mathematics

Article

A Fuzzy Collaborative Approach for Evaluating the Suitability of a Smart Health Practice

Tin-Chih Toly Chen [1], Yu-Cheng Wang [2,*], Yu-Cheng Lin [3], Hsin-Chieh Wu [4] and Hai-Fen Lin [5]

1 Department of Industrial Engineering and Management, National Chiao Tung University, 1001, University Road, Hsinchu 30010, Taiwan; tolychen@ms37.hinet.net
2 Department of Aeronautical Engineering, Chaoyang University of Technology, Taichung 41349, Taiwan
3 Department of Computer-Aided Industrial Design, Overseas Chinese University, Taichung 40721, Taiwan; yclin@ocu.edu.tw
4 Department of Industrial Engineering and Management, Chaoyang University of Technology, Taichung 41349, Taiwan; hcwul@cyut.edu.tw
5 Electronic Systems Research Division, National Chung-Shan Institute of Science & Technology, Taoyuan 32557, Taiwan; belinda.d853843@msa.hinet.net
* Correspondence: tony.cobra@msa.hinet.net

Received: 12 October 2019; Accepted: 2 December 2019; Published: 3 December 2019

Abstract: A fuzzy collaborative approach is proposed in this study to assess the suitability of a smart health practice, which is a challenging task, as the participating decision makers may not reach a consensus. In the fuzzy collaborative approach, each decision maker first applies the alpha-cut operations method to derive the fuzzy weights of the criteria. Then, fuzzy intersection is applied to aggregate the fuzzy weights derived by all decision makers to measure the prior consensus among them. The fuzzy intersection results are then presented to the decision makers so that they can subjectively modify the pairwise comparison results to bring them closer to the fuzzy intersection results. Thereafter, the consensus among decision makers is again measured. The collaboration process will stop when no more modifications are made by any decision maker. Finally, the fuzzy weighted mean-centroid defuzzification method is applied to assess the suitability of a smart health practice. The fuzzy collaborative approach and some existing methods have been applied to assess the suitabilities of eleven smart health practices for a comparison. Among the compared practices, only the fuzzy collaborative approach could guarantee the existence of a full consensus among decision makers after the collaboration process, i.e., that the assessment results were acceptable to all decision makers.

Keywords: smart health; fuzzy collaborative intelligence; fuzzy analytic hierarchy process; suitability

1. Introduction

The application of smart technologies to enhance mobile health care, i.e., so-called smart health, has received a lot of attention [1,2]. As smart health practices are becoming more and more sophisticated, how to recommend suitable smart health practices to a target population becomes a challenging task. For example, Chen and Chiu [3] reviewed the literature and concluded that the most effective smart health practices adopted smart mobile services, smart phones, smart glasses/spectacles/contact lens, and smart surveillance cameras. Haymes et al. [4] applied behavior analysis to find out factors that contributed to the success of smart health practices for individuals with intellectual disabilities. Chiu and Chen [5] assessed the sustainable effectiveness of the adjustment mechanism of a ubiquitous clinic recommendation system by modelling the improvement in the successful recommendation rate as a learning process. Chen [6] put forward a hybrid methodology combining fuzzy geometric mean

(FGM), alpha-cut operations (ACO), and fuzzy weighted mean (FWM) to evaluate the sustainability of a smart health practice, in which FGM, ACO, and FWM were for aggregation, prioritization, and assessment, respectively. Compared with earlier studies, the FGM-ACO-FWM method was more precise because of the application of the exact solution technique ACO. However, whether decision makers reached a consensus was not checked before aggregating their judgments, which was problematic [7]. To resolve this problem, a fuzzy collaborative approach is proposed in this study. In the fuzzy collaborative approach, decision makers' judgments will be aggregated only after they achieve a consensus.

A fuzzy collaborative approach is proposed in this study to evaluate the suitability of a smart health practice. In the proposed methodology, multiple decision makers fulfill the assessment task collaboratively. For each decision maker, ACO is applied to derive the fuzzy weights of criteria. Then, fuzzy intersection (FI) (or the minimum t-norm) is applied to aggregate the fuzzy weights derived by all decision makers. Obviously, the proposed methodology is a posterior-aggregation fuzzy analytic hierarchy process (FAHP) method, while the FGM-ACO-FWM method proposed by Chen [6] is an anterior-aggregation method. The FI results can be used to measure the prior consensus among decision makers. If the FI results are wide, i.e., many possible values are acceptable to all decision makers, then the consensus is high. Subsequently, the FI results are presented to decision makers so that they can subjectively modify the pairwise comparison results to bring them closer to the fuzzy intersection results. Thereafter, the consensus among decision makers is again measured. The collaboration process will stop when no more modifications are made by any decision maker. At last, based on the aggregation results, the FWM method [8] was applied to assess the suitability of a smart health practice. The assessment result is defuzzified using the centroid-defuzzification (CD) method for generating an absolute ranking.

The differences between our proposed methodology and some existing methods are summarized in Table 1. Our proposed methodology is a posterior-aggregation method, while the method proposed by Chen [6] is an anterior-aggregation method. In other words, our proposed methodology checks the existence of a consensus among decision makers, while the method proposed by Chen [6] does not. In addition, our proposed methodology derives the values of fuzzy weights, while the method proposed by Chen [7] only approximates the values of fuzzy weights. As a result, our proposed methodology is more precise and reliable than the method proposed by Chen [7].

Table 1. The differences between the proposed methodology and some existing methods. fuzzy geometric mean (FGM), alpha-cut operations (ACO), and fuzzy weighted mean (FWM), fuzzy intersection (FI).

Method	Smart Technology	Assessment Method	Group Decision Making	Consensus	Aggregation
Chen and Chiu [3]	All	Literature review	No	-	-
Haymes et al. [4]	Not specified	Behavior analysis	No	-	-
Chiu and Chen [5]	Smart mobile services	Learning curve analysis	No	-	-
Chen [6]	All	FGM-ACO-FWM	Yes	Not guaranteed	Anterior-aggregation
Chen [7]	All	FGM-FI-FWM	Yes	Guaranteed	Posterior-aggregation
Our proposed methodology	All	ACO-FI-FWM	Yes	Guaranteed	Posterior-aggregation

The remainder of this paper is organized as follows. Section 2 reviews previous works. Section 3 puts forward the fuzzy collaborative approach for assessing the suitability of a smart health practice. Section 4 provides the results of applying the fuzzy collaborative approach to assess eleven smart health practices, so as to choose the most suitable smart technology application. Three existing methods were also applied to these smart health practices for comparison. Finally, Section 5 presents concluding remarks and lists a few topics worthy of further investigation.

2. Previous Work

Social media, mobile devices, and sensors are valuable for communicating health-related information [9–11]. In particular, the applications of social networking apps to mobile health care are prevalent. For example, Cook et al. [12] compared the average number of Twitter posts by people with depression to that by people without depression, and found a significant difference. The survey done by Reeder and David [13] revealed that the most prevalent applications of smart watches to mobile health care included activity monitoring, heart rate monitoring, speech therapy adherence, diabetes self-management, and the detection of seizures, tremors, scratching, eating, and medication-taking behaviors. Mandal et al. [14] described the substitutable medical applications and reusable technologies (SMART) project launched by Harvard Medical School and Boston Children's Hospital jointly to increase the portability of medical applications. Based on the infrastructure, several apps have been designed. Hamidi [15] proposed a new standard for applying biometric technologies to fast identify the user of a mobile health care service.

According to the survey of Cook et al. [12], due to advances in sensor and wireless communication technologies, more than twenty-one types of sensors have been prevalent on mobile or wearable devices, much more than those in the past [16]. Eklund and Forsman [17] designed a suit of smart work clothes with embedded sensors for monitoring the heart rate and breathing of a worker, so as to provide him/her suggestions to avoid musculoskeletal disorders.

There are a number of mobile health care studies focusing on special groups, e.g., people with extremely bad vision [1], people with intellectual disabilities [4], and older adults [18]. According to the survey by Liu et al. [18], the most suitable smart health practices for older adults adopted smart homes and home-based health-monitoring technologies. Such applications were mostly used to monitor the daily activities, cognitive decline, mental health, and heart conditions of older adults with complex needs.

In the view of Eskofier et al. [19], the ability to walk was critical to the quality of life. For this reason, smart shoes with embedded sensors were applied to monitor the gait and mobility of a user, so as to support healthy living, complement medical diagnostics, and monitor therapeutic outcomes. Smart technologies can be applied to fall detection, for which machine learning and decision tress are the most prevalent data analysis techniques. In the view of Chen et al. [20], health monitoring using traditional wearable devices was not sustainable because of the uncomfortableness of long-term wearing, insufficient accuracy, etc. This problem is expected to be alleviated soon with rapid advances in wearable technologies.

3. Methodology

The fuzzy collaborative approach proposed in this study is composed of three major parts: ACO, FI, and FWM. A similar treatment was taken by Duman et al. [21] that combined fuzzy decision-making trial and evaluation laboratory (DEMATEL), analytic network process (ANP), and an artificial neural network (ANN). In addition, the fuzzy collaborative approach is a posterior-aggregation method. Recently, Chen [6] proposed the FGM-ACO-FWM method for a similar purpose. The differences between the two methods is highlighted by Figure 1. A recent survey of FAHP refers to [22].

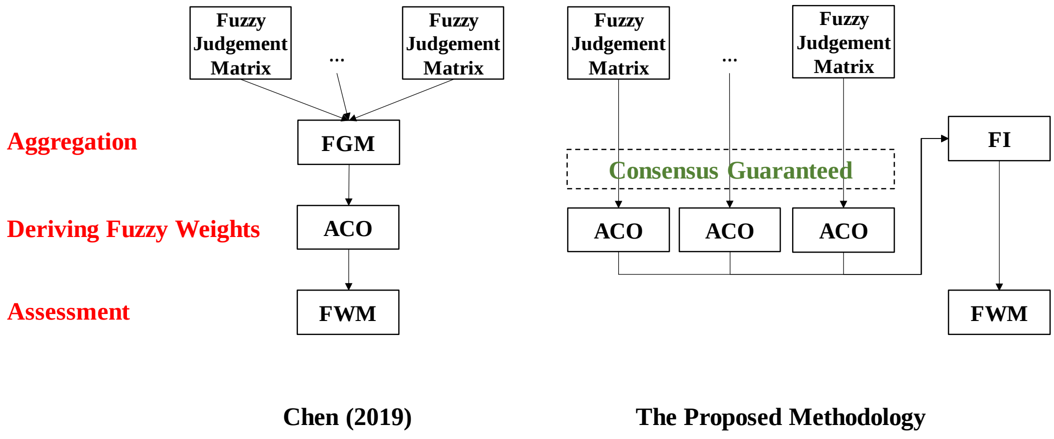

Figure 1. Comparison with a recent method.

3.1. Deriving Fuzzy Weights for Each Decision Maker Using ACO

In the proposed methodology, a team of K decision makers is formed. First, each decision maker compares the relative weights of criteria for assessing the suitability of a smart health practice in pairs. The results are used to construct a fuzzy pairwise comparison matrix as

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

where

$$\widetilde{a}_{ij}(k) = \begin{cases} 1 & \text{if} \quad i = j \\ \frac{1}{\widetilde{a}_{ji}(k)} & \text{otherwise} \end{cases};\ i,\ j\ =\ 1\ \sim\ n;\ k\ =\ 1\ \sim\ K \tag{2}$$

$\widetilde{a}_{ij}(k)$ is the relative weight of criterion i over criterion j judged by decision maker k. Equation (2) is the reciprocal requirement. $\widetilde{a}_{ij}(k)$ are mapped to triangular fuzzy numbers (TFNs) satisfying $a_{ij2}(k) = \{1,3,5,7,9\}$, $a_{ij1}(k) = \max(a_{ij2}(k) - 4, 1)$, and $a_{ij3}(k) = \min(a_{ij2}(k) + 4, 9)$ (see Figure 2). In this way, the fuzzy weights derived by decision makers are more likely to overlap before collaboration. However, that does not mean that the TFNs used in this study are better or more suitable than those adopted in [23,24]. Regardless of which set of TFNs is used, decision makers can reach a consensus after several rounds of collaboration using the proposed methodology. However, this is obviously based on the assumption that all decision makers accept that these TFNs reflect their preferences. If this assumption holds, in our view, it is more likely for each fuzzy judgment matrix to be consistent. A positive comparison satisfies $\widetilde{a}_{ij}(k) \geq 1$.

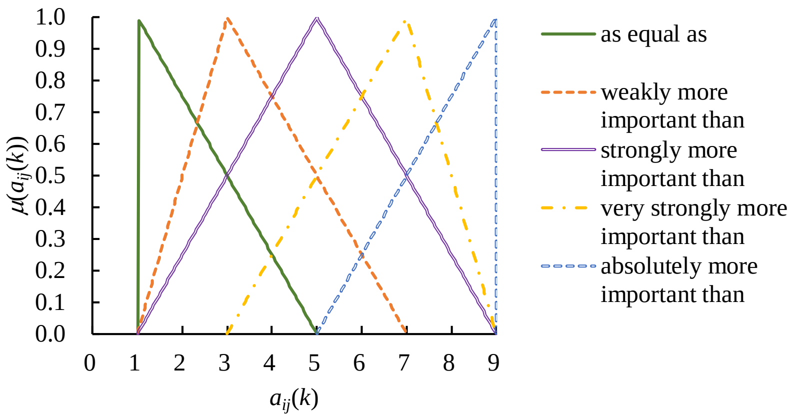

Figure 2. Triangular fuzzy numbers (TFNs) used in the proposed methodology.

Subsequently, a fuzzy eigen analysis is performed to derive the fuzzy eigenvalue and eigenvector of $\widetilde{\mathbf{A}}$ [25,26]:

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

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

where $(-)$ and $(\times)$ indicates fuzzy subtraction and multiplication, respectively. However, solving the two equations is a computationally intensive task. To address this, most of the past studies applied approximation techniques such as FGM [27] and fuzzy extent analysis (FEA) [28]. In contrast, an exact technique such as ACO is able to derive the values of $\widetilde{\lambda}$ and $\widetilde{\mathbf{x}}$.

The α cut of a fuzzy variable $y(\alpha) = [y^L(\alpha), y^R(\alpha)]$ is an interval. In ACO, the fuzzy parameters and variables in Equations (3) and (4) are replaced with their α cuts:

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

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

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

Substituting (5–7) into (3–4) gives

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

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

If the possible values of α are enumerated, e.g., every 0.1, then Equations (8) and (9) need to be solved $10 \cdot 2^{C_2^n} + 1$ times, from which the minimal and maximal results specify the lower and upper bounds of the α cut [29–31]:

$$\begin{aligned} w_i(\alpha) &= [w_i^L(\alpha), w_i^R(\alpha)] \\ &= [\min_* \frac{x_i^*(\alpha)}{\sum_{j=1}^n x_j^*(\alpha)}, \max_* \frac{x_i^*(\alpha)}{\sum_{j=1}^n x_j^*(\alpha)}] \end{aligned} \tag{10}$$

where * can be L or R, indicating the left or right α cut of the variable, respectively. The pseudo code for implementing ACO is shown in Figure 3.

```
FOR each value of α
  FOR the two α cuts of the first positive comparison
    ……
      FOR the two α cuts of the last positive comparison
        Derive the maximal eigenvalue and weight from A(α)
        IF the derived maximal eigenvalue < the minimum of the fuzzy maximal eigenvalue THEN
          UPDATE the minimum of the fuzzy maximal eigenvalue to the derived maximal eigenvalue
        END IF
        IF the derived maximal eigenvalue > the maximum of the fuzzy maximal eigenvalue THEN
          UPDATE the maximum of the fuzzy maximal eigenvalue to the derived maximal eigenvalue
        END IF
        FOR each fuzzy weight
          IF the derived weight < the minimum of the fuzzy weight THEN
            UPDATE the minimum of the fuzzy weight to the derived weight
          END IF
          IF the derived weight > the maximum of the fuzzy weight THEN
            UPDATE the maximum of the fuzzy weight to the derived weight
          END IF
        END LOOP
      END LOOP
    ……
  END LOOP
END LOOP
```

Figure 3. Pseudo code for implementing ACO.

Based on $\widetilde{\lambda}$, Satty [23] suggested evaluating the consistency among fuzzy pairwise comparison results as

$$\text{Consistency index}: \ \widetilde{C.I.}(m) = \frac{\widetilde{\lambda}_{\max}(m) - n}{n-1} \tag{11}$$

$$\text{Consistency ratio}: \ \widetilde{C.R.}(m) = \frac{\widetilde{C.I.}(m)}{R.I.} \tag{12}$$

where *R.I.* is the randomized consistency index.

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

After the negotiation process, the FI result of the fuzzy weights derived by all decision makers is adopted to represent their consensus [32–36]. When a consensus among all decision makers does not exist, an alternative is to seek for the consensus among only some of the decision makers [37].

The membership function of the FI result is given by

$$\mu_{\widetilde{FI}(\{\widetilde{w}_i(k)\}}(x) = \min_k(\mu_{\widetilde{w}_i(k)}(x)) \tag{13}$$

as shown in Figure 4. If the TFNs for linguistic terms have narrow ranges, fuzzy weights may not overlap and $\widetilde{FI}(\{\widetilde{w}_i(k)\})$ will be an empty (null) set, as illustrated in Figure 5.

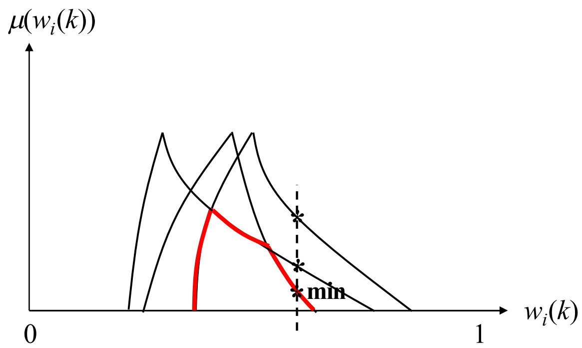

Figure 4. The FI result.

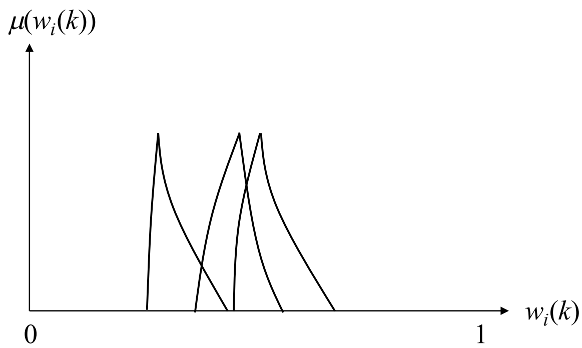

Figure 5. The FI result is a null set if TFNs have narrow ranges.

Alternatively, $\widetilde{FI}(\{\widetilde{w}_i(k)\})$ can be represented with its α cut as

$$FI^L(\{\widetilde{w}_i(k)\})(\alpha) = \max_k(w_i^L(k)(\alpha)) \tag{14}$$

$$FI^R(\{\widetilde{w}_i(k)\})(\alpha\} = \min_k(w_i^R(k)(\alpha)) \tag{15}$$

as illustrated in Figure 6.

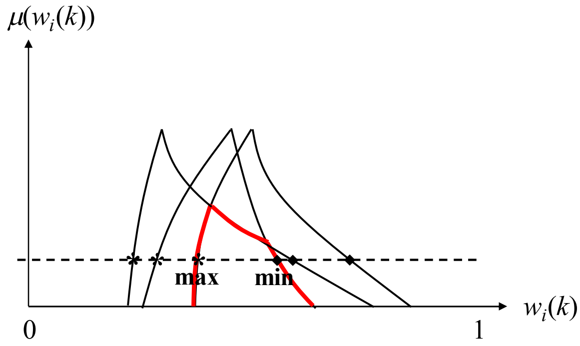

Figure 6. The α cut of the FI result.

If decision makers are of unequal importance levels, FI is not suitable. To address this issue, the fuzzy weighted intersection (FWI) can be sought for instead.

Definition 1. *Let $\widetilde{w}_i(1) \sim \widetilde{w}_i(K)$ be the fuzzy weights derived by K decision makers. The importance of decision maker k is $\omega(k)$. Then the fuzzy weighted intersection (FWI) of fuzzy weights, indicated with $\widetilde{FWI}(\{\widetilde{w}_i(k)|k = 1 \sim K)\}$ is expected to meet the following requirements:*

(i) $\widetilde{FWI}(\{\widetilde{w}_i(k)\}) = \widetilde{w}_i(g)$ *if* $\omega_g = 1$ *for some g: If a decision maker is absolutely important, then the value of $\widetilde{w}_i$ is determined solely by the decision maker.*

(ii) $\widetilde{FWI}(\{\widetilde{w}_i(k)\}) = \widetilde{FI}(\{\widetilde{w}_i(k)\})$ *if* $\omega_k = 1/K\ \forall\ k$: *If all decision makers are equally important, then the value of $\widetilde{w}_i$ is determined by the consensus among the decision makers.*

(iii) $\left|\mu_{\widetilde{FWI}}(x) - \mu_{\widetilde{w}_i(g_1)}(x)\right| \geq \left|\mu_{\widetilde{FWI}}(x) - \mu_{\widetilde{w}_i(g_2)}(x)\right|$ *if* $\omega_{g_1} \leq \omega_{g_2}\ \forall\ g_1 \neq g_2$: *If decision maker g_2 is more important than decision maker g_1, then the value of $\widetilde{w}_i$ is closer to the value derived by decision maker g_2 than to that by decision maker g_1.*

In theory, there are numerous possible FWI operators. A FWI operator considers the membership function value, rather than the value, of a fuzzy weight, which is obviously distinct from the common aggregator such as FWM.

3.3. Assessing the Suitability of a Smart Health Practice Using FWM

Subsequently, FWM is applied to assess the suitability of a smart health practice, for which the FI result provides the required fuzzy weights:

$$\widetilde{S}_q = \frac{\sum\limits_{i=1}^{n} (\widetilde{FI}(\{\widetilde{w}_i(k)\})(\times)\widetilde{p}_{qi})}{\sum\limits_{i=1}^{n} \widetilde{FI}(\{\widetilde{w}_i(k)\})} \tag{16}$$

where $\widetilde{S}_q$ is the suitability of the q-th smart health practice; $\widetilde{p}_{qi}$ is the performance of the q-th smart health practice in optimizing the i-th criterion. A FWM problem is not easy to solve because the dividend and divisor of Equation (16) are dependent [8]. Nevertheless, for comparison, only the dividend of Equation (16) needs to be calculated, since the divisor is the same for all alternatives:

$$\widetilde{S}_q = \sum_{i=1}^{n} (\widetilde{FI}(\{\widetilde{w}_i(k)\})(\times)\widetilde{p}_{qi}). \tag{17}$$

The α cut of $\widetilde{S}_q$ is defined as the interval $[S_q^L, S_q^R]$ that can be derived as

$$S_q^L(\alpha) = \sum_{i=1}^{n} (FI^L(\{\widetilde{w}_i(k)\})(\alpha) p_{qi}^L(\alpha)) \tag{18}$$

$$S_q^R(\alpha) = \sum_{i=1}^{n} (FI^R(\{\widetilde{w}_i(k)\})(\alpha) p_{qi}^R(\alpha)) \tag{19}$$

according to the alpha-cut operations. The assessment result is then defuzzified using the prevalent CD method [38]. However, the alpha-cut operations method takes samples uniformly along the y-axis, as illustrated in Figure 7, while the CD method distributes samples evenly along the x-axis. To resolve this inconsistency, a possible way is to divide the range of $\widetilde{S}_q$ into Γ equal intervals:

$$\widetilde{S}_q = \{[\frac{\Gamma-\eta+1}{\Gamma} S_q^L(0) + \frac{\eta-1}{\Gamma} S_q^R(0),\ \frac{\Gamma-\eta}{\Gamma} S_q^L(0) + \frac{\eta}{\Gamma} S_q^R(0)] | \eta = 1 \sim \Gamma\} \tag{20}$$

as illustrated in Figure 8. The center of the η-th interval is indicated with $C_q(\eta)$:

$$\begin{aligned} C_q(\eta) &= \tfrac{1}{2}(\tfrac{\Gamma-\eta+1}{\Gamma} S_q^L(0) + \tfrac{\eta-1}{\Gamma} S_q^R(0) + \tfrac{\Gamma-\eta}{\Gamma} S_q^L(0) + \tfrac{\eta}{\Gamma} S_q^R(0)) \\ &= \tfrac{2\Gamma-2\eta+1}{2\Gamma} S_q^L(0) + \tfrac{2\eta-1}{2\Gamma} S_q^R(0) \end{aligned} \tag{21}$$

$C_q(\eta)$ can be determined by interpolating the two closest values of $\widetilde{S}_q$:

$$\begin{aligned} \mu_{\widetilde{S}_q}(C_q(\eta)) &= \frac{C_q(\eta) - \max\limits_{S_q^*(\alpha)\le C_q(\eta)} S_q^*(\alpha)}{(\min\limits_{S_q^*(\alpha)\ge C_q(\eta)} S_q^*(\alpha) - \max\limits_{S_q^*(\alpha)\le C_q(\eta)} S_q^*(\alpha))} \cdot \min_{S_q^*(\alpha)\ge C_q(\eta)} \alpha \\ &+ \frac{\min\limits_{S_q^*(\alpha)\ge C_q(\eta)} S_q^*(\alpha) - C_q(\eta)}{(\min\limits_{S_q^*(\alpha)\ge C_q(\eta)} S_q^*(\alpha) - \max\limits_{S_q^*(\alpha)\le C_q(\eta)} S_q^*(\alpha))} \cdot \max_{S_q^*(\alpha)\le C_q(\eta)} \alpha \end{aligned} \tag{22}$$

where * can be R or L. Then, the centroid of $\widetilde{S}_q$ is the derived as follows:

$$COG(\widetilde{S}_q) = \frac{\sum\limits_{\eta=1}^{\Gamma} (\mu_{\widetilde{S}_q}(C_q(\eta)) C_q(\eta))}{\sum\limits_{\eta=1}^{\Gamma} \mu_{\widetilde{S}_q}(C_q(\eta))}. \tag{23}$$

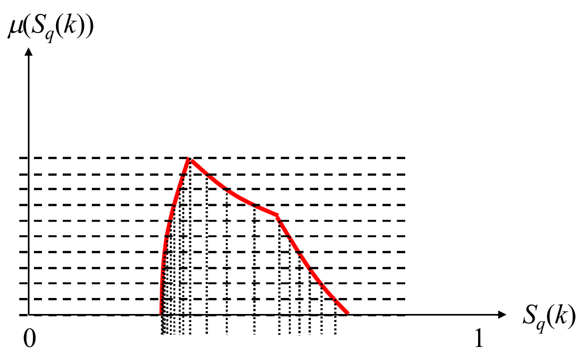

Figure 7. The way of taking samples in the alpha-cut operations method.

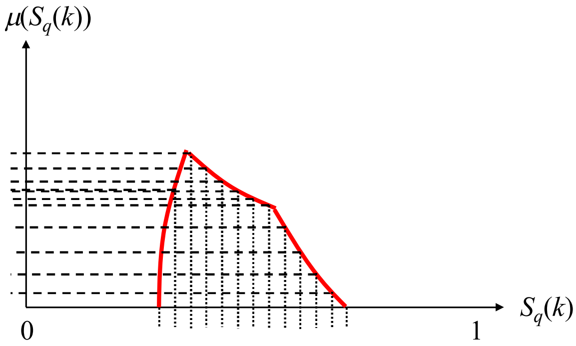

Figure 8. The way of taking samples in the centroid-defuzzification (CD) method.

4. Application

With advances in transportation, sensing, and communication technologies, smart health becomes a critical issue [39]. There have been a number of smart health practices, however, and how to choose the most suitable smart health practice is a challenging task. To fulfill this task, the proposed methodology has been applied to assess and compare the suitabilities of eleven smart health practices. Chen [6] evaluated the sustainability of a smart health practice, in which five criteria—unobtrusiveness, supporting online social networking, compliance with related medical laws, the size of the health care market, and the correct identification of a user's need and situation, were considered. Compared with sustainability, suitability is a shorter-term concept. For this reason, the following five criteria were considered in this study instead [6,40–48]:

(1) C1: unobtrusiveness,
(2) C2: supporting online social networking,
(3) C3: cost effectiveness,
(4) C4: availability of mobile health care facilities, and
(5) C5: correct, reliable, and robust identification of a user's need and situation.

In addition, two less relevant smart health practices, smart connected vehicles and smart defense technologies, were excluded from the experiment. The proposed methodology was applied as follows.

First, a team of three decision makers, including an information management professor, a computer-aided industrial design professor, and an ambient intelligence (AmI) decision maker, was formed. Each decision maker compared the relative weights of criteria in pairs. The results are summarized in Table 2.

Table 2. The results of pairwise comparisons.

	C1	C2	C3	C4	C5
C1	1	(1, 5, 9), (3, 7, 9), (3, 7, 9)	(1, 1, 5), (1, 5, 9), (1, 1, 5)	(3, 7, 9), (5, 9, 9), (1, 1, 5)	(1, 5, 9), (1, 5, 9), (1, 3, 7)
C2	-	1	(1, 1, 5), (1, 4, 8), (1, 3, 7)	(3, 7, 9), (1, 3, 7), (1, 1, 5)	-
C3	-	-	1	-	(1, 5, 9), (1, 4, 8), (1, 5, 9)
C4	-	-	(1, 1, 5), (1, 3, 7), (1, 1, 5)	1	(3, 7, 9), (1, 5, 9), (1, 3, 7)
C5	-	(1, 3, 7), (1, 5, 9), (1, 4, 8)	-	-	1

Each decision maker applied ACO to derive fuzzy eigenvalues and the fuzzy weights of criteria. The results are summarized in Figures 9 and 10, respectively. In our view, if the linguistic terms adopted in the proposed methodology reflected the preferences of decision makers, it was more likely for their fuzzy judgment matrixes to be consistent. To ensure this, the fuzzy consistency index $\widetilde{C.I.}(k)$ should be less than the threshold of 0.1 for each decision maker, by requesting:

$$\mu_{\widetilde{C.I.}(k)}(0.1) \geq 0 \quad \forall\, k \tag{24}$$

According to the experimental results, Condition (23) was successfully satisfied. In contrast, if the commonly adopted linguistic terms were adopted, $\widetilde{C.I.}(k)$ was always greater than 0.1. This result supported the suitability of the linguistic terms adopted in the proposed methodology.

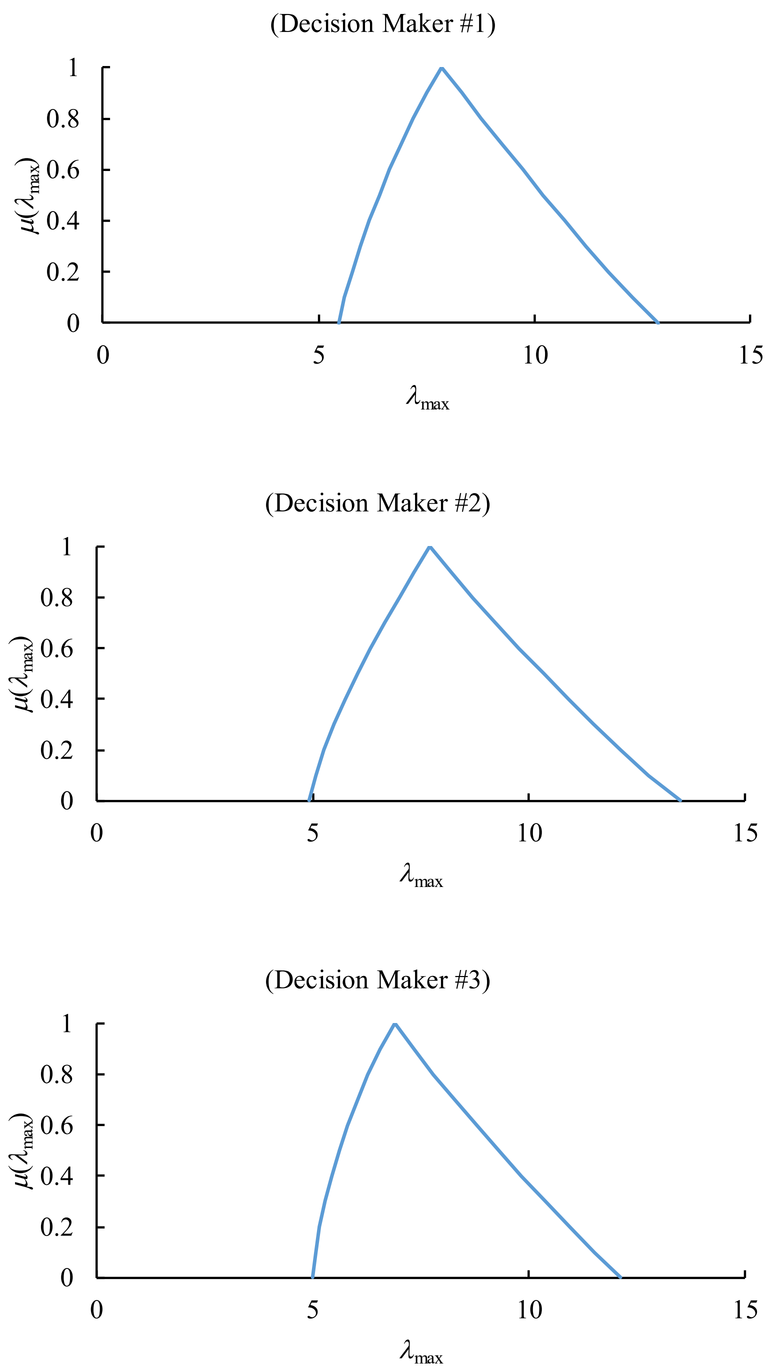

Figure 9. Fuzzy eigenvalues derived by decision makers.

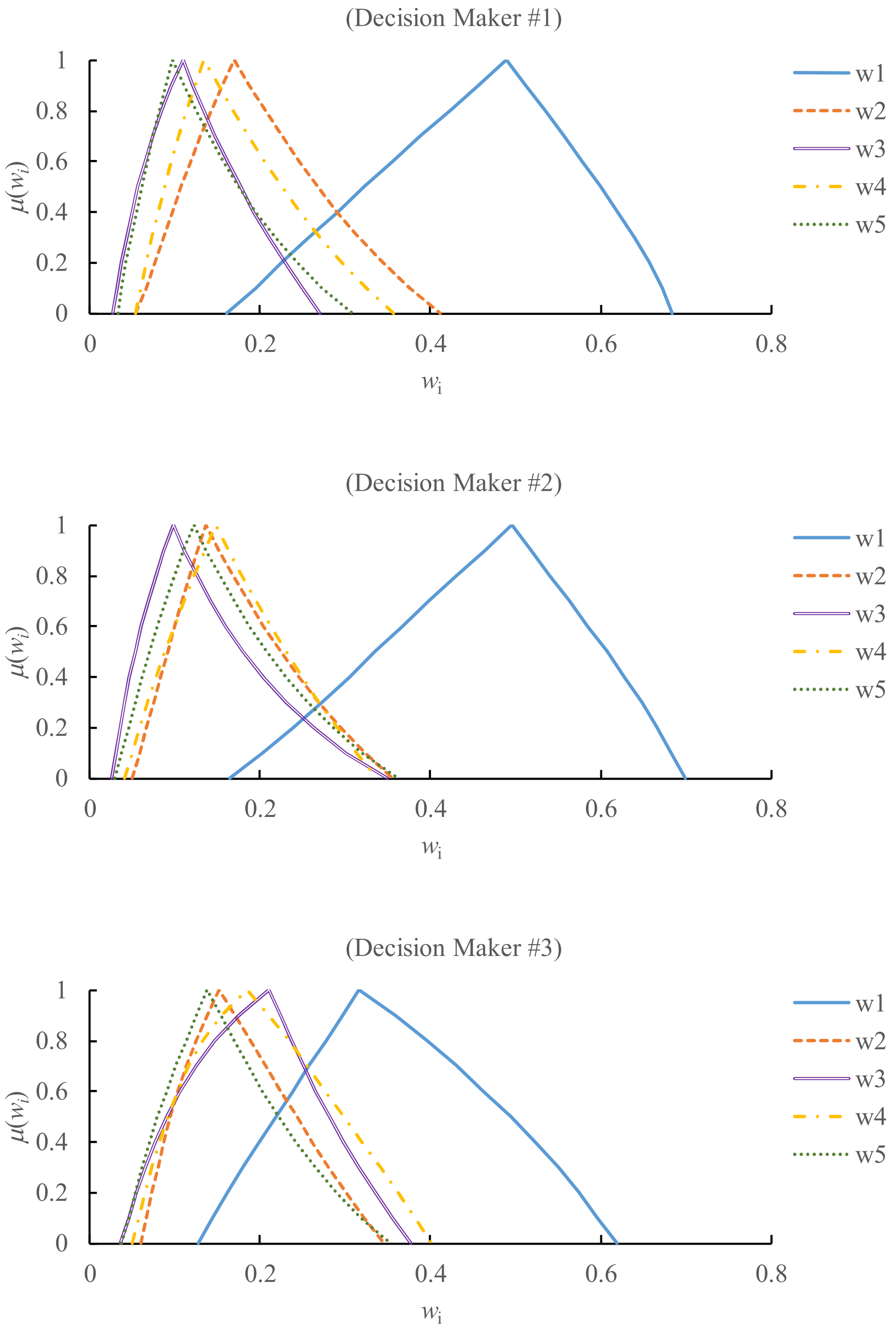

Figure 10. Fuzzy weights derived by decision makers.

In this experiment, decision makers were equally important. Therefore, FI was considered effective for aggregating the fuzzy weights derived by all decision makers. The results are shown in Figure 11. The results showed that a prior consensus has been achieved among decision makers regarding the values of each fuzzy weight.

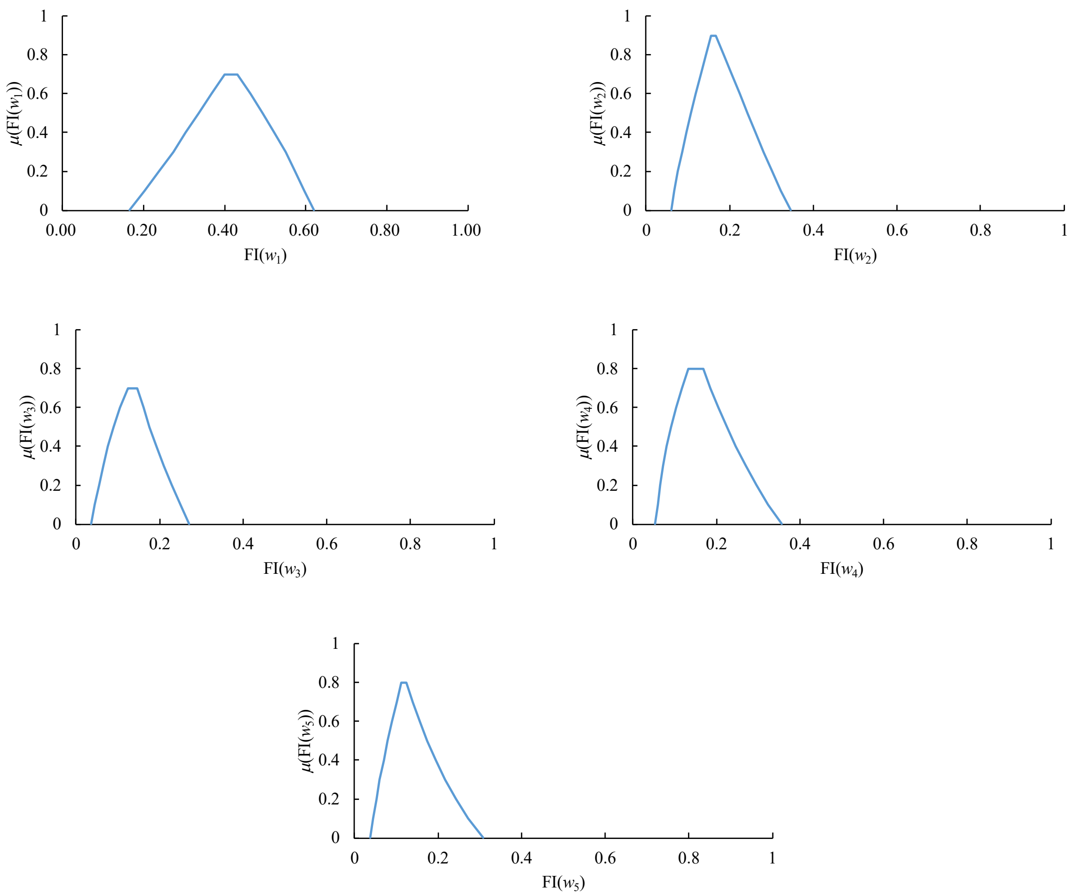

Figure 11. The FI results.

The FI results were presented to decision makers for them to consider when modifying their pairwise comparison results. The modified pairwise comparison results are summarized in Table 3. ACO was again applied to derive fuzzy weights for each decision maker. Then, FI was applied to measure the consensus among decision makers after collaboration. The results are summarized in Figure 12. After collaboration, the FI results became wider, showing a higher consensus since more possible values were acceptable to all decision makers. Taking $\widetilde{w}_4$ as an example, the FI results before and after collaboration are compared in Figure 13. The collaboration stopped because no decision maker made any further modification.

Table 3. The modified pairwise comparison results.

	C1	**C2**	**C3**	**C4**	**C5**
C1	1	(1, 5, 9), (3, 7, 9), (3, 7, 9)	(1, 1, 5), (1, 3, 7), (1, 1, 5)	(3, 7, 9), (1, 5, 9), (1, 1, 5)	(1, 5, 9), (1, 5, 9), (1, 3, 7)
C2	-	1	(1, 1, 5), (1, 1, 5), (1, 3, 7)	(3, 7, 9), (1, 5, 9), (1, 1, 5)	-
C3	-	-	1	-	(1, 5, 9), (1, 4, 8), (1, 5, 9)
C4	-	-	(1, 1, 5), (1, 3, 7), (1, 1, 5)	1	(3, 7, 9), (1, 4, 8), (1, 3, 7)
C5	-	(1, 3, 7), (1, 5, 9), (1, 4, 8)	-	-	1

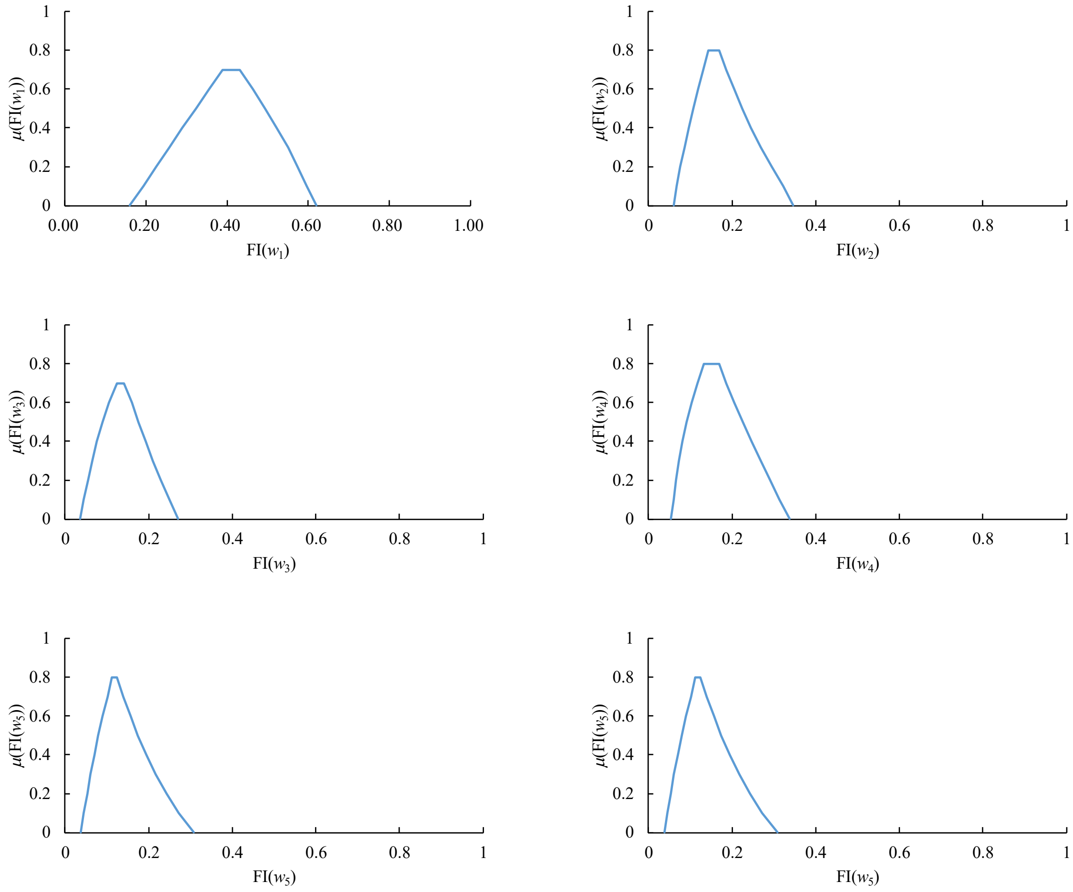

Figure 12. The FI results after collaboration.

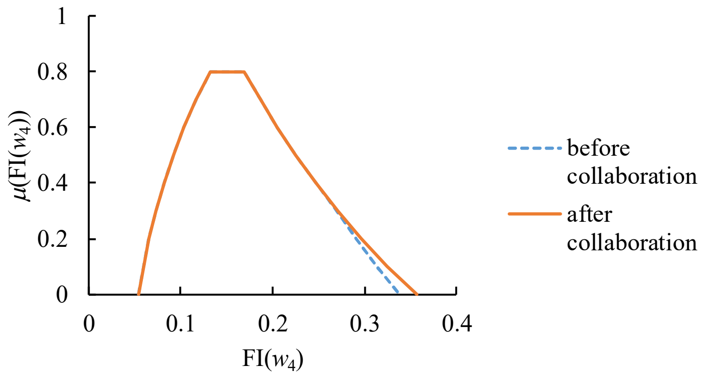

Figure 13. The FI results of $\widetilde{w}_4$ before and after collaboration.

The suitabilities of eleven smart health practices were assessed. To this end, the performances of these smart health practices in optimizing the five criterion were evaluated by the same decision makers using the following linguistic terms [3]:

Very poor: (0, 0, 1),
Poor: (0, 1, 2),
Moderate: (1.5, 2.5, 3.5),
Good: (3, 4, 5), and
Very good: (4, 5, 5).

The evaluations by decision makers were aggregated in a similar way. Specifically speaking, decision makers were asked to modify their evaluations slightly until these evaluations overlapped.

Then, the evaluations by all decision makers were averaged. The results are summarized in Table 4. It can be seen that none of the smart health practices dominated the others, causing difficulty in choosing from them. In addition, it was noteworthy that the cost effectiveness of smart phones was high, while that of smart watches was low, due to the fact that smart phones were much more prevalent than smart watches. Therefore, a decision maker did not consider buying his/her smart phone as an additional investment.

Table 4. Performances of eleven smart technologies along five dimensions.

Smart Health Practice	C1 (Unobtrusiveness)	C2 (Online Social Networking)	C3 (Cost Effectiveness)	C4 (Availability of Mobile Health Care Facilities)	C5 (Correct, Reliable, and Robust Identification)
Smart body analyzers	(1.00, 2.00, 3.00)	(1.00, 2.00, 3.00)	(0.00, 1.00, 2.00)	(0.00, 1.00, 2.00)	(2.50, 3.50, 4.50)
Smart clothes	(0.00, 1.00, 2.00)	(0.00, 1.00, 2.00)	(0.00, 1.00, 2.00)	(0.00, 1.00, 2.00)	(2.50, 3.50, 4.50)
Smart glasses	(0.00, 1.00, 2.00)	(3.33, 4.33, 5.00)	(0.00, 1.00, 2.00)	(2.00, 3.00, 4.00)	(2.50, 3.50, 4.50)
Smart mobile services	(3.67, 4.67, 5.00)	(3.67, 4.67, 5.00)	(3.67, 4.67, 5.00)	(3.67, 4.67, 5.00)	(3.33, 4.33, 5.00)
Smart motion sensors	(2.00, 3.00, 4.00)	(0.00, 1.00, 2.00)	(0.00, 1.00, 2.00)	(0.00, 1.00, 2.00)	(3.67, 4.67, 5.00)
Smart phones	(3.67, 4.67, 5.00)	(3.67, 4.67, 5.00)	(2.50, 3.50, 4.50)	(3.67, 4.67, 5.00)	(3.67, 4.67, 5.00)
Smart smoke alarms	(2.00, 3.00, 4.00)	(0.00, 1.00, 2.00)	(1.00, 2.00, 3.00)	(2.00, 3.00, 4.00)	(3.67, 4.67, 5.00)
Smart toilets	(1.00, 2.00, 3.00)	(0.00, 1.00, 2.00)	(0.00, 1.00, 2.00)	(0.00, 1.00, 2.00)	(2.00, 3.00, 4.00)
Smart watches	(3.67, 4.67, 5.00)	(2.50, 3.50, 4.50)	(1.00, 2.00, 3.00)	(3.67, 4.67, 5.00)	(3.67, 4.67, 5.00)
Smart wheelchairs	(2.50, 3.50, 4.50)	(0.00, 1.00, 2.00)	(0.00, 1.00, 2.00)	(2.00, 3.00, 4.00)	(2.00, 3.00, 4.00)
Smart wigs	(2.00, 3.00, 4.00)	(0.00, 1.00, 2.00)	(0.00, 1.00, 2.00)	(0.00, 1.00, 2.00)	(2.50, 3.50, 4.50)

FWM was applied to assess the suitability of each smart health practice, for which the fuzzy collaborative FAHP approach provided the required fuzzy weights. The results are summarized in Figure 14.

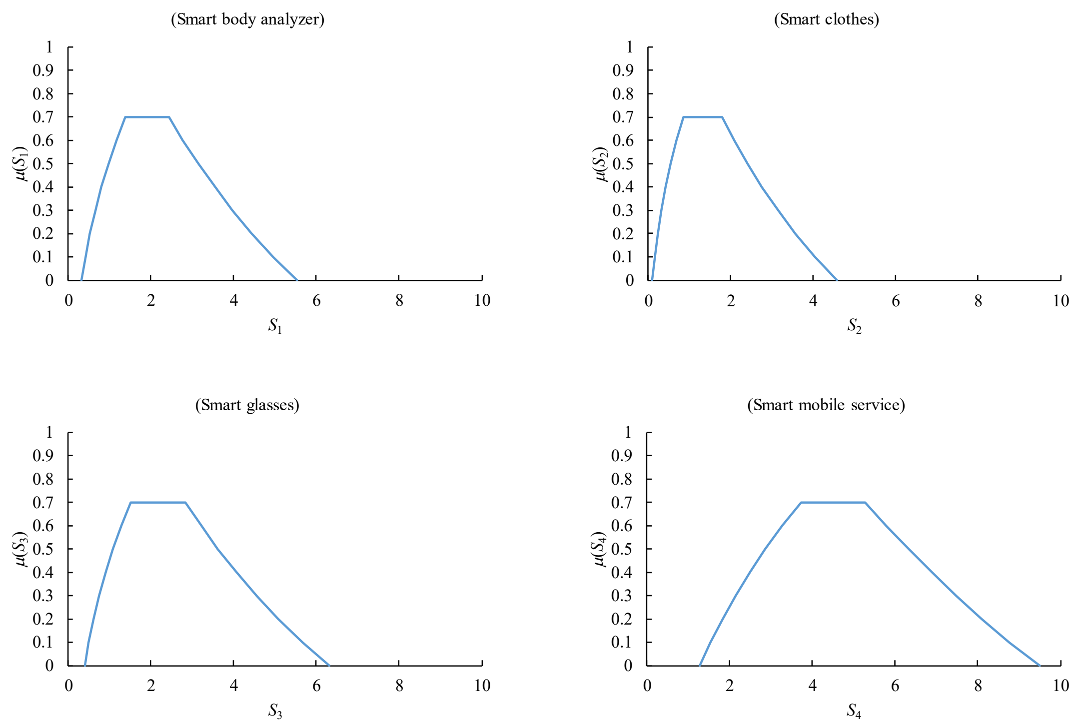

Figure 14. *Cont.*

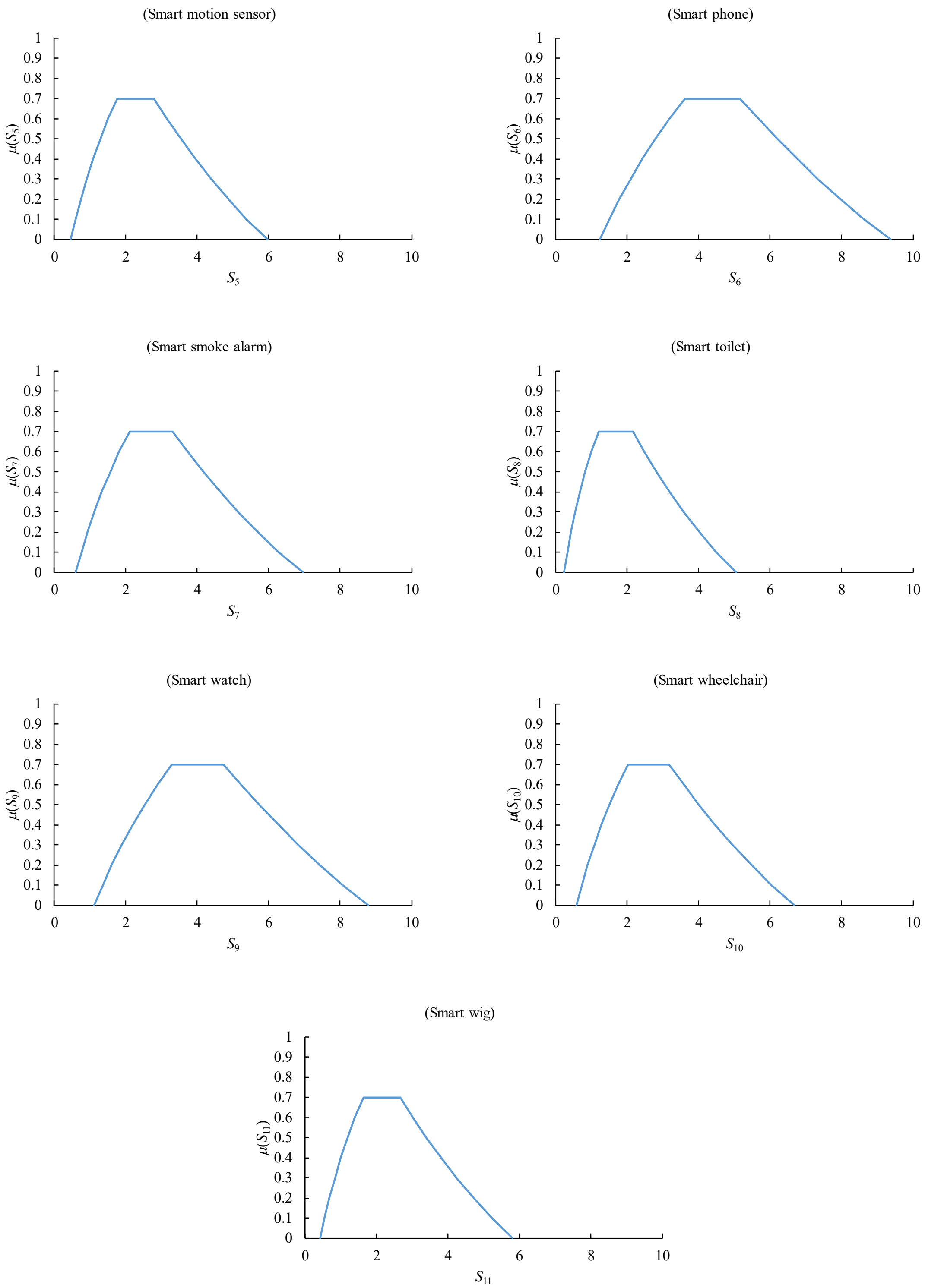

Figure 14. FWM results.

For generating an absolute ranking, CD was applied to defuzzify the fuzzy suitability of each smart health practice. The results are summarized in Table 5.

Table 5. Defuzzification results.

Smart Health Practice	Defuzzified Suitability
Smart body analyzers	2.10
Smart clothes	1.52
Smart glasses	2.40
Smart mobile services	4.64
Smart motion sensors	2.45
Smart phones	4.54
Smart smoke alarms	2.91
Smart toilets	1.86
Smart watches	4.17
Smart wheelchairs	2.79
Smart wigs	2.33

According to the experimental results,

(1) Smart mobile services were the most suitable smart health practice, while smart clothes were still the least suitable smart health practice, owing to their obtrusiveness.

(2) The suitabilities of the eleven smart health practices were ranked. The results are shown in Figure 15. The ranking results of the sustainabilities of these smart health practices, retrieved from Chen [6], are also presented in this figure for comparison. Obviously, there are some differences between the two results. For example, the suitability of smart body analyzers was low, but its suitability was high, showing the great potential of smart body analyzers in the future.

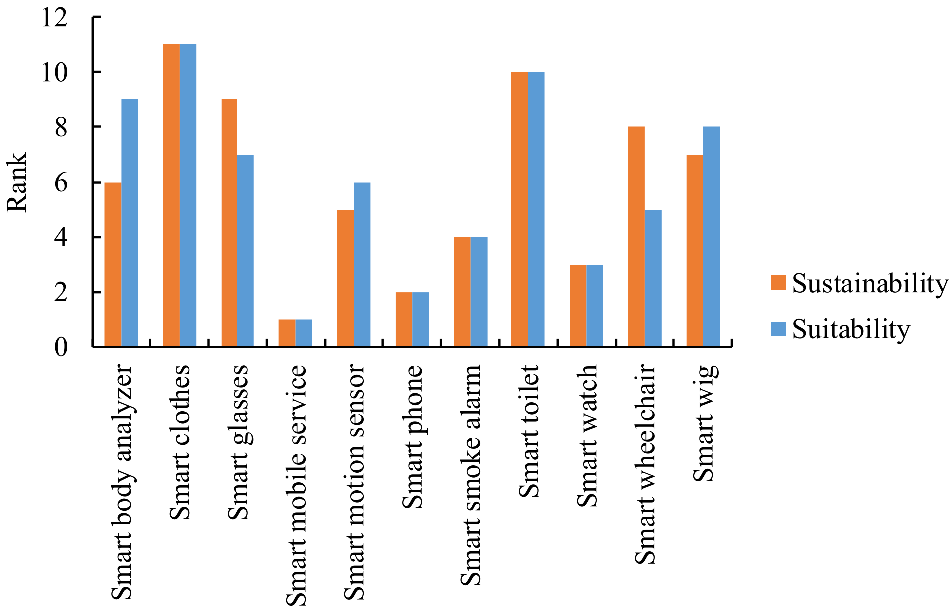

Figure 15. Comparing the suitability and sustainability of each smart technology application.

(3) In the experiment, decision makers modified their fuzzy judgment results just once to achieve a higher consensus, yet this was not always the case since modifications were subjectively made. It was possible for decision makers to undergo many rounds of collaboration before achieving a higher consensus. To tackle this problem, a mechanism for facilitating the collaboration process among decision makers should be designed.

(4) The efficiency of ACO was a problem to the application of the fuzzy collaborative approach, and needed to be enhanced somehow, e.g., by applying a genetic algorithm. In previous studies, there were two major ways of combining genetic algorithms with fuzzy analytic hierarchy analysis. The first way obtains the weights of criteria by using fuzzy analytic hierarchy analysis, which

designs the fitness function of the genetic algorithm to compare various alternatives. The second way solves a multi-objective optimization problem with a genetic algorithm to obtain multiple Pareto-optimal solutions, and then performs a fuzzy analytic hierarchy analysis to set the weights of the objective functions to further compare these Pareto-optimal solutions. The motive for applying a genetic algorithm in this study is different from those in previous studies.

(5) Three existing methods, fuzzy ordered weighted average (FOWA), fuzzy geometric mean (FGM)-FWM, and the fuzzy extent analysis (FEA)-weighted average (WA) method proposed by Chang [29], were also applied to assess the suitability of each smart health practice for comparison. In FOWA, the moderately optimistic strategy was adopted. In FGM-FWM, fuzzy weights were approximated using FGM and expressed in terms of TFNs. In FEA-WA, since the weights estimated using FEA were crisp, WA, rather than FWM, was applied to assess the suitability of each smart health practice. Finally, the suitabilities of all smart health practices were ranked. The ranking results using various methods are compared in Figure 16. In sum, these methods came to the same conclusions about the suitabilities of smart mobile services and smart phones. In contrast, the suitabilities of other smart health practices assessed using different methods were not the same.

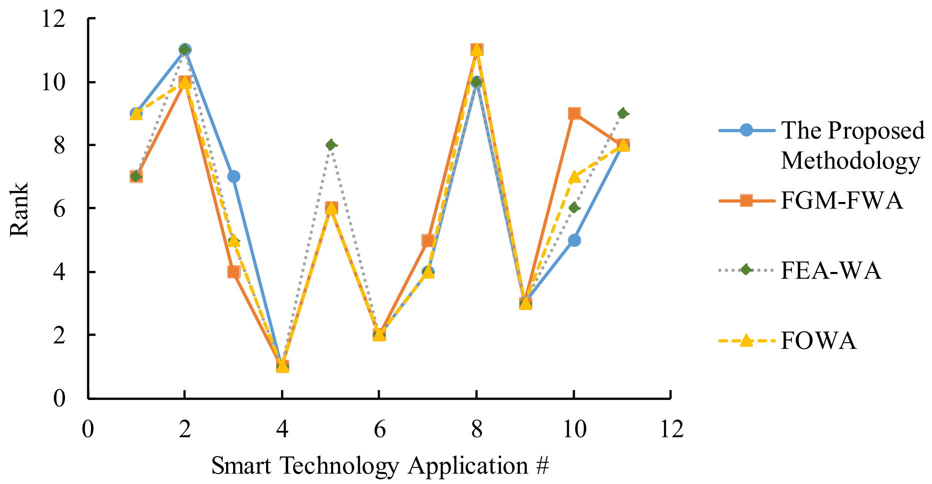

Figure 16. Comparing the results using various methods: fuzzy geometric mean (FGM)-fuzzy weighted average (FWA); fuzzy extent analysis (FEA)-weighted average (WA); fuzzy ordered weighted average (FOWA).

5. Conclusions

Smart health is the context-aware complement of mobile health within a smart city [49]. In the past work, a great deal of effort has been made to promote the smart health in a city or region [50]. However, assessing the suitability of a smart health practice is still a challenging task because the applied smart technology is still evolving. To this end, several group-based decision-making FAHP methods have been devised. However, the prerequisite for such group-based decision-making FAHP methods is the existence of a consensus among the participating decision makers, which has rarely been checked. To address this issue, this study puts forward a fuzzy collaborative approach that is the joint application of ACO, FI, and FWM. In particular, FI is applied to assess the consensus among decision makers before the collaboration process. The FI results are presented to decision makers, so that they can subjectively modify the pairwise comparison results to bring them closer to the FI results. Thereafter, the consensus among decision makers is again measured. The collaboration process continues until no further modifications are made by decision makers. Last, the FWM-CD method is applied to assess the suitability of a smart health practice.

To elaborate the effectiveness of the fuzzy collaborative approach, we assessed the suitabilities of eleven smart health practices. According to the experimental results, the following conclusions were drawn:

(1) Smart mobile services and smart clothes were evaluated as the most suitable and the least suitable smart health practices, respectively.
(2) The suitabilities of smart mobile services and smart phones evaluated using various methods were identical. In contrast, the suitabilities of other smart health practices, assessed using various methods, differed.
(3) Among the compared methods, only the fuzzy collaborative approach could guarantee the existence of a consensus among decision makers. In other words, only the results assessed using the fuzzy collaborative approach were acceptable to all decision makers.

Smart technologies are still evolving. Therefore, the suitability of a smart health practice needs to be re-assessed in the near future. In addition, other types of methods can also be applied to assess the suitability of a smart health practice.

Author Contributions: Data curation, T.-C.T.C. and Y.-C.W.; methodology, T.-C.T.C. and Y.-C.W.; writing—original draft preparation, T.-C.T.C. and Y.-C.W.; writing—review and editing, T.-C.T.C., Y.-C.W., Y.-C.L., H.-C.W. and H.-F.L.

Acknowledgments: This study was sponsored by Ambient Intelligence Association of Taiwan (AIAT) under Grant NCTU 1083RD2187.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Jordan, M. What Is 'Smart' Technology? Available online: http://knowit.co.nz/2011/08/what-is-smart-technology (accessed on 12 October 2019).
2. Silva, B.M.; Rodrigues, J.J.; de la Torre Díez, I.; López-Coronado, M.; Saleem, K. Mobile-health: A review of current state in 2015. *J. Biomed. Inform.* **2015**, *56*, 265–272. [CrossRef] [PubMed]
3. Chen, T.; Chiu, M.-C. Smart technologies for assisting the life quality of persons in a mobile environment: A review. *J. Ambient. Intell. Humaniz. Comput.* **2018**, *9*, 319327. [CrossRef]
4. Haymes, L.K.; Storey, K.; Maldonado, A.; Post, M.; Montgomery, J. Using applied behavior analysis and smart technology for meeting the health needs of individuals with intellectual disabilities. *Dev. Neurorehabilit.* **2015**, *18*, 407–419. [CrossRef]
5. Chiu, M.-C.; Chen, T.-C.T. Assessing sustainable effectiveness of the adjustment mechanism of a ubiquitous clinic recommendation system. *Health Care Manag. Sci.* **2019**, 1–10. [CrossRef]
6. Chen, T.-C.T. Evaluating the sustainability of a smart technology application to mobile health care: The FGM–ACO–FWA approach. *Complex Intell. Syst.* **2019**, 1–13. [CrossRef]
7. Chen, T.-C.T. Guaranteed-consensus posterior-aggregation fuzzy analytic hierarchy process method. *Neural Comput. Appl.* **2019**, 1–12. [CrossRef]
8. Liu, F.; Mendel, J.M. Aggregation using the fuzzy weighted average as computed by the Karnik–Mendel algorithms. *IEEE Trans. Fuzzy Syst.* **2008**, *16*, 1–12.
9. Steele, R. Social media, mobile devices and sensors: Categorizing new techniques for health communication. In Proceedings of the 2011 Fifth International Conference on Sensing Technology, Palmerston North, New Zealand, 28 November–1 December 2011; pp. 187–192.
10. Hswen, Y.; Murti, V.; Vormawor, A.A.; Bhattacharjee, R.; Naslund, J.A. Virtual avatars, gaming, and social media: Designing a mobile health app to help children choose healthier food options. *J. Mob. Technol. Med.* **2013**, *2*, 8. [CrossRef] [PubMed]
11. Petersen, C.; DeMuro, P. Legal and regulatory considerations associated with use of patient-generated health data from social media and mobile health (mHealth) devices. *Appl. Clin. Inform.* **2015**, *6*, 16–26. [PubMed]
12. Cook, D.J.; Duncan, G.; Sprint, G.; Fritz, R.L. Using smart city technology to make healthcare smarter. *Proc. IEEE* **2018**, *106*, 708–722. [CrossRef]

13. Reeder, B.; David, A. Health at hand: A systematic review of smart watch uses for health and wellness. *J. Biomed. Inform.* **2016**, *63*, 269–276. [CrossRef] [PubMed]
14. Mandel, J.C.; Kreda, D.A.; Mandl, K.D.; Kohane, I.S.; Ramoni, R.B. SMART on FHIR: A standards-based, interoperable apps platform for electronic health records. *J. Am. Med Inform. Assoc.* **2016**, *23*, 899–908. [CrossRef] [PubMed]
15. Hamidi, H. An approach to develop the smart health using Internet of Things and authentication based on biometric technology. *Future Gener. Comput. Syst.* **2019**, *91*, 434–449. [CrossRef]
16. Rathod, R. Sensors Used in Smartphone. Available online: http://myphonefactor.in/2012/04/sensors-used-in-a-smartphone/ (accessed on 10 October 2019).
17. Eklund, J.; Forsman, M. Smart work clothes give better health-Through improved work technique, work organization and production technology. In *Congress of the International Ergonomics Association*; Springer: Berlin/Heidelberg, Germany, 2018; pp. 515–519.
18. Liu, L.; Stroulia, E.; Nikolaidis, I.; Miguel-Cruz, A.; Rincon, A.R. Smart homes and home health monitoring technologies for older adults: A systematic review. *Int. J. Med Inform.* **2016**, *91*, 44–59. [CrossRef] [PubMed]
19. Eskofier, B.M.; Lee, S.I.; Baron, M.; Simon, A.; Martindale, C.F.; Gaßner, H.; Klucken, J. An overview of smart shoes in the internet of health things: Gait and mobility assessment in health promotion and disease monitoring. *Appl. Sci.* **2017**, *7*, 986. [CrossRef]
20. Chen, M.; Ma, Y.; Song, J.; Lai, C.F.; Hu, B. Smart clothing: Connecting human with clouds and big data for sustainable health monitoring. *Mob. Netw. Appl.* **2016**, *21*, 825–845. [CrossRef]
21. Duman, G.M.; El-Sayed, A.; Kongar, E.; Gupta, S.M. An intelligent multiattribute group decision-making approach with preference elicitation for performance evaluation. *IEEE Trans. Eng. Manag.* **2019**, 1–17. [CrossRef]
22. Kubler, S.; Robert, J.; Derigent, W.; Voisin, A.; Le Traon, Y. A state-of the-art survey & testbed of fuzzy AHP (FAHP) applications. *Expert Syst. Appl.* **2016**, *65*, 398–422.
23. Saaty, T.L. Decision making—the analytic hierarchy and network processes (AHP/ANP). *J. Syst. Sci. Syst. Eng.* **2004**, *13*, 1–35. [CrossRef]
24. Zheng, G.; Zhu, N.; Tian, Z.; Chen, Y.; Sun, B. Application of a trapezoidal fuzzy AHP method for work safety evaluation and early warning rating of hot and humid environments. *Saf. Sci.* **2012**, *50*, 228–239. [CrossRef]
25. Michael, H. *Applied Fuzzy Arithmetic an Introduction with Engineering Applications*; Springer: Berlin/Heidelberg, Germany, 2005.
26. Golub, G.H.; Van Loan, C.F. *Matrix Computations*; Johns Hopkins: Baltimore, MD, USA, 1996; p. 694.
27. Saaty, T.L. *The Analytic Hierarchy Process*; McGraw-Hill: New York, NY, USA, 1980; p. 324.
28. Wang, Y.-C.; Chen, T.; Yeh, Y.-L. Advanced 3D printing technologies for the aircraft industry: A fuzzy systematic approach for assessing the critical factors. *Int. J. Adv. Manuf. Technol.* **2018**, 1–11. [CrossRef]
29. Chang, D.-Y. Applications of the extent analysis method on fuzzy AHP. *Eur. J. Oper. Res.* **1996**, *95*, 649–655. [CrossRef]
30. Wang, Y.C.; Chen, T. A fuzzy collaborative forecasting approach for forecasting the productivity of a factory. *Adv. Mech. Eng.* **2013**, *5*, 234571. [CrossRef]
31. Al-Refaie, A.; Aldwairi, R.; Chen, T. Optimizing performance of rigid polyurethane foam using FGP models. *J. Ambient Intell. Humaniz. Comput.* **2018**, *9*, 351–366. [CrossRef]
32. Csutora, R.; Buckley, J.J. Fuzzy hierarchical analysis: The Lambda-Max method. *Fuzzy Sets Syst.* **2001**, *120*, 181–195. [CrossRef]
33. Chen, T. An effective fuzzy collaborative forecasting approach for predicting the job cycle time in wafer fabrication. *Comput. Ind. Eng.* **2013**, *66*, 834–848. [CrossRef]
34. Yolcu, O.C.; Yolcu, U.; Egrioglu, E.; Aladag, C.H. High order fuzzy time series forecasting method based on an intersection operation. *Appl. Math. Model.* **2016**, *40*, 8750–8765. [CrossRef]
35. Chen, T. A heterogeneous fuzzy collaborative intelligence approach for forecasting the product yield. *Appl. Soft Comput.* **2017**, *57*, 210–224. [CrossRef]
36. Wang, Y.-C.; Chen, T.-C.T. A direct-solution fuzzy collaborative intelligence approach for yield forecasting in semiconductor manufacturing. *Procedia Manuf.* **2018**, *17*, 110–117. [CrossRef]
37. Wang, Y.C.; Chen, T.C.T. A partial-consensus posterior-aggregation FAHP method—supplier selection problem as an example. *Mathematics* **2019**, *7*, 179. [CrossRef]

38. Chen, T.-C.T.; Honda, K. *Fuzzy Collaborative Forecasting and Clustering: Methodology, System Architecture, and Applications*; Springer: Cham, Switzerland, 2019; p. 89.
39. Van Broekhoven, E.; De Baets, B. Fast and accurate center of gravity defuzzification of fuzzy system outputs defined on trapezoidal fuzzy partitions. *Fuzzy Sets Syst.* **2006**, *157*, 904–918. [CrossRef]
40. Ventola, C.L. Mobile devices and apps for health care professionals: Uses and benefits. *Pharm. Ther.* **2014**, *39*, 356.
41. Demiris, G.; Hensel, B.K.; Skubic, M.; Rantz, M. Senior residents' perceived need of and preferences for "smart home" sensor technologies. *Int. J. Technol. Assess. Health Care* **2008**, *24*, 120–124. [CrossRef] [PubMed]
42. Vodopivec-Jamsek, V.; de Jongh, T.; Gurol-Urganci, I.; Atun, R.; Car, J. Mobile phone messaging for preventive health care. *Cochrane Database Syst. Rev.* **2012**, *12*, CD007457. [CrossRef] [PubMed]
43. Sarasohn-Kahn, J. How Smartphones are Changing Health Care for Consumers and Providers. Available online: https://www.chcf.org/wp-content/uploads/2017/12/PDF-HowSmartphonesChangingHealthCare.pdf (accessed on 3 July 2019).
44. Bieber, G.; Kirste, T.; Urban, B. Ambient interaction by smart watches. In Proceedings of the 5th International Conference on PErvasive Technologies Related to Assistive Environments, Heraklion, Crete, Greece, 6–8 June 2012. article no. 39.
45. Free, C.; Phillips, G.; Galli, L.; Watson, L.; Felix, L.; Edwards, P.; Haines, A. The effectiveness of mobile-health technology-based health behaviour change or disease management interventions for health care consumers: A systematic review. *PLoS Med.* **2013**, *10*, e1001362. [CrossRef]
46. Porzi, L.; Messelodi, S.; Modena, C.M.; Ricci, E. A smart watch-based gesture recognition system for assisting people with visual impairments. In Proceedings of the 3rd ACM International Workshop on Interactive Multimedia on Mobile Portable Devices, Barcelona, Spain, 22 October 2013; pp. 19–24.
47. Hamel, M.B.; Cortez, N.G.; Cohen, I.G.; Kesselheim, A.S. FDA regulation of mobile health technologies. *New Engl. J. Med.* **2014**, *371*, 372.
48. Shcherbina, A.; Mattsson, C.M.; Waggott, D.; Salisbury, H.; Christle, J.W.; Hastie, T.; Ashley, E.A. Accuracy in wrist-worn, sensor-based measurements of heart rate and energy expenditure in a diverse cohort. *J. Pers. Med.* **2017**, *7*, 3. [CrossRef]
49. Solanas, A.; Patsakis, C.; Conti, M.; Vlachos, I.S.; Ramos, V.; Falcone, F.; Postolache, O.; Perez-martinez, P.A.; Pietro, R.D.; Perrea, D.N.; et al. Smart health: A context-aware health paradigm within smart cities. *IEEE Commun. Mag.* **2014**, *52*, 74–81. [CrossRef]
50. Baig, M.M.; Gholamhosseini, H. Smart health monitoring systems: An overview of design and modeling. *J. Med Syst.* **2013**, *37*, 9898. [CrossRef]