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Evaluating the Suitability of a Smart Technology Application for Fall Detection Using a Fuzzy Collaborative Intelligence Approach

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Abstract: Fall detection is a critical task in an aging society. To fulfill this task, smart technology applications have great potential. However, it is not easy to choose a suitable smart technology application for fall detection. To address this issue, a fuzzy collaborative intelligence approach is proposed in this study. In the fuzzy collaborative intelligence approach, alpha-cut operations are applied to derive the fuzzy weights of criteria for each decision maker. Then, fuzzy intersection is applied to aggregate the fuzzy weights derived by all decision makers. Subsequently, the fuzzy technique for order preference by similarity to the ideal solution is applied to assess the suitability of a smart technology application for fall detection. The fuzzy collaborative intelligence approach is a posterior-aggregation method that guarantees a consensus exists among decision makers. After applying the fuzzy collaborative intelligence approach to assess the suitabilities of four existing smart technology applications for fall detection, the most and least suitable smart technology applications were smart carpet and smart cane, respectively. In addition, the ranking result using the proposed methodology was somewhat different from those using three existing methods.

Keywords: fall detection; smart technology; fuzzy collaborative intelligence; fuzzy technique for order preference by similarity to ideal solution; TOPSIS

1. Introduction

As people get older, fall detection and prevention becomes a more critical task [1]. In addition, children like to run and jump and may easily fall down accidently. People who are in poor health, have specific diseases (e.g., paralysis due to a stroke or epileptic seizure, dizziness and syncope caused by an epileptic fit or cardiovascular collapse), or have been injured in accidents are also prone to falling [2,3]. The importance of fall detection resides in the fact that the earlier a fall is reported, the lower the rate of morbidity (or mortality) becomes [4,5]. However, falling is a complicated process, making it difficult to detect [2,6]. To address this issue, smart technologies can be applied.

Smart technologies include smart clothes, smart glasses, smart watches, smart phones, smart motion sensors, smart smoke alarms, smart body analyzers, smart connected vehicles, smart toilets, smart wigs, smart mobile services, smart defense technology, smart wheelchairs, and others. A smart technology is equipped with sensors, connected to the Internet, used interactively, and to some extent



intelligent [7,8]. There have been a number of smart technology applications for fall detection, e.g., smart canes [9], smart carpets [10], the joint use of smart phones and other smart devices [2,11–13], smart tiles [14]. While smart technologies are getting more and more diverse, each smart technology application for fall detection has its own advantages and disadvantages. As a result, how to choose suitable smart technology applications for fall detection becomes a challenging task [6]. Furthermore, it is difficult to compare different fall detection systems because of the lack of a common framework [2].

Some of the relevant literature are reviewed as follows. Mubashir et al. [15] listed five criteria for choosing a suitable smart technology application for fall detection: low costs, unobtrusiveness, accuracy, easiness to setup, and robustness. De Lima et al. [16] attached various (combinations of) sensors, including a tri-axial accelerometer, force and bending sensor, and gyroscope, to the chest, insole, and lower back of a subject to find out the most suitable smart sensor application for fall detection. Chen [17] proposed the fuzzy geometric mean (FGM)-alpha-cut operations (ACO)-fuzzy weighted average (FWA) method to evaluate the sustainability of a smart technology application in mobile health care, including fall detection, in which decision makers' judgments were aggregated using FGM before deriving the fuzzy weights of criteria using ACO. Subsequently, the derived fuzzy weights were fed into the FWA method to evaluate the sustainability of a smart technology application in mobile health care. A problem with the FGM-ACO-FWA method was that whether decision makers did reach a consensus was not checked. In sum, existing methods are subject to the following problems:

- Most of the past studies in this field just listed the criteria for choosing a suitable smart technology application for fall detection, the conclusions of which cannot be applied to perform a quantitative and precise comparison;
- (2) Some studies, such as De Lima et al. [16], conducted experimentation to compare the suitabilities of smart technology applications for fall detection. However, only very few specific smart technology applications were compared.

To solve these problems, a fuzzy collaborative intelligence approach is proposed in this study.

A fuzzy collaborative intelligence approach is proposed in this study to evaluate the suitability of a smart technology application for fall detection. In the proposed methodology, first, factors critical to the suitability of a smart technology application for fall detection are found out through reviewing the literature and current practice. Based on the critical factors, the corresponding criteria are established. Subsequently, multiple decision makers fulfill the assessment task collaboratively. For each decision maker, ACO is applied to derive the fuzzy weights of criteria. To make sure that there is a consensus among decision makers, the guaranteed-consensus fuzzy analytic hierarchy process (FAHP) method proposed by Chen [18] is applied. Subsequently, fuzzy intersection (FI) is applied to aggregate the fuzzy weights of criteria derived by all decision makers. Finally, the aggregation result is fed into the fuzzy technique for order preference by similarity to the ideal solution (TOPSIS) method [19] to assess the suitability of a smart technology application for fall detection. The assessment result is defuzzified using the center-of-gravity (COG) method for generating an absolute ranking. The novelty of the fuzzy collaborative intelligence approach resides in the following aspects:

- (1) The fuzzy collaborative intelligence approach is a posterior-aggregation FAHP method, while most existing group-based FAHP methods are anterior-aggregation methods [20];
- (2) In the fuzzy collaborative intelligence approach, decision makers' judgments are aggregated using FI, while in existing group-based FAHP methods, decision makers' judgement are usually aggregated using FGM. FI can help check the existence of a consensus, and is considered to be better than FGM [21];
- (3) Although there have been some studies combining FAHP and fuzzy TOPSIS, these studies approximated, rather than derived, the values of fuzzy weights by applying FGM or fuzzy extent analysis (FEA) [22,23]. In contrast, the fuzzy collaborative intelligence approach derived the values of fuzzy weights by applying ACO;

(4) Most of the past studies applied FWA instead of fuzzy TOPSIS to assess the sustainability or suitability of a smart technology application. Compared to FWA, fuzzy TOPSIS is more sensitive in detecting a minor difference in sustainability or suitability.

The differences between the proposed methodology and some existing methods are summarized in Table 1.

Method	Smart Technology	Assessment Method	Group Decision Making	Consensus	Aggregation
Mubashir et al. [15]	All	Criteria to check	No		
De Lima et al. [16]	Smart sensors	Experimentation	No		
Chen [17]	All	FGM-ACO-FWA	Yes	Not guaranteed	Anterior-aggregation
The proposed methodology	All	ACO-FI-fuzzy TOPSIS	Yes	Guaranteed	Posterior-aggregation

Table 1. Differences between the proposed methodology and some existing methods.

The remainder of this paper is organized as follows. Section 2 is dedicated to the literature review. Section 3 introduces the fuzzy collaborative intelligence approach for assessing the suitability of a smart technology application for fall detection. Section 4 provides the results of applying the fuzzy collaborative intelligence approach to assess several smart technology applications for fall detection, so as to recommend the most suitable smart technology application. Some existing methods are also applied to assess these smart technology applications for comparison. Finally, Section 5 concludes this study and provides some topics for future research.

2. Literature Review

2.1. Smart Technology Applications for Fall Detection

Wang et al. [5] classified existing fall detection systems into four categories: ambient device-based systems, vision-based systems, wearable device-based systems, and smart phone-based systems. Measures for evaluating the performance of a fall detection system included precision, false alarm rate, and efficiency [5].

Li et al. [24] attached two sensors to the chest and right thigh of a subject in an experimental setting. Each sensor was composed of a tri-axial accelerometer and a tri-axial gyroscope. An algorithm was proposed to detect the subject's fall based on the readings of the two sensors. Similarly, a smart phone was applied for fall detection in practice by analyzing the readings of the accelerometer and gyroscope on the smart phone [12], which was a challenging task because a user's hand gesture and motion are diverse and vary continuously. To address this issue, the joint use of a smart watch and a smart phone was adopted [13], in which the smart watch sensed a user's hand gesture and motion, while the smart phone reasoned and communicated with the backend server, which was more effective than using a smart phone alone. However, a user had to bring both smart devices simultaneously. Nowadays, the newest smart watch can fulfill all tasks by itself [25]. Accompanying this, many apps with advanced reasoning algorithms have been designed [26,27].

Senouci et al. [28] designed a smart camera-based fall detection system. Two classification methods, support vector machine (SVM) and Adaboost, were applied to analyze the recorded images. The experimental results revealed that for fall detection SVM achieved a higher classification accuracy, while AdaBoost was more efficient. Miao et al. [29] established a systematic procedure to analyze a neuromorphic vision dataset recorded with dynamic vision sensors to detect the fall of a pedestrian. From the viewpoint of Wang et al. [5], the wireless signal in an environment was affected by human motions in the environment, which could be utilized to detect a fall.

According to Ojetola et al. [12], the difficulties of fall detection with smart technology applications include the setting of thresholds for distinguishing falls from non-falls, the generalization of the

algorithm to other subject groups, the validation of the method (or system) in real life, and the ability to detect in real time. For fall detection in the public domain, the disruption caused by installing an additional hardware was a barrier to the widespread deployment of fall detection systems in residential regions [5]. Optimizing a smart technology application for fall detection or a smart fall detection system is a much more difficult task [16]. In addition, the quality of the sensed data is undoubtedly critical to the effectiveness of the subsequent analysis and decision-making process [30,31].

2.2. Fuzzy TOPSIS

TOPSIS was first fuzzified by Chen [32]. Subsequently, fuzzy TOPSIS has been extensively applied to multiple-criteria decision-making problems in various fields. Basically, fuzzy TOPSIS can be applied alone, based on the values of fuzzy weights specified by decision makers. Nevertheless, the joint application of FAHP and fuzzy TOPSIS is prevalent. For example, Wang et al. [33] proposed a fuzzy hierarchical TOPSIS method for supplier selection, in which FAHP provided the values of fuzzy weights required for fuzzy TOPSIS. In addition, the *p*-norm metric method was also applied to simplify the measurement of the distance between two triangular fuzzy numbers (TFNs). Büyüközkan and Çifçi [34] applied a similar method to compare the green competencies of suppliers. In addition, the fuzzy decision-making trial and evaluation laboratory model (DEMATEL) was also used to extract the mutual relationships of interdependencies within criteria and the strength of each interdependence. Junior et al. [35] compared the advantages and disadvantages of fuzzy TOPSIS and FAHP on supplier selection, and concluded that fuzzy TOPSIS performed better with regard to the change of alternatives or criteria, agility, and the number of criteria and alternatives. However, the compared FAHP method was FEA, which was based on simplification, making the complication somewhat unfair.

3. The Proposed Methodology

The fuzzy collaborative intelligence approach proposed in this study incorporates ACO, FI, and fuzzy TOPSIS, and applies the guaranteed-consensus FAHP method proposed by Chen [18]. In addition, the fuzzy collaborative intelligence approach is a posterior-aggregation method. In contrast, the FGM-ACO-FWA method proposed by Chen [17] was an anterior-aggregation method. A comparison of the two methods is shown in Figure 1.



Figure 1. Comparison of the two methods.

3.1. Deriving the Fuzzy Weights of Criteria Using ACO

In the proposed methodology, a group of *K* decision makers is formed. First, each decision maker performs a pairwise comparison of the relative weights of criteria for assessing the suitability of a

smart technology application for fall detection. The results are represented with the following fuzzy pairwise comparison matrix:

$$\mathbf{A}_{n \times n}(k) = [\tilde{a}_{ij}(k)]; \, i, \, j = 1 \sim n; \, k = 1 \sim K,$$
 (1)

where:

$$\widetilde{a}_{ij}(k) = \{ \begin{array}{ccc} 1 & \text{if} & i = j \\ \frac{1}{\widetilde{a}_{ij}(k)} & \text{otherwise} \end{array} ; i, j = 1 \sim n; k = 1 \sim K$$

$$(2)$$

 $\tilde{a}_{ij}(k)$ is the pairwise comparison result by decision maker *k* regarding the relative weight of criterion *i* over criterion *j*. Equation (2) is the reciprocal requirement. Each pairwise comparison result is chosen from the following linguistic terms:

As important as: $\tilde{a}_{ij}(k) = (1, 1, 5)$, Slightly more important than: $\tilde{a}_{ij}(k) = (1, 3, 7)$, Considerably more important than: $\tilde{a}_{ij}(k) = (1, 5, 9)$, Extremely more important than: $\tilde{a}_{ij}(k) = (3, 7, 9)$, Absolutely more important than: $\tilde{a}_{ij}(k) = (5, 9, 9)$.

The linguistic terms are mapped to triangular fuzzy numbers (TFNs) (see Figure 2), whose ranges are wider than those of the commonly applied TFNs to increase the possibility of reaching a consensus [18].



Figure 2. Triangular fuzzy numbers (TFNs) used in the fuzzy collaborative intelligence approach.

In this way, the fuzzy weights by the decision makers will overlap with each other, guaranteeing the existence of a consensus. If a relative weight is between two linguistic terms, then the average of the two successive TFNs can be chosen. $\tilde{a}_{ij}(k)$ is a positive comparison if $\tilde{a}_{ij}(k) \ge 1$.

Subsequently, the fuzzy eigenvalue and eigenvector of \mathbf{A} , indicated respectively with λ and $\tilde{\mathbf{x}}$, are derived by solving the following two equations [36]:

$$\det(\mathbf{A}(-)\lambda\mathbf{I}) = 0, \tag{3}$$

and:

$$(\widetilde{\mathbf{A}}(-)\widetilde{\lambda}\mathbf{I})(\times)\widetilde{\mathbf{x}} = 0, \tag{4}$$

where (–) and (×) denote fuzzy subtraction and multiplication, respectively. However, the two equations are not easy to solve. To address this difficulty, most of the past studies applied approximation techniques such as FGM [37] and FEA [38]. In contrast, in the proposed methodology, ACO is applied to derive the exact values of $\tilde{\lambda}$ and $\tilde{\mathbf{x}}$.

First, the fuzzy parameters and variables in Equations (3) and (4) are represented with their α cuts:

$$a_{ij}(\alpha) = [a_{ij}^L(\alpha), a_{ij}^R(\alpha)],$$
(5)

$$\lambda(\alpha) = [\lambda^{L}(\alpha), \lambda^{R}(\alpha)],$$
(6)

$$\mathbf{x}(\alpha) = [\mathbf{x}^{\mathbf{L}}(\alpha), \, \mathbf{x}^{\mathbf{R}}(\alpha)], \tag{7}$$

where *L* and *R* indicate the left and right α cuts of a fuzzy variable, respectively. As a result,

$$\det(\mathbf{A}(\alpha) - \lambda(\alpha)\mathbf{I}) = 0, \tag{8}$$

$$(\mathbf{A}(\alpha) - \lambda(\alpha)\mathbf{I})\mathbf{x}(\alpha) = 0.$$
(9)

If α takes 11 possible values (0, 0.1, ..., 1), Equations (8) and (9) need to be solved 10 $2^{C_2^n} + 1$ times, from which the minimal and maximal values of the results are used to construct the α cut of a fuzzy weight [39]:

$$w_{i}(\alpha) = [w_{i}^{L}(\alpha), w_{i}^{R}(\alpha)]$$

=
$$[\min_{*} \frac{x_{i}^{*}(\alpha)}{\sum\limits_{i=1}^{n} x_{i}^{*}(\alpha)}, \max_{*} \frac{x_{i}^{*}(\alpha)}{\sum\limits_{i=1}^{n} x_{i}^{*}(\alpha)}]$$
(10)

It is noted that \tilde{w}_i is no longer a TFN because the process involves many fuzzy multiplications and divisions [40].

3.2. Aggregating the Fuzzy Weights Derived by All Decision Makers Using FI

FI has been extensively applied in fuzzy collaborative forecasting studies to aggregate multiple decision makers' forecasts [37,40,41]. According to the view of Chen and Honda [42], a FAHP problem can be considered an unsupervised fuzzy collaborative forecasting problem.

The FI of the fuzzy weights by decision makers is indicated with $FI({\tilde{w}_i(k)})$, for which membership function is given by:

$$\mu_{\widetilde{FI}(\{\widetilde{w}_i(k)\}}(x) = \min_k(\mu_{\widetilde{w}_i(k)}(x)), \tag{11}$$

as shown in Figure 3, which is a polygon-shaped fuzzy number with curved edges.



Figure 3. The fuzzy intersection (FI) result.

The α cut of $\widetilde{FI}({\{\widetilde{w}_i(k)\}})$ can be obtained as:

$$FI^{L}(\{\widetilde{w}_{i}(k)\})(\alpha) = \max_{k}(w_{i}^{L}(k)(\alpha)),$$
(12)

$$FI^{R}(\{\widetilde{w}_{i}(k)\})(\alpha) = \min_{k}(w_{i}^{R}(k)(\alpha)),$$
(13)

as illustrated in Figure 4.



Figure 4. The α cut of the FI result.

3.3. Assessing the Suitability of a Smart Technology Application Using Fuzzy TOPSIS

Subsequently, the prevalent fuzzy TOPSIS method is applied to assess the suitability of a smart technology application for fall detection. First, the performance of a smart technology application in optimizing each criterion is normalized using the fuzzy distributive normalization:

$$\widetilde{\rho}_{qi} = \frac{\widetilde{p}_{qi}}{\sqrt{\sum\limits_{\phi=1}^{Q} \widetilde{p}_{\phi i}^{2}}} = \frac{1}{\sqrt{1 + \sum\limits_{\phi \neq q} (\frac{\widetilde{p}_{\phi i}}{\widetilde{p}_{qi}})^{2}}}$$
(14)

where \tilde{p}_{qi} is the performance of the *q*-th smart technology application in optimizing the *i*-th criterion; $\tilde{\rho}_{qi}$ is the normalized performance. Obviously,

$$\rho_{qi}^{L}(\alpha) = \frac{1}{\sqrt{1 + \sum_{\phi \neq q} \left(\frac{p_{\phi i}^{R}(\alpha)}{\overline{p}_{qi}^{L}(\alpha)}\right)^{2}}},$$
(15)

$$\rho_{qi}^{R}(\alpha) = \frac{1}{\sqrt{1 + \sum_{\phi \neq q} \left(\frac{p_{\phi i}^{L}(\alpha)}{\tilde{p}_{qi}^{R}(\alpha)}\right)^{2}}}.$$
(16)

Subsequently, the fuzzy weighted score is calculated based on the fuzzy weights derived using the fuzzy collaborative intelligence approach:

$$\widetilde{s}_{qi} = \widetilde{w}_i(\times)\widetilde{\rho}_{qi}.$$
(17)

Equivalently,

$$s_{qi}^L = w_i^L(\alpha) \rho_{qi}^L(\alpha), \tag{18}$$

$$s_{qi}^{R} = w_{i}^{R}(\alpha)\rho_{qi}^{R}(\alpha).$$
(19)

The fuzzy ideal (zenith) point and the fuzzy anti-ideal (nadir) point are specified, respectively, as:

$$\widetilde{\Lambda}^+ = \{ \widetilde{\Lambda}_i^+ \} = \{ \max_{q} \widetilde{s}_{qi} \},$$
(20)

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$$\widetilde{\Lambda}^{-} = \{ \widetilde{\Lambda}_{i}^{-} \} = \{ \min_{q} \widetilde{s}_{qi} \},$$
(21)

with the following α cuts:

$$[\Lambda^{+L}(\alpha), \Lambda^{+R}(\alpha)] = \{ [\Lambda_i^{+L}(\alpha), \Lambda_i^{+R}(\alpha)] \}, = \{ [\max_q s_{qi}^L(\alpha), \max_q s_{qi}^R(\alpha)] \},$$
(22)

$$[\Lambda^{-L}(\alpha), \Lambda^{-R}(\alpha)] = \{ [\Lambda_i^{-L}(\alpha), \Lambda_i^{-R}(\alpha)] \}, = \{ [\min_q s_{qi}^L(\alpha), \min_q s_{qi}^R(\alpha)] \}.$$
(23)

The fuzzy distance from each smart technology application to the two points are calculated, respectively, as:

$$\widetilde{d}_{q}^{+} = \sqrt{\sum_{i=1}^{n} \left(\widetilde{\Lambda}_{i}^{+}(-)\widetilde{s}_{qi}\right)^{2}},$$
(24)

$$\widetilde{d}_{q}^{-} = \sqrt{\sum_{i=1}^{n} \left(\widetilde{\Delta}_{i}^{-}(-)\widetilde{s}_{qi}\right)^{2}}.$$
(25)

Equivalently,

$$d_{q}^{+L}(\alpha) = \sqrt{\sum_{i=1}^{n} \left(\max(\Lambda_{i}^{+L}(\alpha) - s_{qi}^{R}(\alpha), 0) \right)^{2}},$$
(26)

$$d_{q}^{+R}(\alpha) = \sqrt{\sum_{i=1}^{n} (\Lambda_{i}^{+R}(\alpha) - s_{qi}^{L}(\alpha))^{2}},$$
(27)

$$d_{q}^{-L}(\alpha) = \sqrt{\sum_{i=1}^{n} \left(\min(\Lambda_{i}^{-R}(\alpha) - s_{qi}^{L}(\alpha), 0)\right)^{2}},$$
(28)

$$d_{q}^{-R}(\alpha) = \sqrt{\sum_{i=1}^{n} (\Lambda_{i}^{-L}(\alpha) - s_{qi}^{R}(\alpha))^{2}}.$$
(29)

Finally, the fuzzy closeness of each smart technology application is obtained as:

$$\widetilde{C}_q = \frac{\widetilde{d}_q^-}{\widetilde{d}_q^+(+)\widetilde{d}_q^-}.$$
(30)

Therefore,

$$C_{q}^{L}(\alpha) = \min(\frac{d_{q}^{-R}(\alpha)}{d_{q}^{+R}(\alpha) + d_{q}^{-R}(\alpha)}, \frac{d_{q}^{-L}(\alpha)}{d_{q}^{+R}(\alpha) + d_{q}^{-L}(\alpha)}),$$
(31)

$$C_{q}^{R}(\alpha) = \max(\frac{d_{q}^{-R}(\alpha)}{d_{q}^{+L}(\alpha) + d_{q}^{-R}(\alpha)}, \frac{d_{q}^{-L}(\alpha)}{d_{q}^{+L}(\alpha) + d_{q}^{-L}(\alpha)}).$$
(32)

A smart technology application is more suitable for fall detection if its fuzzy closeness is higher. To get an absolute ranking, the fuzzy closeness has to be defuzzified, as stated in the next section.

3.4. Defuzzifying the Assessment Result Using COG

The assessment result is then defuzzified using the prevalent COG method [43]. First, because the COG method requires that samples be taken regularly along the *x* axis, the range of \tilde{C}_q is divided into Γ equal intervals:

$$\widetilde{C}_{q} = \left\{ \left[\frac{\Gamma - \eta + 1}{\Gamma} C_{q}^{L}(0) + \frac{\eta - 1}{\Gamma} C_{q}^{R}(0), \frac{\Gamma - \eta}{\Gamma} C_{q}^{L}(0) + \frac{\eta}{\Gamma} C_{q}^{R}(0) \right] \middle| \eta = 1 \sim \Gamma \right\}.$$
(33)

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The center of the η -th interval is indicated with $\Omega_q(\eta)$:

$$\Omega_{q}(\eta) = \frac{1}{2} \left(\frac{\Gamma - \eta + 1}{\Gamma} C_{q}^{L}(0) + \frac{\eta - 1}{\Gamma} C_{q}^{R}(0) + \frac{\Gamma - \eta}{\Gamma} C_{q}^{L}(0) + \frac{\eta}{\Gamma} C_{q}^{R}(0) \right) \\ = \frac{2\Gamma - 2\eta + 1}{2\Gamma} C_{q}^{L}(0) + \frac{2\eta - 1}{2\Gamma} C_{q}^{R}(0).$$
(34)

The membership of $\Omega_q(\eta)$ is determined by interpolating those of the two closest α cuts of C_q :

$$\mu_{\widetilde{C}_{q}}(\Omega_{q}(\eta)) = \frac{\Omega_{q}(\eta) - \max_{C_{q}^{*}(\alpha) \leq \Omega_{q}(\eta)} C_{q}^{*}(\alpha)}{(\min_{C_{q}^{*}(\alpha) \geq \Omega_{q}(\eta)} C_{q}^{*}(\alpha) - \max_{C_{q}^{*}(\alpha) \leq \Omega_{q}(\eta)} C_{q}^{*}(\alpha))} \cdot \min_{C_{q}^{*}(\alpha) \geq \Omega_{q}(\eta)} \alpha} + \frac{\min_{C_{q}^{*}(\alpha) \geq \Omega_{q}(\eta)} C_{q}^{*}(\alpha) - \Omega_{q}(\eta)}{(\min_{C_{q}^{*}(\alpha) \geq \Omega_{q}(\eta)} C_{q}^{*}(\alpha) - C_{q}^{*}(\alpha) \leq \Omega_{q}(\eta)} \cdot \max_{C_{q}^{*}(\alpha) \leq \Omega_{q}(\eta)} \alpha},$$
(35)

where * can be *R* or *L*. Then, COG is calculated based on the centers of intervals:

$$COG(\widetilde{C}_q) = \frac{\sum_{\eta=1}^{\Gamma} (\mu_{\widetilde{C}_q}(\Omega_q(\eta))\Omega_q(\eta))}{\sum_{\eta=1}^{\Gamma} \mu_{\widetilde{C}_q}(\Omega_q(\eta))}.$$
(36)

4. Application

To illustrate the applicability of the fuzzy collaborative intelligence approach, it was applied to evaluate the suitabilities of four smart technology applications for fall detection:

- (1) Setting up multiple surveillance cameras [44] or a single omnidirectional camera [45] in the activity area of the subject to record and analyze their motions;
- (2) Attaching proximity sensors to the walking aid (such as a cane or a walker) of the subject. A sudden movement of the subject or an increased distance between the subject and the walking aid can be interpreted as a possible fall [9];
- (3) Covering the floor with a smart carpet or smart tiles. Then, a possible fall can be detected if a number of the embedded pressure sensors are activated simultaneously [14];
- (4) Using an app on the smart phone, smart watch, or another smart device of the subject based on the detection results of the accelerometer and gyroscope [12,13].

After reviewing the relevant literature and current practice, the following five criteria were considered critical to the suitability of a smart technology application for fall detection, as illustrated in Figure 5:

- (1) C1: unobtrusiveness [10,11];
- (2) C2: the simultaneous application to multiple subjects [9,44];
- (3) C3: privacy [1];
- (4) C4: the purchasing, installation, computation, and energy costs [1,9]; and
- (5) C5: the correct, reliable, and robust identification of a fall [1,12].

To determine the weights of the criteria, the fuzzy collaborative intelligence approach was applied.



Figure 5. The fall detection problem.

First, a group of three decision makers was formed. Each decision maker performed a pairwise comparison of the relative weights of criteria. The results are summarized in Table 2. Obviously, there were considerable differences in decision makers' judgments. In this situation, aggregating decision makers' judgments directly was inappropriate. After each decision maker derived fuzzy weights, the inconsistent pairwise comparison results done by the decision maker had been compromised, which was the better time to aggregate decision makers' judgments.

	C1	C2	C3	C4	C5
C1	1	(3, 7, 9), (1, 5, 9), (5, 9, 9)	(1, 1, 5), 1/(1, 3, 7), 1/(1, 1, 5)	1/(3, 7, 9), (1, 3, 7), 1/(1, 1, 5)	1/(5, 9, 9), 1/(1, 3, 7), 1/(3, 7, 9)
C2	1/(3, 7, 9), 1/(1, 5, 9), 1/(5, 9, 9)	1	1/(1, 3, 7), 1/(1, 1, 5), (1, 1, 5)	1/(3, 7, 9), 1/(1, 3, 7), 1/(3, 7, 9)	1/(3, 7, 9), 1/(3, 7, 9), 1/(5, 9, 9)
C3	1/(1, 1, 5), (1, 3, 7), (1, 1, 5)	(1, 3, 7), (1, 1, 5), 1/(1, 1, 5)	1	1/(1, 1, 5), 1/(1, 3, 7), (1, 1, 5)	1/(1, 1, 5), 1/(1, 3, 7), (1, 1, 5)
C4	(3, 7, 9), 1/(1, 3, 7), (1, 1, 5)	(3, 7, 9), (1, 3, 7), (3, 7, 9)	(1, 1, 5), (1, 3, 7), 1/(1, 1, 5)	1	(1, 3, 7), 1/(1, 1, 5), (1, 1, 5)
C5	(5, 9, 9), (1, 3, 7), (3, 7, 9)	(3, 7, 9), (3, 7, 7), (5, 9, 9)	(3, 7, 9), 1/(1, 3, 7), (1, 1, 5)	1/(1, 3, 7), (1, 1, 5), 1/(1, 1, 5)	1

Table 2. Results of pairwise comparisons.

Each decision maker applied ACO to derive the fuzzy eigenvalue and the fuzzy weights of criteria. The results are summarized in Figures 6 and 7, respectively.

Subsequently, to aggregate the fuzzy weights derived by all decision makers, FI was applied. The results are shown in Figure 8. As expected, decision makers achieved a consensus regarding the values of each fuzzy weight.



Figure 6. Fuzzy eigenvalues derived by (a) decision maker #1; (b) decision maker #2; (c) decision maker #3.



Figure 7. Fuzzy weights derived by (a) decision maker #1; (b) decision maker #2; (c) decision maker #3.

The suitabilities of the four smart technology applications for fall detection were assessed. To this end, the performances of the four smart technology applications in optimizing the five criteria were evaluated by the same decision makers using the following linguistic terms [46]:

Very poor: (1, 1, 2); Poor: (1, 2, 3); Moderate: (2, 3, 4); Good: (3, 4, 5); Very good: (4, 5, 5).



Figure 8. Cont.



Figure 8. The FI results of (a) \widetilde{w}_1 ; (b) \widetilde{w}_2 ; (c) \widetilde{w}_3 ; (d) \widetilde{w}_4 ; (e) \widetilde{w}_5 .

The evaluations by all decision makers were averaged. The results are summarized in Table 3. It can be seen that none of the smart technology applications dominated another, causing difficulty in choosing from them.

Smart Technology Application	C1 (Unobtrusiveness)	C2 (Simultaneous Multiple Subjects)	C3 (Privacy)	C4 (Costs)	C5 (Correct, Reliable, and Robust Identification)
Smart surveillance system	(3.00, 4.00, 4.67)	(3.67, 4.67, 5.00)	(1.33, 2.00, 3.00)	(1.17, 2.17, 3.17)	(2.83, 3.83, 4.50)
Smart cane	(2.67, 3.67, 4.67)	(1.00, 1.00, 2.00)	(2.33, 3.33, 4.33)	(2.00, 3.00, 4.00)	(1.67, 2.67, 3.67)
Smart carpet	(4.00, 5.00, 5.00)	(2.33, 3.33, 4.33)	(3.33, 4.33, 5.00)	(1.67, 2.67, 3.67)	(2.00, 3.00, 4.00)
Smart phone/watch and app	(4.00, 5.00, 5.00)	(1.00, 1.00, 2.00)	(1.67, 2.67, 3.67)	(3.00, 4.00, 4.67)	(1.67, 2.67, 3.67)

Table 3. Performances of four smart technology applications along the five dimensions.

Fuzzy TOPSIS was applied to assess the suitability of each smart technology application for fall detection. First, the performance of a smart technology application in optimizing each criterion was normalized using fuzzy distributive normalization. The results are summarized in Table 4.

Smart Technology Application	C1 (Unobtrusiveness)	C2 (Simultaneous Multiple Subjects)	C3 (Privacy)	C4 (Costs)	C5 (Correct, Reliable, and Robust Identification)
Smart surveillance system	(0.33, 0.45, 0.60)	(0.58, 0.79, 0.88)	(0.17, 0.31, 0.56)	(0.16, 0.36, 0.62)	(0.40, 0.62, 0.82)
Smart cane	(0.30, 0.41, 0.59)	(0.14, 0.17, 0.41)	(0.32, 0.52, 0.74)	(0.28, 0.49, 0.74)	(0.23, 0.43, 0.69)
Smart carpet	(0.43, 0.56, 0.66)	(0.38, 0.56, 0.74)	(0.46, 0.68, 0.85)	(0.23, 0.44, 0.70)	(0.28, 0.49, 0.74)
Smart phone/watch and app	(0.43, 0.56, 0.66)	(0.14, 0.17, 0.41)	(0.22, 0.42, 0.65)	(0.43, 0.66, 0.85)	(0.23, 0.43, 0.69)

Table 4. Normalized performances.

Subsequently, the fuzzy weighted scores, in terms of α cuts, were calculated based on the derived fuzzy weights. The results are summarized in Table 5.

Smart Technology Application	C1 (Unobtrusiveness) (α:α cut)	C2 (Simultaneous Multiple Subjects) (α:α cut)	C3 (Privacy) (α : α cut)	C4 (Costs) (α:α cut)	C5 (Correct, Reliable, and Robust Identification) (α : α cut)
Smart surveillance system	0.00: [0.02, 0.14] 0.10: [0.03, 0.13] 0.20: [0.03, 0.12] 0.30: [0.03, 0.11] 0.40: [0.04, 0.10] 0.50: [0.05, 0.09] 0.60: [0.05, 0.08] 0.66: [0.06, 0.07]	0.00: [0.02, 0.08] 0.10: [0.02, 0.07] 0.20: [0.03, 0.06] 0.30: [0.03, 0.05] 0.40: [0.03, 0.05] 0.50: [0.03, 0.04] 0.60: [0.03, 0.04] 0.65: [0.03, 0.04]	$\begin{array}{c} 0.00; \ [0.02, \ 0.14] \\ 0.10; \ [0.02, \ 0.13] \\ 0.20; \ [0.02, \ 0.12] \\ 0.30; \ [0.03, \ 0.11] \\ 0.40; \ [0.03, \ 0.09] \\ 0.50; \ [0.03, \ 0.09] \\ 0.60; \ [0.03, \ 0.08] \\ 0.70; \ [0.04, \ 0.08] \\ 0.80; \ [0.04, \ 0.07] \\ 0.90; \ [0.05, \ 0.06] \\ 0.97; \ [0.05, \ 0.05] \\ \end{array}$	0.00: [0.03, 0.26] 0.10: [0.04, 0.24] 0.20: [0.05, 0.21] 0.30: [0.06, 0.19] 0.40: [0.07, 0.17] 0.49: [0.08, 0.16]	0.00: [0.06, 0.36] 0.10: [0.07, 0.35] 0.20: [0.08, 0.34] 0.30: [0.09, 0.32] 0.40: [0.10, 0.30] 0.50: [0.11, 0.28] 0.60: [0.13, 0.26] 0.70: [0.15, 0.24] 0.80: [0.17, 0.22] 0.85: [0.19, 0.21]
Smart cane	$\begin{array}{c} 0.00: \ [0.02, \ 0.14] \\ 0.10: \ [0.02, \ 0.13] \\ 0.20: \ [0.03, \ 0.12] \\ 0.30: \ [0.03, \ 0.10] \\ 0.40: \ [0.04, \ 0.09] \\ 0.50: \ [0.04, \ 0.08] \\ 0.60: \ [0.05, \ 0.07] \\ 0.66: \ [0.05, \ 0.07] \end{array}$	$\begin{array}{c} 0.00; \ [0.01, \ 0.04] \\ 0.10; \ [0.01, \ 0.03] \\ 0.20; \ [0.01, \ 0.03] \\ 0.30; \ [0.01, \ 0.02] \\ 0.40; \ [0.01, \ 0.02] \\ 0.50; \ [0.01, \ 0.01] \\ 0.60; \ [0.01, \ 0.01] \\ 0.65; \ [0.01, \ 0.01] \end{array}$	$\begin{array}{c} 0.00; \ [0.03, \ 0.19] \\ 0.10; \ [0.04, \ 0.17] \\ 0.20; \ [0.04, \ 0.16] \\ 0.30; \ [0.04, \ 0.15] \\ 0.40; \ [0.05, \ 0.14] \\ 0.50; \ [0.05, \ 0.13] \\ 0.60; \ [0.06, \ 0.12] \\ 0.70; \ [0.06, \ 0.11] \\ 0.80; \ [0.07, \ 0.11] \\ 0.90; \ [0.08, \ 0.10] \\ 0.97; \ [0.09, \ 0.09] \end{array}$	0.00: [0.06, 0.31] 0.10: [0.07, 0.28] 0.20: [0.08, 0.26] 0.30: [0.10, 0.24] 0.40: [0.11, 0.21] 0.49: [0.12, 0.20]	$\begin{array}{c} 0.00: \left[0.04, 0.31\right] \\ 0.10: \left[0.04, 0.29\right] \\ 0.20: \left[0.05, 0.28\right] \\ 0.30: \left[0.06, 0.26\right] \\ 0.40: \left[0.06, 0.24\right] \\ 0.50: \left[0.07, 0.22\right] \\ 0.60: \left[0.09, 0.20\right] \\ 0.70: \left[0.10, 0.18\right] \\ 0.80: \left[0.12, 0.16\right] \\ 0.85: \left[0.13, 0.15\right] \end{array}$
Smart carpet	0.00: [0.03, 0.16] 0.10: [0.03, 0.15] 0.20: [0.04, 0.13] 0.30: [0.04, 0.12] 0.40: [0.05, 0.11] 0.50: [0.06, 0.10] 0.60: [0.07, 0.09] 0.66: [0.07, 0.09]	0.00: [0.01, 0.07] 0.10: [0.02, 0.06] 0.20: [0.02, 0.05] 0.30: [0.02, 0.04] 0.40: [0.02, 0.04] 0.50: [0.02, 0.03] 0.60: [0.02, 0.03] 0.65: [0.02, 0.03]	$\begin{array}{c} 0.00; \ [0.05, \ 0.21] \\ 0.10; \ [0.05, \ 0.2] \\ 0.20; \ [0.06, \ 0.19] \\ 0.30; \ [0.06, \ 0.18] \\ 0.40; \ [0.07, \ 0.16] \\ 0.60; \ [0.08, \ 0.15] \\ 0.70; \ [0.08, \ 0.14] \\ 0.80; \ [0.09, \ 0.13] \\ 0.90; \ [0.10, \ 0.13] \\ 0.97; \ [0.11, \ 0.12] \end{array}$	0.00: [0.05, 0.29] 0.10: [0.06, 0.27] 0.20: [0.07, 0.24] 0.30: [0.08, 0.22] 0.40: [0.10, 0.20] 0.49: [0.11, 0.18]	0.00: [0.04, 0.33] 0.10: [0.05, 0.31] 0.20: [0.06, 0.30] 0.30: [0.07, 0.28] 0.40: [0.07, 0.26] 0.50: [0.08, 0.24] 0.60: [0.10, 0.22] 0.70: [0.11, 0.20] 0.80: [0.14, 0.18] 0.85: [0.15, 0.17]
Smart phone/watch and app	0.00: [0.03, 0.16] 0.10: [0.03, 0.15] 0.20: [0.04, 0.13] 0.30: [0.04, 0.12] 0.40: [0.05, 0.11] 0.50: [0.06, 0.10] 0.60: [0.07, 0.09] 0.66: [0.07, 0.09]	0.00: [0.01, 0.04] 0.10: [0.01, 0.03] 0.20: [0.01, 0.03] 0.30: [0.01, 0.02] 0.40: [0.01, 0.02] 0.50: [0.01, 0.01] 0.60: [0.01, 0.01] 0.65: [0.01, 0.01]	$\begin{array}{c} 0.00; \ [0.02, \ 0.16] \\ 0.10; \ [0.03, \ 0.15] \\ 0.20; \ [0.03, \ 0.14] \\ 0.30; \ [0.03, \ 0.13] \\ 0.40; \ [0.04, \ 0.12] \\ 0.50; \ [0.04, \ 0.11] \\ 0.60; \ [0.04, \ 0.10] \\ 0.70; \ [0.05, \ 0.09] \\ 0.80; \ [0.05, \ 0.09] \\ 0.90; \ [0.06, \ 0.08] \\ 0.97; \ [0.07, \ 0.07] \\ \end{array}$	0.00: [0.09, 0.36] 0.10: [0.11, 0.33] 0.20: [0.12, 0.31] 0.30: [0.14, 0.28] 0.40: [0.16, 0.26] 0.49: [0.17, 0.24]	$\begin{array}{c} 0.00: \left[0.04, 0.31\right]\\ 0.10: \left[0.04, 0.29\right]\\ 0.20: \left[0.05, 0.28\right]\\ 0.30: \left[0.06, 0.26\right]\\ 0.40: \left[0.06, 0.24\right]\\ 0.50: \left[0.07, 0.22\right]\\ 0.60: \left[0.09, 0.20\right]\\ 0.70: \left[0.10, 0.18\right]\\ 0.80: \left[0.12, 0.16\right]\\ 0.85: \left[0.13, 0.15\right] \end{array}$

Tal	ole	5.	Fuzzy	weig	hted	scores.
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Based on the fuzzy weighted scores of all smart technology applications, the fuzzy ideal point and the fuzzy anti-ideal point were defined, as shown in Table 6. Subsequently, the distances from

each smart technology application to the two points were measured, respectively. The results are summarized in Table 7.

Reference Point	C1 (Unobtrusiveness) (α:α cut)	C2 (Simultaneous Multiple Subjects) (α:α cut)	C3 (Privacy) (α:α cut)	C4 (Costs) (α:α cut)	C5 (Correct, Reliable, and Robust Identification) (α:α cut)
Fuzzy ideal point	0.00: [0.03, 0.16] 0.10: [0.03, 0.15] 0.20: [0.04, 0.13] 0.30: [0.04, 0.12] 0.40: [0.05, 0.11] 0.50: [0.06, 0.10] 0.60: [0.07, 0.09] 0.66: [0.07, 0.09]	0.00: [0.02, 0.08] 0.10: [0.02, 0.07] 0.20: [0.03, 0.06] 0.30: [0.03, 0.05] 0.40: [0.03, 0.05] 0.50: [0.03, 0.04] 0.60: [0.03, 0.04] 0.65: [0.03, 0.04]	$\begin{array}{c} 0.00; [0.05, 0.21] \\ 0.10; [0.05, 0.20] \\ 0.20; [0.06, 0.19] \\ 0.30; [0.06, 0.18] \\ 0.40; [0.07, 0.17] \\ 0.50; [0.07, 0.16] \\ 0.60; [0.08, 0.15] \\ 0.70; [0.08, 0.14] \\ 0.80; [0.09, 0.13] \\ 0.90; [0.10, 0.13] \\ 0.97; [0.11, 0.12] \end{array}$	0.00: [0.09, 0.36] 0.10: [0.11, 0.33] 0.20: [0.12, 0.31] 0.30: [0.14, 0.28] 0.40: [0.16, 0.26] 0.49: [0.17, 0.24]	$\begin{array}{c} 0.00; \ [0.06, \ 0.36] \\ 0.10; \ [0.07, \ 0.35] \\ 0.20; \ [0.08, \ 0.34] \\ 0.30; \ [0.09, \ 0.32] \\ 0.40; \ [0.10, \ 0.30] \\ 0.50; \ [0.11, \ 0.28] \\ 0.60; \ [0.13, \ 0.26] \\ 0.70; \ [0.15, \ 0.24] \\ 0.80; \ [0.17, \ 0.22] \\ 0.85; \ [0.19, \ 0.21] \end{array}$
Fuzzy anti-ideal point	$\begin{array}{c} 0.00: \ [0.02, \ 0.14] \\ 0.10: \ [0.02, \ 0.13] \\ 0.20: \ [0.03, \ 0.12] \\ 0.30: \ [0.03, \ 0.10] \\ 0.40: \ [0.04, \ 0.09] \\ 0.50: \ [0.04, \ 0.08] \\ 0.60: \ [0.05, \ 0.07] \\ 0.66: \ [0.05, \ 0.07] \end{array}$	0.00: [0.01, 0.04] 0.10: [0.01, 0.03] 0.20: [0.01, 0.03] 0.30: [0.01, 0.02] 0.40: [0.01, 0.02] 0.50: [0.01, 0.01] 0.60: [0.01, 0.01] 0.65: [0.01, 0.01]	$\begin{array}{c} 0.00; \ [0.02, \ 0.14] \\ 0.10; \ [0.02, \ 0.13] \\ 0.20; \ [0.02, \ 0.12] \\ 0.30; \ [0.03, \ 0.11] \\ 0.40; \ [0.03, \ 0.10] \\ 0.50; \ [0.03, \ 0.09] \\ 0.60; \ [0.03, \ 0.08] \\ 0.70; \ [0.04, \ 0.08] \\ 0.80; \ [0.04, \ 0.07] \\ 0.90; \ [0.05, \ 0.05] \\ \end{array}$	0.00: [0.03, 0.26] 0.10: [0.04, 0.24] 0.20: [0.05, 0.21] 0.30: [0.06, 0.19] 0.40: [0.07, 0.17] 0.49: [0.08, 0.16]	$\begin{array}{c} 0.00; \ [0.04, \ 0.31] \\ 0.10; \ [0.04, \ 0.29] \\ 0.20; \ [0.05, \ 0.28] \\ 0.30; \ [0.06, \ 0.26] \\ 0.40; \ [0.06, \ 0.24] \\ 0.50; \ [0.07, \ 0.22] \\ 0.60; \ [0.09, \ 0.20] \\ 0.70; \ [0.10, \ 0.18] \\ 0.80; \ [0.12, \ 0.16] \\ 0.85; \ [0.13, \ 0.15] \end{array}$

Table 6. The fuzzy ideal point and the fuzzy anti-ideal point.

 Table 7. Distances between each smart technology application and the two points.

Smart Technology Application	$\widetilde{d}_{q}^{+}(\alpha:\alpha \operatorname{cut})$	$\widetilde{d_q}$ (a:a cut)
	0.00: [0.00, 0.51]	0.00: [0.00, 0.44]
	0.10: [0.00, 0.46]	0.10: [0.02, 0.40]
Smart aurillance austern	0.20: [0.00, 0.41]	0.00: [0.03, 0.36]
Smart survemance system	0.30: [0.00, 0.37]	0.30: [0.03, 0.32]
	0.40: [0.00, 0.32]	0.40: [0.04, 0.28]
	0.50: [0.01, 0.27]	0.50: [0.04, 0.24]
	0.00: [0.00, 0.50]	0.00: [0.00, 0.44]
	0.10: [0.00, 0.46]	0.10: [0.02, 0.39]
Smart cano	0.20: [0.00, 0.41]	0.20: [0.03, 0.35]
Smart cane	0.30: [0.01, 0.36]	0.30: [0.03, 0.31]
	0.40: [0.01, 0.31]	0.40: [0.04, 0.26]
	0.50: [0.02, 0.27]	0.50: [0.04, 0.22]
	0.00: [0.00, 0.50]	0.00: [0.00, 0.46]
	0.10: [0.00, 0.45]	0.10: [0.02, 0.42]
Smart carnot	0.20: [0.00, 0.40]	0.20: [0.03, 0.37]
Sinart carpet	0.30: [0.00, 0.35]	0.30: [0.03, 0.33]
	0.40: [0.00, 0.30]	0.40: [0.04, 0.29]
	0.50: [0.00, 0.26]	0.50: [0.04, 0.24]
	0.00: [0.00, 0.49]	0.00: [0.00, 0.47]
	0.10: [0.00, 0.44]	0.10: [0.02, 0.42]
Smart phone/watch and app	0.20: [0.00, 0.39]	0.20: [0.03, 0.38]
Small phone/watch and app	0.30: [0.01, 0.35]	0.30: [0.03, 0.33]
	0.40: [0.01, 0.30]	0.40: [0.04, 0.28]
	0.50: [0.02, 0.25]	0.50: [0.04, 0.24]

Finally, the fuzzy closeness of each smart technology application was derived. The results are shown in Table 8.

Smart Technology Application	\widetilde{C}_q (<i>a</i> : <i>a</i> cut)
	0.00: [0.00, 1.00]
	0.10: [0.05, 1.00]
Smart surveillance system	0.20: [0.06, 1.00]
Smart survemance system	0.30: [0.08, 1.00]
	0.40: [0.10, 1.00]
	0.50: [0.14, 0.95]
	0.00: [0.00, 1.00]
	0.10: [0.05, 1.00]
Smart cano	0.20: [0.06, 1.00]
Siliait calle	0.30: [0.08, 0.98]
	0.40: [0.10, 0.97]
	0.50: [0.14, 0.92]
	0.00: [0.00, 1.00]
	0.10: [0.05, 1.00]
Creart correct	0.20: [0.06, 1.00]
Smart carpet	0.30: [0.08, 1.00]
	0.40: [0.11, 1.00]
	0.50: [0.14, 1.00]
	0.00: [0.00, 1.00]
	0.10: [0.05, 1.00]
Smart phone/watch and app	0.20: [0.06, 1.00]
Smart phone/watch and app	0.30: [0.08, 0.98]
	0.40: [0.11, 0.97]
	0.50: [0.15, 0.92]

Table 8. Fuzzy closeness of each smart technology application.

Subsequently, COG was applied to defuzzify the fuzzy sustainability of each smart technology application for fall detection. The results are summarized in Table 9.

Smart Technology Application	Defuzzified Closeness
Smart surveillance system	0.543
Smart cane	0.530
Smart carpet	0.552
Smart phone/watch and app	0.534

Table 9. Defuzzification result	ts
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According to the experimental results,

- Among the four smart technology applications for fall detection, the application of smart carpet achieved the highest suitability, which was obviously due to its capability of detecting multiple subjects' falls simultaneously and the protection of a subject's privacy;
- (2) In contrast, the application of a smart cane was considered the least suitable. A smart cane could support only a single subject, which made it relatively expensive;
- (3) For a comparison, three existing methods, FGM-FWA, FEA-FWA, and FGM-ACO-FWA [17], were also applied to assess the same smart technology applications for fall detection. In FGM-FWA, decision makers' judgments were aggregated using FGM. The fuzzy weights of criteria were also approximated using FGM. Then, FWA was applied to assess the suitability of each same smart technology application for fall detection. In FEA-WA, decision makers' judgments were aggregated using FGM as well. Then, the weights were estimated using FEA in crisp values. Nevertheless, the performances in optimizing the criteria were expressed in fuzzy values. Therefore, FWA was still applied to assess the suitability of each same smart technology application for fall detection. FGM-ACO-FWA is an anterior-aggregation FAHP method, i.e., experts' judgments

were aggregated using FGM before deriving a single set of fuzzy weights using ACO. The ranking results obtained using various methods are compared in Figure 9. Obviously, the ranking result using the proposed methodology was somewhat different from those using existing methods. According to the proposed methodology, a smart surveillance system was more suitable than the combination of smart phone/watch and app, while existing methods drew the opposite conclusion;

- (4) In existing methods, FWA was applied to assess the suitability of a smart technology application for fall detection, in which the weighted performance in optimizing a criterion could be compensated directly (or linearly) by that in optimizing another. In contrast, in the fuzzy collaborative intelligence approach, fuzzy TOPSIS was applied for the same purpose, in which the weighted performance was involved in a quadratic function (i.e., the Euclidean distance) that magnified the difference between the weighted performances of two methods. As a result, fuzzy TOPSIS was considered to be more sensitive than FWA;
- (5) After detecting a possible fall, it is an urgent task to deliver the nearby medical service to the affected or injured elderly person [47], which obviously relies on a correct detection of the elderly person's location and the quality of geospatial data [31].



Figure 9. Comparison of the ranking results using various methods.

5. Conclusions

The advent of an aging society makes the detection of falls more important. Much evidence has revealed that the applications of smart technologies have great potential for improving the effectiveness and efficiency of fall detection. However, existing smart technology applications for fall detection have their own advantages and disadvantages. As a result, a decision maker has to choose a suitable smart technology application for fall detection from existing ones based on their own judgment. To this end, a fuzzy collaborative intelligence approach was proposed in this study. In the fuzzy collaborative intelligence approach was proposed in this study. In the fuzzy collaborative intelligence approach applied to derive the fuzzy weights of criteria for each decision maker. Then, FI is applied to aggregate the fuzzy weights derived by all decision makers. In this way, whether decision makers have achieved a consensus can be confirmed. Subsequently, fuzzy TOPSIS is applied to assess the suitability of a smart technology application for fall detection. The assessment result is defuzzified using COG for generating an absolute ranking.

The fuzzy collaborative intelligence approach was applied to assess the suitabilities of four existing smart technology applications for fall detection. According to the experimental results, the following conclusions were drawn:

 Five factors critical to the applications of smart technologies for fall detection were identified as unobtrusiveness, the simultaneous application to multiple subjects, privacy, the purchasing, installation, computation, and energy costs, and the correct, reliable, and robust identification of a fall;

- (2) Among the four smart technology applications for fall detection, the most and least suitable applications were smart carpet and smart cane, respectively;
- (3) The ranking result using the proposed methodology was somewhat different from those using three existing methods.

Smart technologies are still evolving. A smart technology application that is considered unsuitable now may become suitable in the future. Therefore, the same assessment has to be done repeatedly every few years. In addition, more smart technology applications for fall detection are expected to emerge. The scope of this study can be extended to cover these new smart technology applications for fall detection. Furthermore, other multiple-criteria decision-making methods, such as the full consistency method [48] and simulation-based methods [49], can also be applied for the same purpose. These constitute some directions for future research.

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