Case Study

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Assessing the sustainability of smart healthcare applications using a multi-perspective fuzzy comprehensive evaluation approach

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Abstract

A smart healthcare application can be judged as sustainable if it was already widely used before and will also be prevalent in the future. In contrast, if a smart healthcare application developed during the COVID-19 pandemic is not used after it, then it is not sustainable. Assessing the sustainability of smart healthcare applications is a critical task for their users and suppliers. However, it is also a challenging task due to the availability of data, users' subjective beliefs, and different perspectives. In response to this problem, this study proposes a multi-perspective fuzzy comprehensive evaluation approach to evaluate the sustainability of a smart healthcare application from qualitative, multi-criteria decision-making and time-series perspectives. The proposed methodology has been used to evaluate the sustainability of eight smart healthcare applications. The experimental results showed that the sustainability of a smart healthcare application evaluated from different perspectives may be different. Nevertheless, another technique can be used to confirm the evaluation result generated using one technique. In other words, these views compensate for each other.

Keywords

Smart healthcare application, sustainability, evaluation, qualitative, multi-criteria decision-making, time-series

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Introduction

Sustainability is a method of consuming resources to meet the needs of the present without compromising the ability to meet the needs of the future.[1,2] Sustainability includes three dimensions: economic, environmental, and social.[3] The sustainability of a technology usually means that it contributes to economic growth and its use consumes little energy, does not cause any harm to the environment, and does not deprive others (including future generations) of available resources.[4] However, such a definition is based on a prerequisite that the technology must be used continuously for a long time.[2,4] Otherwise, there is no need to discuss the sustainability of a technology.

This study aims to assess the sustainability of smart healthcare applications. The motivation is that some smart technologies believed to have great potential for healthcare have proven ineffective during the COVID-19 pandemic,[5,6] raising the question of whether some smart healthcare applications are sustainable and others are not.[4–6] This question is important for the following reasons:

- For healthcare service providers, if they do not distinguish the changes in the acceptance of different smart healthcare applications during the COVID-19 pandemic, their investment will be blind and not necessarily return.[7,8]
- For users, they should choose sustainable smart healthcare applications. Otherwise, it will be difficult to seek support from smart healthcare providers in the future.[9,10]

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Chen[4] proposed a fuzzy geometric mean (FGM)–alpha cut operations (ACO)–fuzzy weighted average (FWA) approach to evaluate the sustainability of a smart healthcare application, where FGM was used to aggregate the opinions of multiple experts, ACO was used to derive the fuzzy priorities of criteria, and FWA was used for evaluation. Tat et al.[11] evaluated the sustainability of smart textiles, a potential smart healthcare application, in terms of energy harvesting and conservation and personalized temperature regulation. Several studies[12] assert that the market size for related smart healthcare applications continues to grow significantly. However, after the COVID-19 pandemic, some people have lost interest in relevant smart healthcare applications, as such applications were far less effective than physical contact tracing methods.[13] Chen and Lin[6] considered the multiple viewpoints that a decision maker might hold on the relative priorities of criteria and proposed an FGM decomposition-based fuzzy technique for ordering preference by similarity to ideal solution (FTOPSIS) approach to assess the sustainability of smart healthcare applications. The fuzzy judgment matrix of the decision maker was decomposed by solving a multiobjective fuzzy integer-nonlinear programming problem[14,15] to discover his/her multiple viewpoints. The most effective smart healthcare applications during the COVID-19 pandemic included robots, smartphone apps, wearable sensors and devices, and remote temperature scanners, while wireless medical sensor networks were less practical, which was different than expected.[16,17] Therefore, Chen and Wang[17] proposed a calibrated FGM (cFGM)–FTOPSIS method to assess the sustainability of smart healthcare applications after the COVID-19 pandemic. By improving the accuracy of deriving fuzzy priorities using cFGM, the evaluation results were more convincing.[18] Chen and Chiu[19] proposed a hybridizing subjective and objective fuzzy group decision-making approach with explainable artificial intelligence to reassess the sustainability of smart healthcare applications based on the evidence gathered during the COVID-19 pandemic, in which a fuzzy nonlinear programming problem was solved to combine subjective judgment and objective evidence in deriving the fuzzy priorities of criteria.

Existing methods have the following problems:

- Most existing methods are from a multi-criteria decision-making (MCDM) perspective.[6,11,17,19–21] Methods from other perspectives are lacking and may yield different evaluation results.
- Existing methods have not considered all possible factors affecting the sustainability of a smart healthcare application.[22,23]
- It would be more flexible if a method could evaluate the sustainability of a smart healthcare application based on various data types and availability.[24,25]

In response to these problems, this study proposes a multi-perspective fuzzy comprehensive evaluation method to evaluate the sustainability of smart healthcare applications. The proposed methodology consists of three fuzzy techniques from qualitative,[8,10,26–29] MCDM,[6,11,17,19–21] and time-series perspectives,[28,30] respectively. Fuzzy techniques are considered suitable because they can easily and naturally deal with the uncertainty of sustainability and incorporate experts' subjective judgments on it.[31–34] Furthermore, applying various fuzzy techniques simultaneously can deal with problems when data types and availability vary.

The differences between the proposed methodology and some existing methods in this field are summarized in Table 1. A total of 23 relevant references were found by searching Google Scholar using the keyword "sustainability smart healthcare." After excluding references that are less relevant (e.g. IT-intensive, financial, etc.)[35–38] or have not proposed any method for assessment,[39,40] the methods mentioned in seven references were compared. In addition, in this table, only the properties of these methods are compared based on explicit facts, without subjective judgments.

Literature review

According to Demirkan,[41] cost-effectiveness and low risk are the key factors for the sustainable development of smart healthcare applications. To this end, he established a system framework to conceptualize data-driven, mobile, and cloud-enabled smart healthcare systems to improve cost-effectiveness and reduce the risk of related applications.

A similar view was also held by Lin et al.[42] However, sometimes effectiveness far outweighs cost-effectiveness, especially when smart technologies are applied for medical purposes. Furthermore, the cost of smart healthcare applications is determined by their supply and demand, both of which are highly stochastic. Furthermore, the cost-effectiveness of smart healthcare applications cannot be directly assessed. For example, a remote temperature scanner can be used to monitor the body temperature of thousands of customers visiting a department store; therefore, the more customers that visit the store, the more cost-effective the remote temperature scanner will be.

A smart healthcare application is sustainable if it can provide value-added services based on vaccination information or recovery status from the COVID-19 pandemic. In the view of Wu et al.,[43] although the demand for vaccination information is now declining, providing different services to travelers with unequal vaccination status can still minimize health risks. Additionally, post-pandemic travel is no longer as convenient and flexible as it used to be due to hotel staff shortages and in-house facilities to be restored. Smartphone apps, such as apps for recommending travel destinations or outdoor recreation, can help people organize relaxing activities that are good for their physical

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

Method	Smart healthcare applications	Evaluation method type	Number of evaluation methods simultaneously applied	Considered period
Chen and Lin[6]	All possible applications	MCDM	1	During and after the COVID-19 pandemic
Tat et al.[11]	Smart textiles	MCDM	1	Before the COVID-19 pandemic
Umair et al.[12]	IoT	Time series	1	During the COVID-19 pandemic
Chen and Wang[17]	All possible applications	MCDM	1	After the COVID-19 pandemic
Chen and Chiu[19]	All possible applications	MCDM	1	After the COVID-19 pandemic
Aminikhanghahi et al.[28]	Smart home	Time series	1	Before the COVID-19 pandemic
Lichter et al.[29]	Smart hospital	Online review	1	Before the COVID-19 pandemic
Proposed methodology	All possible applications	Hybrid	3	After the COVID-19 pandemic

MCDM: multi-criteria decision-making; IoT: internet of things.

and mental health. However, travel destination or outdoor recreation recommendation apps are less relevant for healthcare, but become stronger due to consideration of vaccination, infection, and regulatory information to address inconvenience and achieve sustainable development during the COVID-19 pandemic.

A similar review was performed by Ramírez-Moreno et al.,[44] who argued that the sustainability of cities lies in the transition to smart cities, where sensors play an important role. Furthermore, in smart cities, sensors should be widely used to collect information on energy, health, mobility, security, water, and waste management.

Theoretically, methods for assessing the sustainability of smart healthcare applications can be divided into three categories[6,11,12,17–19,28]:

- Qualitative methods: In a qualitative method, the requirements for sustainable smart healthcare applications are listed. The more requirements that a smart healthcare application meets, the stronger the sustainability of the smart healthcare application becomes.
- MCDM methods: In an MCDM method, the criteria for assessing the sustainability of smart healthcare applications are established. The performance of a smart healthcare application is then evaluated against each criterion. Subsequently, the evaluation results of all the criteria are aggregated to represent the sustainability of the smart healthcare application.
- Time-series methods: The time-series method considers the growth of the market size as a time series, thereby predicting the market size in the next few years based on the past. If the market for a smart healthcare application maintains growth in the foreseeable future, the smart healthcare application can be said to be sustainable.

Proposed methodology

The proposed methodology jointly uses three fuzzy techniques to assess the sustainability of a smart healthcare application. Three fuzzy techniques cover all the previously mentioned categories and are applied according to the availability of various types of data (see Figure 1).

Qualitative technique

The sustainability of smart healthcare applications can be assessed by considering the following criteria[19,23]:

- If a smart healthcare application can provide value-added services, then it will be sustainable.[19,23,45]
- Smart healthcare applications are sustainable if they are cost-effective.[19,23,46]
- Smart healthcare applications are sustainable if they can promote healthy mobility for the public.[10,19,23,47,48]
- A smart healthcare application is sustainable if it is necessary or irreplaceable.[10,19,42,49]
- Smart healthcare applications are sustainable if they can be combined with other applications to achieve synergies.[10,19,42,50,51]
- Smart healthcare applications are sustainable if they are easy to implement and maintain.[10,19,42]

as illustrated in Figure 2.

Based on these criteria, the sustainability of smart healthcare applications is assessed based on the subjective

Figure 1. Applications of the three fuzzy techniques according to the availability of various types of data.

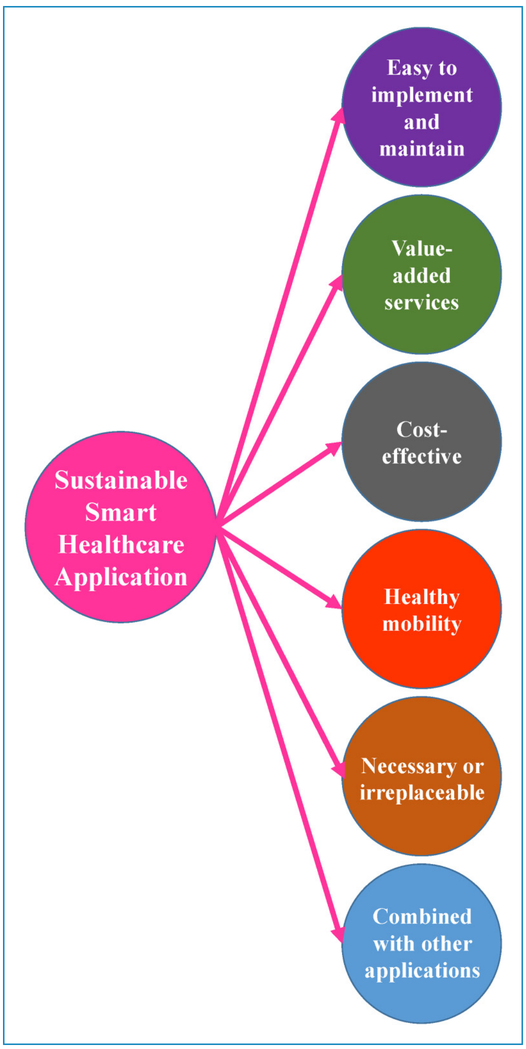

Figure 2. Sustainability of a smart healthcare application.

beliefs of decision makers, who can be developers of smart healthcare applications, market analysts, or medical or healthcare professionals seeking opportunities to leverage smart technologies to enhance healthcare delivery. However, smart healthcare application developers care about the wide application of smart healthcare applications. Market analysts consider the sales and profits from the use of the application to provide healthcare services. Healthcare professionals, on the other hand, highlight how the application facilitates healthcare delivery to patients. Their focus is biased toward a few specific aspects of sustainable development, risking imprecise assessments.

The more criteria a smart healthcare application meets, the more sustainable it is. However, to increase differentiability, it is better to specify the degree to which a smart healthcare application satisfies each criterion with a linguistic term, as shown in Table 2.

Subsequently, these linguistic terms are mapped to triangular fuzzy numbers (TFNs) (in Figure 3) to be aggregated.

Definition 1. A TFN $A = (A_1, A_2, A_3)$ is a fuzzy number with the following membership function:

$$\mu_A(x) = \begin{cases} \frac{x - A_1}{A_2 - A_1} & \text{if} \quad A_1 \leq x < A_2 \\ \frac{A_3 - x}{A_3 - A_2} & \text{if} \quad A_2 \leq x < A_3 \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

All fuzzy operations in the proposed methodology are based on the arithmetic of TFN. For this reason, some arithmetic operations on TFNs are introduced below:

1. Fuzzy addition:

$$A(+)B = (A_1 + B_1,\ A_2 + B_2,\ A_3 + B_3) \tag{2}$$

2. Fuzzy subtraction:

$$A(-)B = (A_1 - B_3,\ A_2 - B_2,\ A_3 - B_1) \tag{3}$$

3. Fuzzy multiplication:

$$A(\times)B \cong (A_1B_1,\ A_2B_2,\ A_3B_3) \text{ if } A_1, B_1 \geq 0 \tag{4}$$

4. Fuzzy division:

$$A(/)B \cong (A_1/B_3,\ A_2/B_2,\ A_3/B_1) \quad \text{if } A_1 \geq 0, B_1 > 0 \tag{5}$$

Let the performance of smart healthcare application q in optimizing criterion i be indicated with p_{qi}. For example, according to Table 2 and Figure 2, $p_{q1} = (4,\ 5,\ 5)$. After aggregation using the arithmetic for TFNs,[52,53] the overall performance of the smart healthcare application is derived as

Table 2. Assessing the sustainability of a smart healthcare application.

Criterion	Totally dissatisfied	Somewhat dissatisfied	Moderate	Somewhat satisfied	Completely Satisfied
Can provide value-added services					X
Is cost-effective	X				
Can promote healthy mobility			X		
Is necessary or irreplaceable				X	
Can be combined with other smart technologies					X
Is easy to implement and maintain		X			

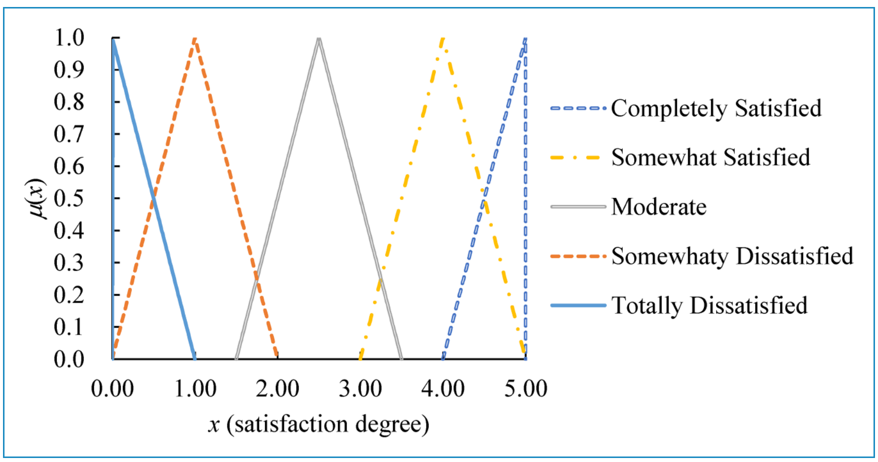

Figure 3. Triangular fuzzy numbers (TFNs) for modeling the satisfaction degree.

$$O_q = (O_{q1},\ O_{q2},\ O_{q3}) = \frac{1}{n}\sum_{i=1}^{n} p_{qi} = (\frac{1}{n}\sum_{i=1}^{n} p_{qi1},\ \frac{1}{n}\sum_{i=1}^{n} p_{qi2},\ \frac{1}{n}\sum_{i=1}^{n} p_{qi3}) \tag{6}$$

A larger O_q represents a higher sustainability of the smart healthcare application[54]:

- Sustainability is "very high" if O_{q2} is closer to 5 than the cores of the other TFNs.
- Sustainability is "high" if O_{q2} is closer to 4.
- Sustainability is "moderate" if O_{q2} is closer to 2.5.
- Sustainability is "low" if O_{q2} is closer to 1.
- Sustainability is "very low" if O_{q2} is closer to 0.

MCDM technique

Many MCDM methods have been to this field, for example, FWA,[4,55] fuzzy analytic hierarchy process (FAHP),[4,6,17,56,57] FTOPSIS,[6,17,58] fuzzy Vise Kriterijumska Optimizacija I Kompromisno Resenje (fuzzy VIKOR),[56,59] fuzzy combinative distance-based assessment,[57] fuzzy inference systems,[60,61] fuzzy measuring attractiveness by a categorical based evaluation technique (fuzzy MACBETH),[62] etc. In the proposed methodology, FAHP and fuzzy VIKOR are used. However, other methods can also be applied for similar purposes.

The first step is to derive the fuzzy priorities of criteria for evaluating the overall performance of a smart healthcare application. To this end, the decision maker compares the relative priorities of the criteria in pairs, and constructs a fuzzy judgment matrix $\boldsymbol{A} = [a_{ij}]$ to store the pairwise comparison results. a_{ij} is the relative priority of criterion i over criterion j. $a_{ji} = 1 / a_{ij}$; $a_{ii} = 1$; $i, j = 1 \sim n$. The fuzzy priorities of criteria are derived from the fuzzy judgment matrix by performing a fuzzy eigen analysis[63]:

$$\det(\boldsymbol{A}(-)\lambda\boldsymbol{I}) = 0 \tag{7}$$

$$(\boldsymbol{A}(-)\lambda\boldsymbol{I})(\times)\boldsymbol{x} = 0 \tag{8}$$

$$w = [w_i] = N(x) \tag{9}$$

where λ and x are the fuzzy maximal eigenvalue and eigenvector of A, respectively; w_i is the fuzzy priority of criterion i. (−) and (×) denote fuzzy subtraction and multiplication, respectively. $N()$ is the normalization function. The pairwise comparison results are consistent if the consistency ratio of A satisfies[64]

$$CR(A) = \frac{\lambda - n}{(n-1)RI} \leq 0.1 \tag{10}$$

RI is the random consistency index.[64] The fuzzy eigen analysis aims to minimize the sum of square deviations[65]:

$$\text{Min } Z_1 = \sum_{i=1}^{n} \sum_{j \neq i} \left(\frac{w_i}{w_j} (-) a_{ij} \right)^2 \tag{11}$$

Solutions to the fuzzy eigenanalysis can be derived exactly using ACO[66] or approximately using FGM,[4,6,23] fuzzy extent analysis,[67] or fuzzy inverse of column sum method.[68]

Subsequently, the derived fuzzy priorities of criteria, as well as the performances of smart healthcare applications to be compared, are fed into the fuzzy VIKOR method. In the fuzzy VIKOR method, the overall performance of smart healthcare application q is evaluated as[56,59]:

$$\begin{aligned} Q_q &= \omega N(S_q)(+)(1-\omega)N(R_q) \\ &= \omega \cdot \frac{S_q(-)\min\limits_r S_r}{\max(\max\limits_r S_r) - \min(\min\limits_r S_r)} (+) \\ &(1-\omega) \cdot \frac{R_q(-)\min\limits_r R_r}{\max(\max\limits_r R_r) - \min(\min\limits_r R_r)}. \end{aligned} \tag{12}$$

where

$$S_q = \sum_{i=1}^{n} (w_i(\times)d_{qi}) \tag{13}$$

$$R_q = \max_i (w_i(\times)d_{qi}). \tag{14}$$

and ω is a pre-specified constant within [0, 1]. d_{qi} is the distance between smart healthcare application q and a reference point (the ideal solution), which is usually measured as[56,59]

$$d_{qi} = \frac{\max\limits_r (p_{ri})(-)p_{qi}}{\max\limits_r (p_{ri3}) - \min\limits_r (p_{ri1})}. \tag{15}$$

Obviously, d_{qi} should be the smaller the better, so are S_q, R_q, and Q_q. S_q evaluates the average performance of smart healthcare application q, while R_q focuses on the worst performance. Q_q is a compromise between S_q and R_q. Basically, the smart healthcare application with the lowest Q_q has the highest sustainability. Information based on S_q and R_q can be used to break possible ties.

Time-series technique

The time-series approach considers the growth of the market size of a smart healthcare application as a time series,[69] thereby predicting the market size in the coming years based on the past. To this end, stochastic, fuzzy, and gray methods[70–72] can deal with inherent uncertainties. Among them, fuzzy methods are particularly suitable due to their ease of understanding and calculation.[73] The time-series technique used in the proposed methodology attempts to fit the relationship between the deseasonalized market size and time with a fuzzy linear regression equation[74–76]:

$$y_t = a(+)bt \tag{16}$$

where a and b are constant. y_t is the predicted deseasonalized market size of the smart healthcare application in period t, which is approximated by a TFN. m_t is the actual value, that is, the deseasonalized market size during period t:

$$m_t = \frac{M_t}{\varphi(t)} \tag{17}$$

M_t is the market size of the smart healthcare application in period t; $\varphi(t)$ is the seasonal relative for period t.[77,78]

Parameters in equation (16) can be derived by solving a quadratic programming (QP) problem[79,80]:

$$\text{Min } Z_2 = \sum_{t=1}^{T} \alpha_t \tag{18}$$

subject to

$$\sum_{t=1}^{T} (y_{t3} - y_{t1}) \leq Td \tag{19}$$

$$y_{t1} = a_1 + b_1 t;\ t = 1 \sim T \tag{20}$$

$$y_{t2} = a_2 + b_2 t;\ t = 1 \sim T \tag{21}$$

$$y_{t3} = a_3 + b_3 t;\ t = 1 \sim T \tag{22}$$

$$(1-\alpha_t)y_{t1} + \alpha_t y_{t2} \leq m_t;\ t = 1 \sim T \tag{23}$$

$$m_t \leq (1-\alpha_t)y_{t3} + \alpha_t y_{t2};\ t = 1 \sim T \tag{24}$$

$$0 \leq \alpha_t \leq 1;\ t = 1 \sim T \tag{25}$$

$$a_1 \leq a_2 \leq a_3 \tag{26}$$

$$b_1 \leq b_2 \leq b_3 \tag{27}$$

where $d \in \mathbf{R}^+$ is the tolerable width of a fuzzy market size forecast.[81,82] α_t indicates the membership of an actual value in the corresponding fuzzy forecast. The objective function is to maximize the average membership (or satisfaction level).

Case study

Background

To illustrate the applicability of the proposed methodology, it has been used to evaluate the sustainability of eight smart healthcare applications (shown in Table 3). These smart healthcare applications were repeatedly mentioned in the literature as the most popular smart healthcare applications before, during, and/or after the COVID-19 pandemic.[2,19,83–86] Whether these smart healthcare applications are sustainable is worth studying.

Application of the proposed methodology

In this case study, the decision maker was a market analysis manager for a healthcare-oriented company that imported and sold wearable devices. First, the qualitative technique was applied to assess the sustainability of the eight smart healthcare applications. To this end, the decision maker filled out the evaluation form (i.e. Table 2) based on his beliefs. The evaluation results are shown in Table 4.

After aggregating the TFNs for representing these linguistic terms, the overall performance (i.e. sustainability) of each smart healthcare application was derived. The results are summarized in Table 5.

Table 3. Smart healthcare applications to be evaluated.

q	Smart technology application
1	Healthcare apps/smartphones
2	Healthcare robots
3	Remote temperature scanners
4	Smart bracelets
5	Smart clothing
6	Smart glasses, spectacles, and contact lenses
7	Smart watches
8	Social-distancing monitors

Second, to apply the MCDM technique, the decision maker compared the relative priorities of criteria in terms of the following fuzzy judgment matrix:

$$A = \begin{bmatrix} 1 & (1,\ 3,\ 5) & (5,\ 7,\ 9) & (1,\ 3,\ 5) & (3,\ 5,\ 7) & (2,\ 4,\ 6) \\ 1/(1,\ 3,\ 5) & 1 & (6,\ 8,\ 9) & (1,\ 3,\ 5) & (2,\ 4,\ 6) & (1,\ 3,\ 5) \\ 1/(5,\ 7,\ 9) & 1/(6,\ 8,\ 9) & 1 & 1/(4,\ 6,\ 8) & 1/(1,\ 3,\ 5) & 1/(5,\ 7,\ 9) \\ 1/(1,\ 3,\ 5) & 1/(1,\ 3,\ 5) & (4,\ 6,\ 8) & 1 & (1,\ 1,\ 3) & 1/(1,\ 3,\ 5) \\ 1/(3,\ 5,\ 7) & 1/(2,\ 4,\ 6) & (1,\ 3,\ 5) & 1/(1,\ 1,\ 3) & 1 & 1/(3,\ 5,\ 7) \\ 1/(2,\ 4,\ 6) & 1/(1,\ 3,\ 5) & (5,\ 7,\ 9) & (1,\ 3,\ 5) & (3,\ 5,\ 7) & 1 \end{bmatrix}$$

cFGM[58] is applied to improve the accuracy and efficiency of approximating the fuzzy priorities of criteria. The results are summarized in Figure 4. The fuzzy consistency ratio was around 0.086.

The performances of smart healthcare applications in and optimizing the various criteria were evaluated and converted into TFNs within [0, 5]. The evaluation results are summarized in Table 6.

The sustainability of each smart healthcare application was then evaluated using fuzzy VIKOR. The evaluation results are summarized in Table 7. After defuzzifying Q_q using the center-of-gravity (COG) method[87]:

$$D(Q_q) = \frac{Q_{q1} + Q_{q2} + Q_{q3}}{3} \tag{28}$$

The sustainability of smart healthcare applications was ranked.

Third, to apply the time-series technique, the global market size of smart watches, in terms of global shipments of organic light-emitting diode smart watches by panel suppliers,[88] was used as an example (see Table 8). There was seasonality in the data. The seasonal relatives were derived. The data after removing seasonality is shown in Table 9.

The QP problem was formulated and solved using Lingo based on the data after removing seasonality. The data from the first eight quarters were used to build the forecasting model, and the remaining data were left to evaluate the forecasting performance ($d = 10$). The optimal solution was

$$a = (0.101,\ 0.101,\ 10.101)$$

$$b = (1.771,\ 1.771,\ 1.771)$$

Subsequently, the seasonal relatives were multiplied by the corresponding fuzzy forecasts. The forecasting results are shown in Figure 5.

Table 4. Evaluation results using the qualitative technique.

Criterion	Totally dissatisfied	Somewhat dissatisfied	Moderate	Somewhat satisfied	Completely satisfied
(Healthcare apps/smartphones)					
Can provide value-added services					X
Is cost-effective					X
Can promote healthy mobility					X
Is necessary or irreplaceable				X	
Can be combined with other smart technologies					X
Is easy to implement and maintain		X			
(Healthcare robots)					
Can provide value-added services				X	
Is cost-effective		X			
Can promote healthy mobility				X	
Is necessary or irreplaceable		X			
Can be combined with other smart technologies			X		
Is easy to implement and maintain		X			
(Remote temperature scanners)					
Can provide value-added services					X
Is cost-effective					X
Can promote healthy mobility				X	
Is necessary or irreplaceable		X			
Can be combined with other smart technologies				X	
Is easy to implement and maintain					X
(Smart bracelets)					
Can provide value-added services					X
Is cost-effective					X
Can promote healthy mobility					X
Is necessary or irreplaceable		X			
Can be combined with other smart technologies					X
Is easy to implement and maintain		X			

(continued)

Table 4. Continued.

Criterion	Totally dissatisfied	Somewhat dissatisfied	Moderate	Somewhat satisfied	Completely satisfied
(Smart clothing)					
Can provide value-added services					X
Is cost-effective		X			
Can promote healthy mobility					X
Is necessary or irreplaceable		X			
Can be combined with other smart technologies					X
Is easy to implement and maintain		X			
(Smart glasses, spectacles, and contact lenses)					
Can provide value-added services					X
Is cost-effective	X				
Can promote healthy mobility					X
Is necessary or irreplaceable			X		
Can be combined with other smart technologies					X
Is easy to implement and maintain	X				
(Smart watches)					
Can provide value-added services					X
Is cost-effective				X	
Can promote healthy mobility					X
Is necessary or irreplaceable		X			
Can be combined with other smart technologies					X
Is easy to implement and maintain		X			
(Social-distancing monitors)					
Can provide value-added services		X			
Is cost-effective		X			
Can promote healthy mobility					X
Is necessary or irreplaceable				X	
Can be combined with other smart technologies					X
Is easy to implement and maintain		X			

Table 5. Sustainability evaluation results of smart healthcare applications.

q	Smart technology application	O_q	Sustainability
1	Healthcare apps/smartphones	(3.17, 4.17, 4.5)	High
2	Healthcare robots	(1.25, 2.25, 3.25)	Moderate
3	Remote temperature scanners	(3, 4, 4.5)	High
4	Smart bracelets	(2.67, 3.67, 4)	High
5	Smart clothing	(2, 3, 3.5)	Moderate
6	Smart glasses, spectacles, and contact lenses	(2.25, 2.92, 3.42)	Moderate
7	Smart watches	(2.5, 3.5, 4)	High
8	Social-distancing monitors	(1.83, 2.83, 3.5)	Moderate

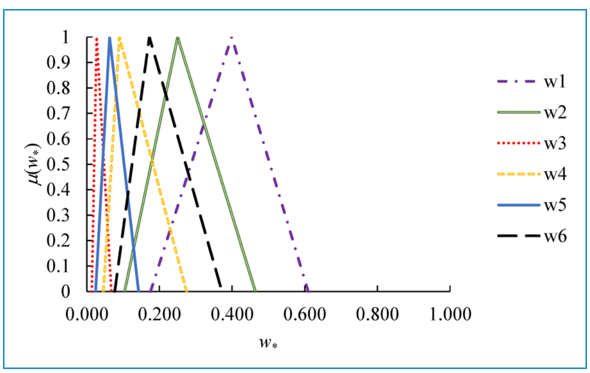

Figure 4. Approximated fuzzy priorities of criteria using calibrated fuzzy geometric mean (cFGM).

Discussion

Based on the experimental results, the following discussion was made:

1. As expected, when the qualitative technique was applied, the smart healthcare application achieving the highest sustainability was healthcare apps/smartphones. Remote temperature scanners took second place due to their success during the COVID-19 pandemic. In contrast, despite the success of healthcare robots in the same period, the decision maker subjectively believed that they would not be very sustainable.
2. Both the qualitative and MCDM techniques suggested that healthcare apps/smartphones were the most sustainable. Smart watches were also recommended by the

Table 6. Performances of smart healthcare applications.

q	p_{q1}	p_{q2}	p_{q3}	p_{q4}	p_{q5}	p_{q6}
1	(3, 4, 5)	(1.5, 2.5, 3.5)	(4, 5, 5)	(3, 4, 5)	(4, 5, 5)	(3, 4, 5)
2	(1.5, 2.5, 3.5)	(0, 0, 1)	(1.5, 2.5, 3.5)	(1.5, 2.5, 3.5)	(1.5, 2.5, 3.5)	(0, 1, 2)
3	(3, 4, 5)	(1.5, 2.5, 3.5)	(1.5, 2.5, 3.5)	(1.5, 2.5, 3.5)	(3, 4, 5)	(1.5, 2.5, 3.5)
4	(1.5, 2.5, 3.5)	(1.5, 2.5, 3.5)	(0, 1, 2)	(3, 4, 5)	(4, 5, 5)	(1.5, 2.5, 3.5)
5	(0, 1, 2)	(0, 1, 2)	(0, 1, 2)	(0, 1, 2)	(4, 5, 5)	(3, 4, 5)
6	(4, 5, 5)	(0, 0, 1)	(1.5, 2.5, 3.5)	(1.5, 2.5, 3.5)	(4, 5, 5)	(0, 0, 1)
7	(3, 4, 5)	(1.5, 2.5, 3.5)	(4, 5, 5)	(3, 4, 5)	(4, 5, 5)	(3, 4, 5)
8	(3, 4, 5)	(1.5, 2.5, 3.5)	(1.5, 2.5, 3.5)	(3, 4, 5)	(4, 5, 5)	(1.5, 2.5, 3.5)

Table 7. Sustainability evaluation results using fuzzy Vise Kriterijumska Optimizacija I Kompromisno Resenje (VIKOR).

q	S_q	R_q	Q_q	$D(Q_q)$	Rank
1	(0, 0.08, 0.67)	(0, 0.08, 0.27)	(0, 0, 0.44)	0.109	1
2	(0.02, 0.39, 1.27)	(0.02, 0.2, 0.46)	(0, 0.2, 0.77)	0.292	7
3	(0, 0.14, 0.83)	(0, 0.08, 0.27)	(0, 0, 0.45)	0.114	4
4	(0.02, 0.22, 0.91)	(0.02, 0.2, 0.43)	(0, 0.19, 0.69)	0.266	6
5	(0.08, 0.5, 1.46)	(0.07, 0.32, 0.61)	(0, 0.38, 1)	0.441	8
6	(0, 0.15, 0.87)	(0, 0.11, 0.46)	(0, 0.05, 0.75)	0.209	5
7	(0, 0.08, 0.67)	(0, 0.08, 0.27)	(0, 0, 0.44)	0.109	1
8	(0, 0.09, 0.71)	(0, 0.08, 0.27)	(0, 0, 0.44)	0.111	3

Table 8. Market size of smart watches.

Period #	Period	Market size (millions)*
1	2017 Q1	6
2	2017 Q2	6.8
3	2017 Q3	7.4
4	2017 Q4	9.5
5	2018 Q1	7
6	2018 Q2	7.8
7	2018 Q3	13.5
8	2018 Q4	22.8
9	2019 Q1	14
10	2019 Q2	14.4
11	2019 Q3	30.1
12	2019 Q4	33.8
13	2020 Q1	22.7
14	2020 Q2	26.5
15	2020 Q3	41.5
16	2020 Q4	44.7

* approximated in terms of global shipments from O'Brien.[88]

MCDM technique, which gave a reason to use a third technique, the time-series technique, to confirm the sustainability of smart watches.

3. In time-series techniques, the fitted linear regression model had a positive slope, indicating continued growth in market size. However, the slope was essentially low ($a_2 = 0.101$) and subject to a lot of uncertainty (a_3 was up to 10.101).
4. The sustainability of smart watches evaluated using various techniques (from different perspectives) were different:
   Qualitative viewpoint: high (the fourth);
   MCDM viewpoint: highest;
   Time series: positive but highly uncertain.
5. The fuzzy market size forecast for each period in test data was defuzzified using the COG method, and then compared with the actual value to evaluate the forecasting accuracy in terms of mean absolute error (MAE), mean absolute percentage error (MAPE), and root mean squared error (RMSE):

$$\mathrm{MAE} = \frac{\sum_{t=1}^{T} |m_t - \mathrm{COG}(y_t)|}{T} \tag{29}$$

$$\mathrm{MAPE} = \frac{\sum_{t=1}^{T} |m_t - \mathrm{COG}(y_t)| \,/\, m_t}{T} \cdot 100\% \tag{30}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{t=1}^{T} (m_t - \mathrm{COG}(y_t))^2}{T}} \tag{31}$$

The evaluation result is
MAE = 3.61 (millions)
MAPE = 12%
RMSE = 4.59 (millions)

Table 9. Market size after removing seasonality.

Period #	Period	Market size after removing seasonality (millions)
1	2017 Q1	7.70
2	2017 Q2	9.35
3	2017 Q3	6.91
4	2017 Q4	7.19
5	2018 Q1	8.99
6	2018 Q2	10.73
7	2018 Q3	12.60
8	2018 Q4	17.25
9	2019 Q1	17.97
10	2019 Q2	19.81
11	2019 Q3	28.09
12	2019 Q4	25.57
13	2020 Q1	29.14
14	2020 Q2	36.45
15	2020 Q3	38.73
16	2020 Q4	33.81

Conclusion

Applying smart technologies to healthcare has become a trend, and various new smart healthcare applications have been launched one after another. After the COVID-19 pandemic, some smart healthcare applications have been shown to be ineffective or inefficient. The sustainability of a smart healthcare application thus becomes an issue. Several studies have been devoted to assessing the sustainability of a smart healthcare application. However, most existing methods are from an MCDM perspective. Methods from other perspectives are lacking and may yield different evaluation results. In addition, it would be more flexible if the evaluation method could handle various data types and availability. For these reasons, this study proposes a multi-perspective fuzzy comprehensive evaluation method to evaluate the sustainability of smart healthcare applications from qualitative, MCDM, and time-series perspectives.

The proposed methodology has been applied to evaluate the sustainability of eight smart healthcare applications. According to the experimental results, the following conclusions were drawn:

- The sustainability of a smart healthcare application evaluated from different perspectives may be different. For example, smart watches were assessed as the most sustainable from an MCDM perspective, but far less sustainable from a qualitative perspective than healthcare apps/smartphones, remote temperature scanners, and smart bracelets.
- Nevertheless, the evaluation results generated using a technique can be confirmed using another technique. For example, both qualitative and MCDM perspectives

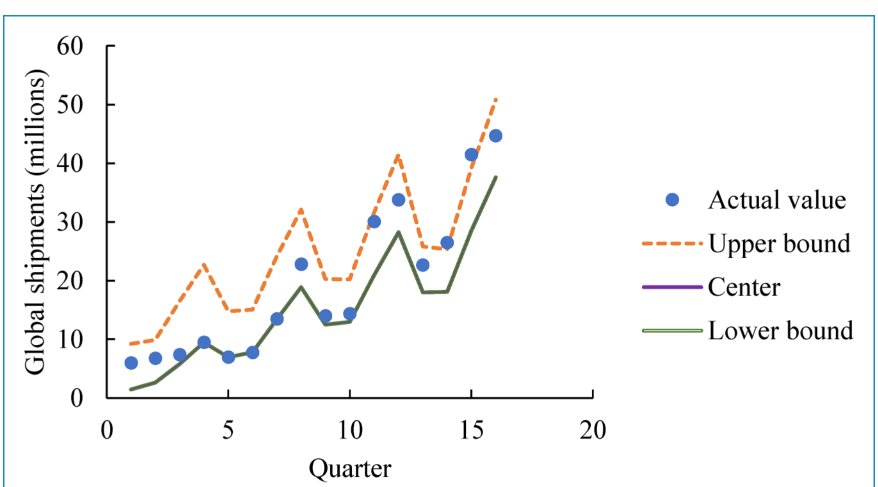

Figure 5. Forecasting results.

evaluated healthcare apps/smartphones as the most sustainable smart healthcare applications. The correlation coefficient between the ranking results from the two perspectives is 0.50, which was not necessarily high enough so different viewpoints should complement each other.
- The qualitative technique required the least amount of data (only the subjective evaluations of decision makers), while the MCDM technique required the largest amount of data (including both the performances of smart technology applications and the subjective evaluations of decision makers). In addition, the data required by the time-series technique was dynamic and one-dimensional, while the data required by the MCDM technique was static and multi-dimensional. Decision makers should base their selection on available data and their own requirements.

There are many methods from every perspective. Choosing different methods to evaluate the sustainability of smart healthcare applications for each perspective is a future research topic. In addition, when there are multiple decision makers, whether the evaluation results from different perspectives will diverge further or not needs to be investigated. These issues constitute suggestions for future research.

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