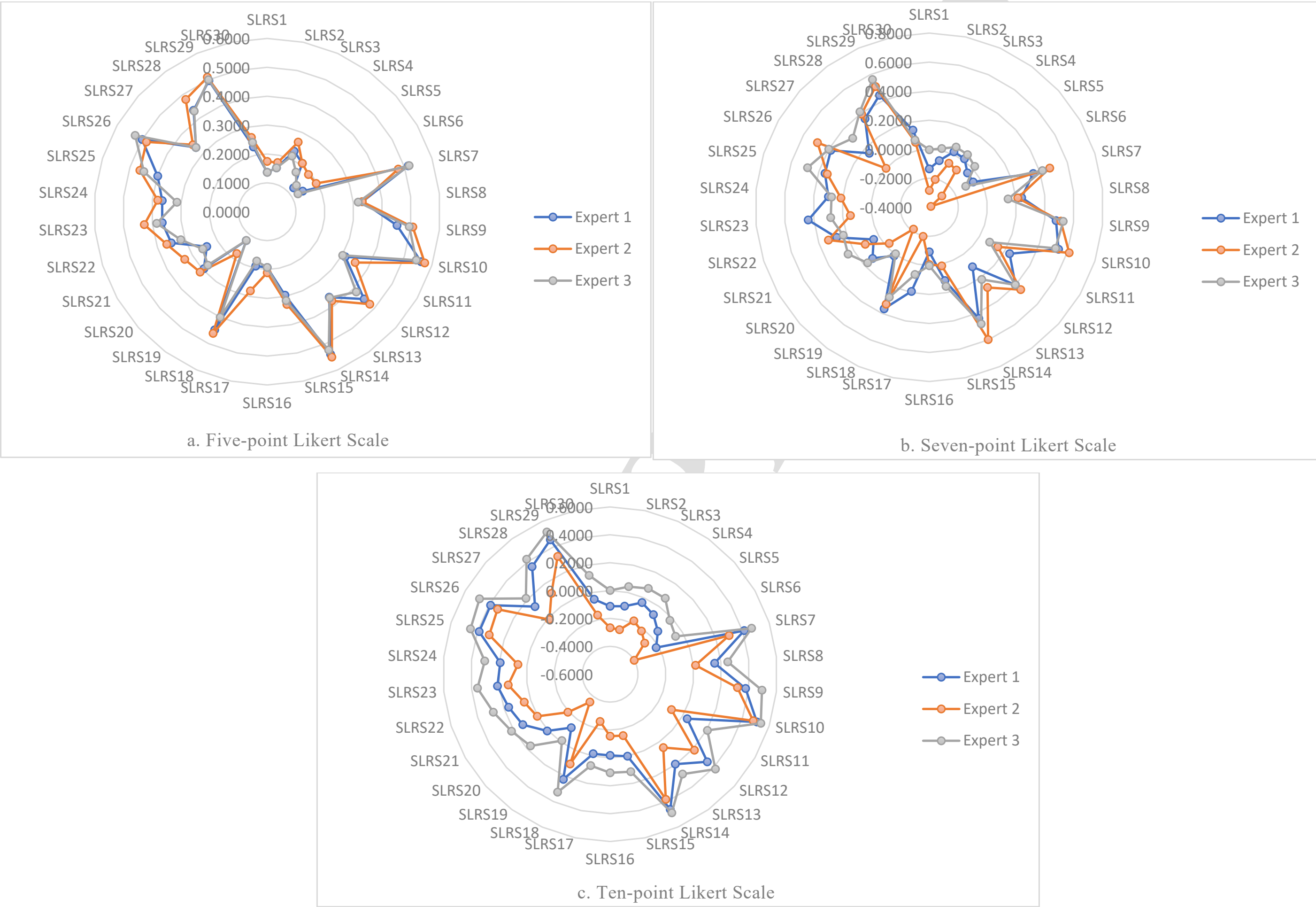

Fig. 2. Benchmarking differences and consensus between three experts within Likert scales: (a) Five, (b) Seven and (c) Ten ($p = 0$ and $q = 1$)

Fig. 2 reveals that some of the SLRS-based wearable sensory devices are identical across different Likert scales. For the five-point Likert scale, only two SLRSs have a consistent position based on three experts' rankings (SLRS10 and SLRS23), and the ratio of identical SLRSs is 6.7%. For the seven-point Likert scale, two SLRSs also maintained their ranking position across the three experts (SLRS2 and SLRS3) with a 6.7% ratio. Finally, for the ten-point Likert scale, five SLRSs have a consistent position based on three experts' rankings (SLRS6, SLRS8, SLRS10, SLRS11 and SLRS22), and the ratio of identical SLRSs is 16.7%.

Fourth, previous findings indicated the clarity of variations between the ranks. Therefore, group benchmarking was applied to aggregate the results of the three experts into a final result by using Equation 12, as explained in Section 3.2 Step 4. The results were divided into three subsections according to the three Likert scales. Table 7 reports the final results of real-time SLRS-based wearable sensory device group benchmarking when $p = 0\ and\ q = 1$. The real-time SLRS with the greatest score was the best, whereas the real-time SLRS with the lowest score was the worst.

Table 7

Real-time SLRS group benchmarking results ($p = 0\ and\ q = 1$).

Systems	Five-point Likert scale		Seven-point Likert scale		Ten-point Likert scale	
	Score	Rank	Score	Rank	Score	Rank
SLRS1	0.1489	29	-0.1409	29	-0.1258	27
SLRS2	0.1616	26	-0.0870	27	-0.1108	26
SLRS3	0.2349	22	0.0017	23	-0.0483	23
SLRS4	0.1947	25	-0.0070	24	-0.0718	25
SLRS5	0.1507	28	-0.1029	28	-0.1428	28
SLRS6	0.1537	27	**-0.1831**	**30**	**-0.2253**	**30**
SLRS7	0.5028	4	0.4154	6	0.3928	6
SLRS8	0.3266	16	0.1995	15	0.1397	15
SLRS9	0.4850	6	0.5060	2	0.3976	5
SLRS10	**0.5592**	**1**	**0.5552**	**1**	**0.5085**	**1**
SLRS11	0.3220	17	0.1551	17	0.0510	18
SLRS12	0.4486	7	0.4148	7	0.3233	8
SLRS13	0.3719	12	0.2016	14	0.1774	13
SLRS14	0.5386	2	0.5048	4	0.4440	2
SLRS15	0.3127	18	0.0951	19	-0.0114	20
SLRS16	0.1992	24	-0.0319	25	-0.0220	21
SLRS17	0.2158	23	0.0235	22	-0.0670	24
SLRS18	0.4363	10	0.3249	10	0.2186	11
SLRS19	**0.1419**	**30**	-0.0683	26	-0.1636	29
SLRS20	0.2948	19	0.0899	21	-0.0053	19

SLRS21	0.2765	20	0.1328	18	0.1151	16
SLRS22	0.3432	14	0.2754	12	0.1651	14
SLRS23	0.3929	11	0.2896	11	0.2353	10
SLRS24	0.3539	13	0.2630	13	0.1874	12
SLRS25	0.4374	9	0.3924	8	0.3847	7
SLRS26	0.5040	3	0.4244	5	0.4016	4
SLRS27	0.3370	15	0.1558	16	0.1081	17
SLRS28	0.4483	8	0.3868	9	0.2963	9
SLRS29	0.5022	5	0.5060	3	0.4322	3
SLRS30	0.2459	21	0.0914	20	-0.0308	22

Table 7 shows that SLRS10 was the best across all the different scales. In contrast, SLRS19 was considered worst for the five-point Likert scale, whereas SLRS6 was worst for the remaining two scales, namely, the seven-point and ten-point scales. Differences, which can be easily identified, were presented from one Likert scale to another. Nonetheless, the difference indicator test was still necessary to compute the differences between the three Likert scales. Therefore, this test was applied for the final group benchmarking results to compute the differences for the final rank using the three Likert scales, as given in Table 8.

Table 8

Result of the difference indicator test for group benchmarking.

Scales	Difference	%	Consensus	%
Five-Seven Scales	22	73.3%	8	26.7%
Five-Ten Scales	23	76.7%	7	23.3%
Seven-Ten Scales	22	73.3%	8	26.7%

Group benchmarking results with their between-scale differences were discussed based on the table results. The following three comparisons were established: (i) five-seven scales, (ii) five-ten scales and (iii) seven-ten scales. The first comparison (Five-Seven Scales) revealed a total of (n = 22/30) differences representing 73.3%, with eight representing 26.7% consistent SLRSs (SLRS1, SLRS5, SLRS10, SLRS11, SLRS12, SLRS18, SLRS23 and SLRS24). The subsequent comparison between the Five-Ten Scales resulted in a total of (n = 23/30) representing 76.7% differences and seven representing 23.3% SLRSs with the same rank (SLRS2, SLRS4, SLRS5, SLRS10, SLRS14, SLRS20 and SLRS22). The last scale comparison between the Seven-Ten Scales presented (n = 22/30) differences, and eight representing 26.7% consistently ranked SLRSs (SLRS3, SLRS5, SLRS6, SLRS7, SLRS8, SLRS10, SLRS28 and SLRS29). Only two SLRSs had the same position in the final rank when the three scales were used (SLRS5 and

SLRS10).

5 Validation and Evaluation

In this section, the proposed method is validated by performing systematic ranking (Section 5.1). Subsequently, a comparative analysis of the proposed method based on the three Likert scales with a single fuzzy set with four benchmark studies is undertaken (Section 5.2).

5.1 Systematic Ranking

The validation of the PFDOSM-PBM results was achieved by verifying the group benchmarking findings of the real-time SLRS-based wearable sensory devices using each expert's opinion matrix across the used Likert scales (five-, seven-and ten-point). Several researchers have used systematic ranking to validate their findings [56,57]. The points listed below summarize the validation procedure:

i. The opinion matrices given were replaced with a numerical scale (see Table 3) and aggregated using the arithmetic mean to produce a final value for each SLRS.

ii. The SLRS alternatives within each opinion matrix and their aggregated values were sorted based on the results of group benchmarking for each Likert scale.

iii. The SLRS alternatives were divided into three equal groups. Notably, the validation was not influenced by the number of groups or alternatives within each group [58,59].

iv. The mean of each group was calculated using Eq. (13), as reported in Table 9.

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i. \quad (13)$$

The validation was based on each group's mean. The group with the lowest mean reflected the most desired real-time SLRS because a lower numerical scale indicates a better alternative (ideal solution), whereas a higher numerical scale indicates a worse alternative. Thus, the mean of the first group across the three Likert scales should be the lowest, which was then compared with the means of the second and third groups to determine the validity of the outcome. The second group's mean should be less than or equal to that of the third group but larger than or equal to that of the first group. Similarly, the third group's mean should be larger than that of the first group and larger than or equal to that of the second group. The results are valid if the estimates support the claim. Table 9 presents the validation of the real-time SLRS group benchmarking results based on the proposed PFDOSM-PBM when $p = 0 \; and \; q = 1$.

Table 9

Group benchmarking results validation across three Likert scales ($p = 0 \; and \; q = 1$).

Groups	Real-time SLRSs based wearable sensory devices	Means

Five-point Likert Scale		
First Group	SLRS10, SLRS14, SLRS26, SLRS7, SLRS29, SLRS9, SLRS12, SLRS28, SLRS25, SLRS18	2.085556
Second Group	SLRS23, SLRS13, SLRS24, SLRS22, SLRS27, SLRS8, SLRS11, SLRS15, SLRS20, SLRS21	2.395556
Third Group	SLRS30, SLRS3, SLRS17, SLRS16, SLRS4, SLRS2, SLRS6, SLRS5, SLRS1, SLRS19	2.681111
Seven-point Likert Scale		
First Group	SLRS10, SLRS9, SLRS29, SLRS14, SLRS26, SLRS7, SLRS12, SLRS25, SLRS28, SLRS18	2.804526749
Second Group	SLRS23, SLRS22, SLRS24, SLRS13, SLRS8, SLRS27, SLRS11, SLRS21, SLRS15, SLRS30	3.19037037
Third Group	SLRS20, SLRS17, SLRS3, SLRS4, SLRS16, SLRS19, SLRS2, SLRS5, SLRS1, SLRS6	3.654197531
Ten-point Likert Scale		
First Group	SLRS10, SLRS14, SLRS29, SLRS26, SLRS9, SLRS7, SLRS25, SLRS12, SLRS28, SLRS23	4.301111111
Second Group	SLRS18, SLRS24, SLRS13, SLRS22, SLRS8, SLRS21, SLRS27, SLRS11, SLRS20, SLRS15	5.248888889
Third Group	SLRS16, SLRS30, SLRS3, SLRS17, SLRS4, SLRS2, SLRS1, SLRS5, SLRS19, SLRS6	6.067777778

Table 9 presents the validation of real-time SLRS benchmarking results obtained by the proposed PFDOSM-PBM. The first groups across all Likert scales had the lowest mean (five-point [2.085556], seven-point [2.804526749] and ten-point [4.301111111]), whereas the second group had a higher mean (five-point [2.395556], seven-point [3.19037037] and ten-point [5.248888889]) than the first group. The third group had a higher mean (five-point [2.681111], seven-point [3.654197531] and ten-point [6.067777778]) than the second and first groups. This result demonstrates that groups derived from the PFDOSM-PBM employing all Likert scale results for evaluating and benchmarking SLRS-based wearable sensory devices were valid and ranked systematically.

5.2 Comparative Analysis

Following [60–62][63], this section compares the proposed study with four benchmark studies, [41], [44], [45] and [47]. The comparisons were conducted based on seven points, as given in Table 10. The first point compares the proposed study with four benchmark studies in terms of the fuzzy set utilized in each. The second point compares the studies in terms of the benchmarking method utilized in each. The third point compares the studies in terms of the aggregation operator utilized in each to find the individual ranking. The fourth point compares the studies in terms of the real-time SLRS alternatives utilized in each. The fifth point compares the studies in terms of the SLRS criteria utilized in each. The sixth point compares the studies in terms of the Likert scale utilized in each. The seventh and last points compare the differences between the utilized multi-Likert scales.

Table 10

Comparison of the proposed and benchmark studies.

Comparisons Points	Proposed method	[41]	[44]	[45]	[47]
Fuzzy sets	PFSs	PFSs	Interval-valued PFSs	Cubic PFSs	Pythagorean m-polar fuzzy sets
Benchmarking method	FDOSM	FDOSM	FDOSM	FDOSM	FDOSM
Aggregation operator	PFIPBM operator	IHAM operator	IPFWA operator	CPFWA operator	PMPFWA operator
SLRS Alternatives	30 alternatives	30 alternatives	30 alternatives	30 alternatives	30 alternatives
SLRS criteria	Two perspectives	One perspective	Two perspectives	Two perspectives	Two perspectives
Likert scale	five-, seven-, and ten-point	five-point	seven-point	ten-point	ten-point
Multi-Likert scales	Achieved	Not addressed	Not addressed	Not addressed	Not addressed

First, PFSs, interval-valued PFSs, cubic PFSs and Pythagorean m-polar fuzzy sets were used by [41], [44], [45] and [47], respectively, as given in Table 10. PFS was the base of the four benchmark studies; therefore, it was selected in the present paper. Second, FDOSM was used to rank real-time SLRS alternatives in all benchmark studies. Thus, it was selected in the present paper for the same purpose. Third, the fuzzy numbers were aggregated using several aggregation operators (*IHAM, IPFWA, CPFWA and PMPFWA* operators) in the FDOSM individual benchmarking of the benchmark studies [41], [44], [45] and [47], respectively. Owing to the benefit of *PBM*, the *PFIPBM* operator was selected to aggregate the fuzzy numbers in the individual benchmarking. Fourth, 30 real-time SLRS alternatives were ranked in the benchmark studies. The same systems were selected for benchmarking in the present paper. Fifth, six criteria under the hand gesture recognition perspective were used by [41] to evaluate the 30 real-time SLRS alternatives, but the remaining benchmark studies [44], [45] and [47] used the 11 criteria under the hand gesture recognition and sensor glove system perspectives. Hence, the present paper selected the same 11 criteria to evaluate the 30 real-time SLRS alternatives. Sixth, each benchmark study utilized a single Likert scale to generate the opinion matrix and fuzzy opinion matrix. For instance, [41] and [44] employed five- and seven-point Likert scales, respectively. However, a ten-point Likert scale was employed by [45] and [47]. In the literature, the influence of utilizing a single Likert scale with multiple fuzzy sets was explored, as given in Table 10, but the influence of using several Likert scales with single fuzzy sets was not discussed. Consequently, this was one of the objectives of the present paper. Seventh, the present paper examined perspectives associated with the employment of a multi-Likert scale, whereas this aspect was not addressed in the benchmark studies. Moreover, the focus of the present work was on data collection based on the three Likert scales. On this basis, collecting data using a five-point Likert scale was favored by experts, as this scale does not present as many difficulties and complexity of comparison as higher scales (seven- and ten-point Likert scales). The wider space of these higher scales is the source of their difficulty and complexity. In light of this, the uncertainty generated using a five-point scale is limited to the variation in expert opinion. While the uncertainty caused by a seven- or ten-point scale is displayed in two shots, they are the diversity in expert opinion and the difficulty in differentiating linguistic expressions.

The aforementioned points reflect the consensus and differences between results based on the three adopted Likert scales. As illustrated in Tables 6 and 8, the kind of Likert scale influenced the final benchmarking outcomes for individuals and groups, respectively. Therefore, based on the multiple scales utilized by the experts, each scale yielded different results.

The five-point Likert scale is superior to other scales because it is flexible, easy to use by experts based on the provided answer in the data collection phase and generates more accurate findings on the basis of uncertainty generated compared to other scales. In other words, we experimentally demonstrate that utilizing the five-point Likert scale to prove the reality states will facilitate and improve the management of uncertainty.

6 Conclusion

The methodology of this comparative study was illustrated based on two sequential phases: real-time SLRS decision matrix adaptation and real-time SLRS benchmarking using PFDOSM-PBM. Thirty American SL alternatives were used as a case study and evaluated based on two perspectives of criteria: hand gesture recognition and sensor glove system. The proposed PFDOSM-PBM method aimed to compare the evaluation and benchmarking of real-time SLRS-based wearable sensory devices using multiple Likert scales (five-, seven- and ten-point) with a single fuzzy set (i.e., PFS) and measure the best scale.

The results revealed the following: (i) The individual benchmarking results of the real-time SLRS varied based on the opinion of the evaluator and the Likert scales employed. (ii) The results of group benchmarking revealed that SLRS10 was the best across all scales, whereas the worst real-time SLRS differed among Likert scales. (iii) The results reveal that the five-point Likert scale is superior to other scales (i.e., seven- and ten-point) as it is flexible, easy to use by experts and generates more accurate findings on the basis of uncertainty compared to other scales. (iv) Statistical test-based objective validation indicated that the ranked SLRS-based wearable sensory devices resulting from PFDOSM-PBM with the use of all Likert scales underwent systematic ranking. (v) The proposed study was evaluated and compared with four benchmark studies based on seven points.

The following interesting areas of research are worth exploring in the future: (i) Different SLRS (e.g., Arabic, Chinese, Thai, Bangle, French, Polish and Japanese) can be evaluated and benchmarked following the proposed methodology. (ii) Several fuzzy types, such as the spherical fuzzy set, linear Diophantine fuzzy rough set or probabilistic hesitant fuzzy set, can be adopted in the FDOSM to compare and determine whether these types can solve the vagueness issue. (iii) Other aggregation operators and score functions can be used with FDOSM to explore the influence on the benchmarking results. (iv) The rank reversal decision-making problem based on FDOSM can be elaborated and focused.

Declaration of competing interest

The authors state that they have no known competing financial interests or personal ties that could be perceived as having influenced the work described in this study.

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Highlights

- Examined the three Likert scales interm of logic and reality based single fuzzy set.
- Constructed decision matrix for 30 real-time SLRSs based on 11 evaluation criteria.
- Extended FDOSM into PFSs based on the PBM operator (named PFDOSM-PBM).
- Benchmarked the real-time SLRSs wearable sensory devices for deaf and mute.

Declaration of interests

☒ 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.

☐ The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: