Prioritizing and aggregating interacting requirements for product-service system development

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Abstract: Requirements evaluation is critically important for the successful development of a product-service system (PSS). The requirements of a PSS often interact with each other, hence significantly influencing requirements evaluation and decision-making processes. The recent literature has proposed some methods such as fuzzy ANP and rough DEMATEL to evaluate interacting PSS requirements and to focus on requirements prioritization. However, aggregation with respect to interacting PSS requirements is seldomly considered. Alternatively, the weighted arithmetic mean method is implicitly used as the aggregation operator to aggregate PSS requirements. Hence, different effects of interactions among any subset of PSS requirements are not considered. This may result in sub-optimal alternatives being adopted for further PSS development. In order to solve this specific problem, a systematic method based on rough-fuzzy DEMATEL, 2-additive fuzzy measures, and the Choquet integral is proposed for aggregating interacting requirements for PSS development along with requirements prioritization. The proposed method utilizes the rough-fuzzy DEMATEL method to determine the weights of interacting PSS requirements when there is a group of experts providing subjective and linguistic assessments of influence strengths. By integrating the Choquet integral with 2-additive fuzzy measures, the proposed method can aggregate interacting PSS requirements non-additively by considering 2-order interactions between any two requirements. To demonstrate its feasibility and advantages, the proposed method is applied to evaluate requirement interactions for a smart wearable medical system.

Keywords: product-service system; requirement interactions; rough-fuzzy DEMATEL; 2-additive fuzzy measures; Choquet integral

1 Introduction

The product-service system (PSS) is an integrated offering of products and services to satisfy customer and other stakeholders' requirements (Mont, 2002; Tukker & Tischner, 2006). As a result, requirements management plays an important role for the successful development of PSS. The main requirements management activities of PSS include requirements elicitation, analysis, specification and forecast. Complete requirements elicitation, rational analysis, undistorted transformation and specification, and accurate forecast should be carefully deployed with respect to characteristics of PSS, which are necessary to ensure successful development of PSS and to deliver differentiating and continuous value to customers. However, the specific characteristics relating to the PSS development, such as heterogeneity, interaction, multiple stakeholder participation and life cycle orientation make requirements management of PSS more challenging and different from conventional requirements management (Nilsson, Sundin, & Lindahl, 2018; Song, 2017).

Due to different stakeholders' preference and PSS heterogeneity, the interaction of PSS requirements is inherently very complex. In other words, the interactions may happen not only among product requirements or service requirements, but also between product requirements and service requirements as well. These complex interactions also introduce different effects such as enhancing, weakening, conflicting and replacing, and so on (Robinson, Pawlowski, & Volkov, 2003; Song, 2017). For example, considering a smart vehicle service system, customers require one product requirement of "high dynamic performance of engine", which interacts with and weakens another product requirement of "low fuel consumption". At the same time, the service requirement "driver behavior monitoring, prediction and recommendation" interacts with and enhances "low fuel consumption". These interacting requirements exist extensively in PSS, and they result in additive independence assumptions among PSS requirements being violated. Then, evaluating these interacting requirements based on additive independence assumption will lead to distorted representation of decision makers' preferences, including inaccurate requirements prioritization and aggregation. Therefore, it is critically important to evaluate interacting requirements to discover their implication for requirements prioritization and non-additive aggregation.

Previous research pays more attention to developing and applying Multi-Attribute Decision Making (MADM) methods to evaluate interacting PSS requirements. While the majority of the MADM methods assume additively independent attributes, e.g. the analytic hierarchy process (AHP) (Biju, Shalij, & Prabhushankar, 2015; Song, Ming, Han, & Wu, 2013), TOPSIS and VIKOR (Watrobski, Jankowski, Ziemba, Karczmarczyk, & Ziolo, 2019), some researchers explored analytic network process (ANP) (Kheybari, Rezaie, & Farazmand, 2020) and Decision Making Trial and Evaluation Laboratory (DEMATEL) (Lee, Li, Yen, & Huang, 2010) for modeling complex interrelationships among PSS requirements. The extensions of ANP and DEMATEL have been developed for evaluating interacting PSS requirements, such as fuzzy ANP (Geng, Chu, Xue, & Zhang, 2010), fuzzy DEMATEL (Geng & Chu, 2012), rough DEMATEL (Song & Cao, 2017), rough-fuzzy DEMATEL-ANP (Z. H. Chen, Ming, Zhang, Yin, & Sun, 2019). In general, the literature only focusses on determining weights for interacting PSS requirements with different types of assessment data, such as crisp assessment data, linguistic assessment data and/or group diverse assessment data. However, aggregation with respect to interacting PSS requirements is rarely considered. Or alternatively, the weighted arithmetic mean is implicitly used as the aggregation operator to aggregate PSS requirements. Hence, different effects of interactions among any subset of PSS requirements remain unconsidered. Obviously, if there are other interactions among any subset of requirements, then their effects should be integrated into the aggregation function, which will lead to different non-additive aggregation functions. While requirements prioritization can determine the relative importance of PSS requirements, requirements aggregation focuses on the whole perceived preference of all requirements together, which is critically important for PSS design optimization and evaluation of alternatives. If requirements are aggregated inaccurately, then sub-optimal alternatives may be adopted for further development and this may lead to costly design iterations, rework, and project delays.

In order to solve this specific gap in research, an integrated method based on rough-fuzzy DEMATEL, 2-additive fuzzy measures, and the Choquet integral is proposed to evaluate interacting requirements for PSS. The main contribution of the proposed method is that PSS requirements are aggregated non-additively by considering second order effects of interactions between any two requirements besides requirement prioritization. The rough-fuzzy DEMATEL method is adopted for modelling influence relationship among requirements and for determining weights for requirements when there are a group of experts giving their subjective and linguistic assessment about influence strength. In particular, the fuzzy measures and Choquet integral are integrated to aggregate interacting PSS requirements since the Choquet integral with respect to fuzzy measures is always considered as an effective method to achieve the aggregation of interacting criteria non-additively in MADM. In terms of identification of fuzzy measures, the 2-additive fuzzy measures are introduced to balance between complexity and accuracy of identification, in which weights of requirements and constraints on degree of interaction act as constraints of an optimization model. With the proposed method, the second order interactions between any pair of requirements are explicitly modeled and a corresponding aggregation function is constructed. To the authors' knowledge, there is no such research in the past to explore prioritization and aggregation together for interacting PSS requirements.

The rest of this paper is organized as follows. Section 2 gives literature review concerning PSS, requirement interactions, evaluation methods of requirement interactions in the field of PSS. Section 3 proposes an integrated method based on rough-fuzzy DEMATEL, 2-additive fuzzy measures and the Choquet integral for evaluating interacting PSS requirements. Section 4 applies the proposed method to evaluate interacting requirements of a smart wearable medical system. Section 5 presents the theoretical and practical implications of this study. Finally, conclusions and suggestions are presented.

2 Literature review

2.1 PSS and requirement interactions

A PSS is a system of products, services, software, supporting networks and infrastructure, which provides integrated offerings of products and services (Mont, 2002; Tukker & Tischner, 2006). Besides the obvious product function, performance, reliability, and aesthetics, many product-related services are enabled by PSS to provide differentiating and continuous value to customers, such as installation, repair and maintenance, upgrading and recycling, monitor and control, product lifecycle management, and financing (Reim, Parida, & Ortqvist, 2015; Szwejczewski, Goffin, & Anagnostopoulos, 2015). With the rapid development of new generation information and communication technologies, such as the Internet of Things, Big Data and Artificial Intelligence, smart PSS is emerging and more and more smart services are enabled based on smart-connected products (Valencia, Mugge, Schoormans, & Schifferstein, 2015; Zheng, Wang, Chen, & Khoo, 2019).

Very complex interactions exist extensively among PSS requirements. PSS requirements include customer and stakeholder requirements, business process requirements, regulatory or environmental requirements, and contractor's requirements at the system level (Berkovich, Leimeister, Hoffmann, &

Krcmar, 2014). These requirements can be derived into product engineering requirements, software engineering requirements and service engineering requirements at the component level. Because of heterogeneity, diversity of stakeholders and others, requirements often interact with each other in a complex way. The study reveals that only a few requirements are singular and that interdependencies between requirements can be classified into functionality-related and value-related interdependencies (Carlshamre, Sandahl, Lindvall, Regnell, & Dag, 2001). Value-related interdependencies include value and cost aspects, and their assessments are subjective. To classify and identify requirement interactions, a four-layered requirement interactions taxonomy is proposed, including "which two elements interact?", "which two attributes interact?", "why two attributes interact?", and "how to detect those interactions?" (Shehata, Eberlein, & Fapojuwo, 2007). These interactions focus on the implementation of function and performance. Dahlstedt et al. address requirements interdependencies from a traceability perspective, and they classify fundamental interdependency into three types, including structural interdependencies, constraint interdependencies, and cost/value interdependencies (Dahlstedt & Persson, 2005). Robinson et al. believe there are three characterizations of requirement interactions, including perceived interaction, logical interaction and implementation interaction (Robinson, et al., 2003). Perceived interaction implies that satisfaction of one requirement will affect the satisfaction of another requirement, while logical interaction is the same as the implementation interaction when the implementation is correct. According to Song, different interactions may exist between product characteristics and service characteristics, including enhancing, weakening, conflicting and replacing, and so on (Song & Cao, 2017). These interactions can be of different nature. For example, a conflict happens when two requirements cannot be implemented at the same time, which falls into implementation-related interaction. Meanwhile, another conflict happens when increasing the satisfaction level of one requirement decreases the satisfaction level of another requirement, which falls into perception-related interaction. Hence, previous research on requirement interactions can usually be classified into implementation-related interactions and perception-related interactions. Implementation-related interactions are usually functionality-related, structural, and logical. Perceived interactions are usually subjective and related to value and preference. Because of the complexity and wide scope, requirement interactions significantly influence requirements management, system development, change management and impact analysis, and others (Papinniemi, Hannola, & Maletz, 2014; Robinson, et al., 2003). Therefore, discovery, evaluation and disposition of these critical relationships are very important.

2.2 Evaluation methods of requirement interactions of PSS

Requirement interactions evaluation in terms of perceived preference is an important part of requirement interactions management. Some researchers have focused on this topic by developing and applying MADM methods to determine weights for requirements. The AHP is the most used method in requirements prioritization (Bukhsh, Bukhsh, & Daneva, 2020). It assumes that the requirements in the same hierarchy should be mutually independent and there is no interaction between them. Hence, the AHP and its extensions, including AHP, fuzzy AHP (Haber, Fargnoli, & Sakao, 2018), rough AHP (Song, et al., 2013) and others, fail to model requirement interactions. In fact, the majority of MADM methods assume those attributes are mutually independent, including TOPSIS, VIKOR, and others (Watrobski, et al., 2019). However, requirement interactions are common in PSS, and it influences the reliability of requirements prioritization and aggregation significantly. If requirement interactions are not appropriately considered, then they lead to erroneous or redundant results.

The ANP is the generalized form of AHP, and it is applied to deal with complex and interrelated relationships between criteria. Fargnoli et al. propose a method based on QFDforPSS and ANP to assess the mutual interactions between the product's and the service's elements (Fargnoli & Haber, 2019). Geng et al. combine the fuzzy theory, group decision-making technique and ANP to determine weights of PSS requirements considering their interdependence, which has an advantage of manipulating uncertainty, group decision making and complex dependency relationships (Geng, et al., 2010). Mistarihi et al. use an integrated method that combines Quality Function Deployment (QFD) and fuzzy ANP to determine weights for engineering characteristics, which considers the mutual dependence between customer needs and engineering characteristics and the inner dependency between them under subjective judgements of intensity of preference (Mistarihi, Okour, & Mumani, 2020). However, the number of pairwise comparisons and calculation workload in the ANP is substantial when the number of PSS requirements are large.

The DEMATEL is a method to analyze direct and indirect causal relationship among system variables or criteria, which can be used for visualizing cause and effect groups and for determining weights for system variables or criteria (Lee, et al., 2010). Geng et al. present a vague set-based DEMATEL method to consider the mutual influence relationships among PSS requirements with uncertainty and vagueness in the evaluation process (Geng & Chu, 2012). Song et al. propose a method based on rough set theory and DEMATEL for assessing requirement interactions under subjective group judgement, where crisp prominence and crisp relation are calculated from rough total relation matrix through multiple operators of modified-CFCS (converting fuzzy values into crisp scores) plus single vector-length (Song & Cao, 2017). Liu et al. revise Song's method by using a simpler operator of average vector-length on rough prominence and rough relation, which has the merit of remaining roughness until the end of weight calculation procedure (Liu & Ming, 2019). Different from the above individual consideration of fuzziness or group diversity, Chen et al. propose a graphic-based rough-fuzzy DEMATEL method to simultaneously manipulate vagueness and group diversity, which is applied to a different topic about evaluating innovative value propositions for smart PSS (Z. H. Chen, Lu, Ming, Zhang, & Zhou, 2020).

There are some combinational applications of DEMATEL and ANP methods. Chen et al. propose a hybrid method for evaluating sustainable value requirement of PSS by integrating the fuzzy set, rough set, DEMATEL and ANP, which can simultaneously deal with judgement vagueness, group decision diversity and complex interrelationships (Z. H. Chen, et al., 2019). However, this method requires large amounts of rough-fuzzy pairwise comparisons because of the application of rough-fuzzy ANP. Different ways of hybridization between DEMATEL and ANP are also available, depending on how DEMATEL being applied in different stages of ANP (C. H. Chen & Tzeng, 2011). A summary of different evaluation methods of requirement interactions is shown in Table 1.

Table 1 Different evaluation methods of requirement interactions

Literature	Method	Linguistic, fuzzy assessment	Group assessment	Requirements prioritization	Requirements aggregation
(Fargnoli & Haber, 2019)	QFDforPSS and ANP	×	×	√	×
(Geng, et al., 2010)	fuzzy theory, group decision-making, ANP	√	√	√	×
(Mistarihi, et al., 2020)	QFD and fuzzy ANP	√	×	√	×
(Geng & Chu, 2012)	vague sets, DEMATEL	√	×	√	×

(Liu & Ming, 2019; Song & Cao, 2017)	Rough set, DEMATEL	×	√	√	×
(Z. H. Chen, et al., 2019)	fuzzy set, rough set, DEMATEL and ANP	√	√	√	×

These methods have made significant contributions to evaluating PSS requirement interactions. Complex dependency or cause-effect relationships have been modeled to determine weights for interacting PSS requirements in the context of intrapersonal judgement fuzziness and/or interpersonal judgement diversity. However, requirements aggregation is seldom considered in the existing PSS literature. While requirements prioritization is beneficial to focus on more important requirements, requirements aggregation pays more attention to the whole effect of all requirement together, which is critically important to design optimization and evaluation of alternatives. The weighted arithmetic mean method is the most common aggregation operator for aggregating criteria in MADM, but it has many well-known disadvantages (Marichal, 2000; Marichal & Roubens, 2000). It cannot express interaction effects among any subset of requirements.

Fuzzy measures and the Choquet integral are powerful tools to aggregate interacting criteria in MADM (Beliakov, James, & Wu, 2020; Grabisch, 2016). A fuzzy measure is a set function, which can assign importance to any subset of criteria and thus can model interaction among any subset of PSS requirements. When the fuzzy measure is used to assign the importance of any subset of PSS requirements, a suitable aggregation operator is the Choquet integral that generalizes the weighted arithmetic mean. However, the number of coefficients to identify a fuzzy measure increase exponentially with number of requirements. To reduce this problem, 2-additive fuzzy measures are introduced to balance between complexity and accuracy, which enables modeling interactions among any two requirements. Therefore, to fill the gap of aggregating interacting PSS requirements non-additively, 2-additive fuzzy measures and the Choquet integral are adopted. At the same time, rough-fuzzy DEMATEL is used to determine weights for PSS requirements when there is a group of experts providing their linguistic assessment of requirements. The weight information also acts as the input to identify 2-additive fuzzy measures.

Therefore, this study combines rough-fuzzy DEMATEL, 2-additive fuzzy measures and the Choquet integral to propose a systematic method for evaluating interactions between PSS requirements. The objective is to build a non-additive aggregation function for interacting PSS requirements besides requirements prioritization.

3 A hybrid framework integrating rough-fuzzy DEMATEL, 2-additive fuzzy measures and the Choquet integral to evaluate interacting requirements

3.1 Mathematical preliminaries

This section introduces the definitions related to fuzzy measures, Möbius transform, 2-additive fuzzy measures, the Choquet integral, importance index, and interaction index.

Definition 1 (Grabisch, 2016) Let $X = \{X_1, \ldots, X_n\}$ be a finite non-empty set of n criteria, and $\mathrm{P(X)}$

be the power set of X. A fuzzy measure on X is a set function $\mu: P(X) \rightarrow [0,1]$, satisfying: (1) Boundary condition: $\mu(\emptyset) = 0$ and $\mu(X) = 1$, and (2) Monotonicity: for any $S, T \in P(X)$, $S \subseteq T \Rightarrow \mu(S) \leq \mu(T)$.

$\mu(S)$ and $\mu(T)$ can be interpreted as the importance of subset S and T, respectively.

Definition 2 (Grabisch, 2016). A set function $m_v: P(X) \rightarrow \mathrm{R}$ is called the Möbius transform of v and it is expressed by:

$$m_v(T) = \sum_{S \subseteq T} (-1)^{|T|-|S|} v(S), \forall S \in P(X) \tag{1}$$

where $|S|$ and $|T|$ are the cardinalities of subsets S and T, respectively. v is a set function $v: P(X) \rightarrow \mathrm{R}$ that can be uniquely expressed by:

$$v(T) = \sum_{S \subseteq T} m_v(S), \forall S \in P(X) \tag{2}$$

In order to establish the Möbius transform of μ, the boundary and monotonicity conditions of the fuzzy measure must be satisfied. Those corresponding conditions in terms of the Möbius transform must have the properties given in Equation (3).

$$\begin{cases} m_\mu(\emptyset) = 0, \sum_{T \subseteq \mathrm{X}} m_\mu(T) = 1 \\ \sum_{\substack{S \subseteq T \\ \forall i \in S}} m_\mu(S) \geq 0, \forall T \subseteq \mathrm{X}, \forall i \in T \end{cases} \tag{3}$$

Definition 3 (Grabisch, 2016). A fuzzy measure μ is 2-additive if its Möbius transform m_μ satisfies: (1) For any $S \in P(X)$, if $|S| > 2$, then $m_\mu(S) = 0$, and (2) For any $S \in P(X)$, if $|S| = 2$, then $\exists m_\mu(S) \neq 0$.

2-additive fuzzy measures can model interactions among at most two criteria. The number of m_μ's to be decided in 2-additivity is $\sum_{l=1}^{2} \binom{n}{l}$, instead of 2^n in general case. 2-additivity is a particular model of k-additive fuzzy measures, which reduces complexity and is also of flexibility in expressiveness. When $k = 1$ in k-additive fuzzy measures, the fuzzy measure μ is 1-additive, which means criteria in the set X are mutual independent.

Definition 4 (Grabisch, 2016). Let $x = \{x_1, \ldots, x_n\} \in [0,1]^n$ be a vector. The Choquet integral of x with respect to the fuzzy measure μ is defined by:

$$C_\mu(x) = \sum_{i=1}^{n} x_{\sigma(i)} [\mu(A_{\sigma(i)}) - \mu(A_{\sigma(i+1)})] \tag{4}$$

where σ is a permutation on x so that $x_{\sigma(1)} \leq \cdots \leq x_{\sigma(n)}$. $A_{\sigma(i)} := \{\sigma(i), \ldots, \sigma(n)\}$ and $A_{\sigma(n+1)} = \emptyset$.

The Choquet integral of x with respect to the Möbius transform of μ is defined by Equation (5), where the symbol $\wedge$ is the minimum operator.

$$C_{m_\mu}(x) = \sum_{T \subseteq \mathrm{X}} m_\mu(T) \wedge_{X_i \in T} x_i \tag{5}$$

Definition 5 (Grabisch, 2016). The global importance of a criterion $X_i \in X$ is measured by the importance index or the Shapley index. The Shapley index of X_i with respect to m_μ is defined by Equation (6), and it is of the property $\sum_{i=1}^{n} \emptyset_{m_\mu}(X_i) = 1$.

$$\emptyset_{m_\mu}(X_i) = \sum_{T \subseteq X\{X_i\}} \frac{1}{|T|+1} m_\mu(T \cup X_i), T \subseteq X \tag{6}$$

Definition 6 (Grabisch, 2016). The degree of interaction among any subset criteria of is measured by the interaction index. The interaction index between X_i and X_j with respect to m_μ is defined by:

$$I_{m_\mu}(X_i, X_j) = \sum_{T \subseteq X\{X_i, X_j\}} \frac{1}{|T|+1} m_\mu(T \cup X_i \cup X_j) \tag{7}$$

The interaction index $I_{m_\mu}(X_i, X_j)$ is of the property $-1 \leq I_{m_\mu}(X_i, X_j) \leq 1$. If $i = j$, then $I_{m_\mu}(X_i, X_j) = \emptyset_{m_\mu}(X_i)$.

3.2 The proposed approach for evaluating interacting PSS requirements

In this section, an integrated approach combining rough-fuzzy DEMATEL, 2-additive fuzzy measures and Choquet integral is proposed to evaluate interacting requirements for PSS. This approach focuses on resolving requirements prioritization and non-additive aggregation under the context of group linguistic judgement. The underlying steps of the proposed approach are modeled using the Icam DEFinition for Function Modelling (IDEF0) methodology (Moreno et al., 2017) and shown in Fig.1.

In particular, weights of PSS requirements are determined based on rough-fuzzy DEMATEL, which has the merit of dealing with cause-effect influence relationships among requirements, linguistic assessment from single expert and diverse assessments from group experts. Besides the weights of the requirements, identification of 2-additive fuzzy measures requires further information, such as the degree of interactions. Quantitative information on degree of interactions between any two requirements is derived from its relationship with weights of the PSS requirements and by considering the strength of interactions between any two requirements. All obtained information is then acted as constraints of an optimization model based on the minimum variance method. After the optimization model is solved, 2-additive fuzzy measures are identified. Finally, PSS requirements are aggregated by utilizing the Choquet integral with respect to 2-additive fuzzy measures.

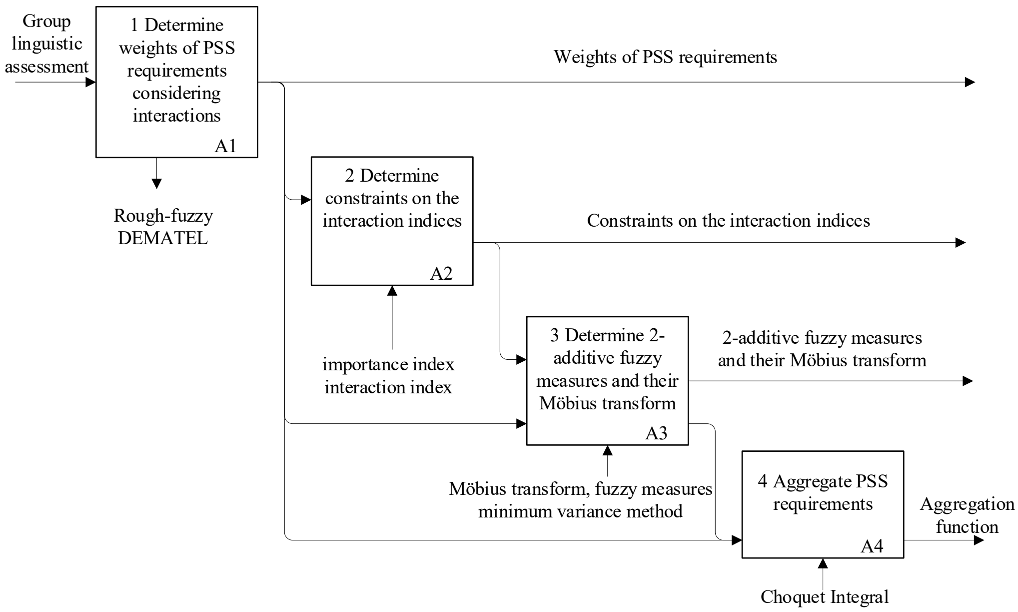

Fig.1. The approach to evaluate interacting PSS requirements

3.2.1 Determine weights of PSS requirements considering interactions

(1) Construct group fuzzy initial direct-relation matrix of PSS requirements

Given a set of n PSS requirements $X = \{X_1, X_2, \dots, X_n\}$, their mutual influence relationships can be structurally expressed by a direct-relation matrix. Assume there is a set of h experts who provide their subjective and linguistic assessment of influence degree between any two requirements. Fuzzy set theory is usually applied to express the fuzziness or imprecision of human cognitive processes, which is thus used for expressing experts' linguistic assessment. In particular, the triangular fuzzy number (TFN) $r_{ij}^k = \left(r_{ij}^{kl}, r_{ij}^{km}, r_{ij}^{ku}\right)$ is used to denote the direct influence degree of X_i on X_j provided by the k^{th} expert, where $r_{ij}^{kl} \leq r_{ij}^{km} \leq r_{ij}^{ku}$. The basic operation of TFN is given in (Sun, 2010). The group fuzzy initial direct-relation matrix IDM can be established by Equation (8).

$$IDM = \left[r_{ij}\right]_{n\times n} = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ r_{n1} & r_{n2} & \cdots & r_{nn} \end{bmatrix}, i, j = 1, \dots, n \tag{8}$$

where $r_{ij} = \left\{r_{ij}^1, r_{ij}^2, \dots, r_{ij}^k, \dots r_{ij}^h\right\}, k = 1, \dots, h$. In particular, if $i = j$, then $r_{ij}^k = (0,0,0)$.

Different measuring scales have been used in the literature, such as 3-level scale, 5-level scale and 7-level scale. Without any loss of generality, the 5-level scale is used to measure the influence degree. The linguistic assessments of influence degree and their corresponding TFN are listed in Table 2.

Table 2. The linguistic assessments of influence degree and their corresponding TFN

Linguistic assessments of influence degree	TFN
NO (N)	(0, 0, 0)
Low (L)	(0, 0.25, 0.5)
Medium (M)	(0.25, 0.5, 0.75)
High (H)	(0.5, 0.75, 1)
Very high (V)	(0.75, 1, 1)

(2) Calculate rough-fuzzy direct-relation matrix and its normalized matrix

The group fuzzy assessment r_{ij} can be converted into a rough-fuzzy interval $\overline{r_{ij}} = \left[\overline{r_{ij}}^{l}, \overline{r_{ij}}^{u}\right]$ through rough set theory, where $\overline{r_{ij}}^{l}$ is a TFN and the lower limit of $\overline{r_{ij}}$, $\overline{r_{ij}}^{u}$ is also a TFN and the upper limit of $\overline{r_{ij}}$. The following procedures are taken to obtain $\overline{r_{ij}}$ from r_{ij}.

Firstly, it is necessary to rank all elements in r_{ij} and order those elements in such a way that $r_{ij}^{(1)} \leq r_{ij}^{(2)} \leq \cdots \leq r_{ij}^{(k)} \leq \cdots \leq r_{ij}^{(n)}$, where $r_{ij}^{()}$ is a permutation on r_{ij}. Secondly, the lower approximation of $r_{ij}^{(k)}$ can be expressed by a set $LA\left(r_{ij}^{(k)}\right) = \left\{r_{ij}^{(1)}, r_{ij}^{(2)}, \dots, r_{ij}^{(k)}\right\}$ and the upper approximation of $r_{ij}^{(k)}$ can be expressed by a set $UA\left(r_{ij}^{(k)}\right) = \left\{r_{ij}^{(k)}, r_{ij}^{(k+1)}, \dots, r_{ij}^{(n)}\right\}$. Then, the average value of elements in the set of $LA\left(r_{ij}^{(k)}\right)$ is defined as the lower limit of the corresponding rough-fuzzy number $r_{ij}^{(k)}$, which is denoted by a TFN $r_{ij}^{(k)l}$. The average value of elements in the set of $UA\left(r_{ij}^{(k)}\right)$ is defined as the upper limit of the corresponding rough-fuzzy number $r_{ij}^{(k)}$, which is denoted by a TFN $r_{ij}^{(k)u}$. Finally, r_{ij} can then be converted into a rough-fuzzy number $\overline{r_{ij}} = \left[\overline{r_{ij}}^{l}, \overline{r_{ij}}^{u}\right]$ with Equation (9).

$$\begin{cases} \overline{r_{ij}}^{l} = \dfrac{\sum_{k=1}^{n} r_{ij}^{(k)l}}{n} \\ \overline{r_{ij}}^{u} = \dfrac{\sum_{k=1}^{n} r_{ij}^{(k)u}}{n} \end{cases} \tag{9}$$

The rough-fuzzy direct-relation matrix RDM can be expressed by Equation (10), where $\overline{r_{ij}}^{l} = \left(\overline{r_{ij}}^{ll}, \overline{r_{ij}}^{lm}, \overline{r_{ij}}^{lu}\right)$ and $\overline{r_{ij}}^{u} = \left(\overline{r_{ij}}^{ul}, \overline{r_{ij}}^{um}, \overline{r_{ij}}^{uu}\right)$ are TFNs.

$$RDM = \left[\overline{r_{ij}}\right]_{n\times n} = \begin{bmatrix} \left[\overline{r_{11}}^{l}, \overline{r_{11}}^{u}\right] & \left[\overline{r_{12}}^{l}, \overline{r_{12}}^{u}\right] & \cdots & \left[\overline{r_{1n}}^{l}, \overline{r_{1n}}^{u}\right] \\ \left[\overline{r_{21}}^{l}, \overline{r_{21}}^{u}\right] & \left[\overline{r_{22}}^{l}, \overline{r_{22}}^{u}\right] & \cdots & \left[\overline{r_{2n}}^{l}, \overline{r_{2n}}^{u}\right] \\ \vdots & \vdots & \ddots & \vdots \\ \left[\overline{r_{n1}}^{l}, \overline{r_{n1}}^{u}\right] & \left[\overline{r_{n2}}^{l}, \overline{r_{n2}}^{u}\right] & \cdots & \left[\overline{r_{nn}}^{l}, \overline{r_{nn}}^{u}\right] \end{bmatrix} \tag{10}$$

The rough-fuzzy direct-relation matrix RDM can be normalized through dividing each element by a rough number $RN(r)$. The normalized rough-fuzzy direct-relation matrix $NRDM$ is calculated by Equation (11).

$$NRDM = \left[\overline{r_{ij}}'\right]_{n\times n} = \left[\frac{\overline{r_{ij}}}{RN(r)}\right]_{n\times n} = \left[\frac{\left(\overline{r_{ij}}^{ll}, \overline{r_{ij}}^{lm}, \overline{r_{ij}}^{lu}\right)}{max_{1\leq i\leq n}\sum_{j=1}^{n}\overline{r_{ij}}^{lu}}, \frac{\left(\overline{r_{ij}}^{ul}, \overline{r_{ij}}^{um}, \overline{r_{ij}}^{uu}\right)}{max_{1\leq i\leq n}\sum_{j=1}^{n}\overline{r_{ij}}^{uu}}\right]_{n\times n} \tag{11}$$

where $RN(r) = \left[max_{1\leq i\leq n}\sum_{j=1}^{n}\overline{r_{ij}}^{lu}, max_{1\leq i\leq n}\sum_{j=1}^{n}\overline{r_{ij}}^{uu}\right]$. Here, for the sake of brevity, the following identity is used: $\overline{r_{ij}}' \equiv [(\overline{r_{ij}}^{ll'}, \overline{r_{ij}}^{lm'}, \overline{r_{ij}}^{lu'}), (\overline{r_{ij}}^{ul'}, \overline{r_{ij}}^{um'}, \overline{r_{ij}}^{uu'})]$.

(3) Calculate rough-fuzzy total-relation matrix

The rough-fuzzy total-relation matrix RTM is calculated with Equation (12) and Equation (13), where I is the unit matrix with dimensions of $n \times n$.

$$RTM = \left[t_{ij}\right]_{n\times n} = \left[t_{ij}^{l}, t_{ij}^{u}\right]_{n\times n} = \left[\left(t_{ij}^{ll}, t_{ij}^{lm}, t_{ij}^{lu}\right), \left(t_{ij}^{ul}, t_{ij}^{um}, t_{ij}^{uu}\right)\right]_{n\times n} \tag{12}$$

$$\begin{cases} \left[t_{ij}^{lx}\right]_{n\times n} = A^{x}(I - A^{x})^{-1}, A^{x} = \left[\overline{r_{ij}}^{lx'}\right]_{n\times n} \\ \left[t_{ij}^{ux}\right]_{n\times n} = B^{x}(I - B^{x})^{-1}, B = \left[\overline{r_{ij}}^{ux'}\right]_{n\times n} \end{cases}, \quad x = l, m, u \tag{13}$$

(4) Calculate crisp prominence and crisp relation

In the rough-fuzzy total-relation matrix RTM, the rough-fuzzy sum of row values and the rough-fuzzy sum of column are denoted by RSR_i and RSC_j, respectively. They are formally expressed in Equation (14).

$$\begin{cases} RSR_i = \left[\left(\sum_{j=1}^{n} t_{ij}^{ll}, \sum_{j=1}^{n} t_{ij}^{lm}, \sum_{j=1}^{n} t_{ij}^{lu}\right), \left(\sum_{j=1}^{n} t_{ij}^{ul}, \sum_{j=1}^{n} t_{ij}^{um}, \sum_{j=1}^{n} t_{ij}^{uu}\right)\right] \\ RSC_j = \left[\left(\sum_{i=1}^{n} t_{ij}^{ll}, \sum_{i=1}^{n} t_{ij}^{lm}, \sum_{i=1}^{n} t_{ij}^{lu}\right), \left(\sum_{i=1}^{n} t_{ij}^{ul}, \sum_{i=1}^{n} t_{ij}^{um}, \sum_{i=1}^{n} t_{ij}^{uu}\right)\right] \end{cases} \tag{14}$$

where RSR_i implies the overall influence of a given requirement X_i on other requirements, and RSC_j implies the overall influence of other requirements on a given requirement X_j.

In order to calculate crisp prominence and crisp relation, the RSR_i and RSC_j are defuzzied into rough numbers. The method of converting a fuzzy number $FN = (l, m, u)$ into a crisp number CN is defined in Equation (15) (Liou & Wang, 1992; Yu & Dat, 2014), where ρ is a parameter to denote experts' risk attitude about the FN.

$$CN = \frac{(1-\rho)l + m + \rho u}{2} \tag{15}$$

If $0.5 < \rho \leq 1$, then experts are optimistic about the FN. If $\rho = 0.5$, then experts are neutral about the FN. If $0 \leq \rho < 0.5$, then experts are pessimistic about the FN.

With Equation (15), the RSR_i and RSC_j can be converted into rough numbers $RSR_i' = \left[RSR_i^{l'}, RSR_i^{u'}\right]$ and $RSC_j' = \left[RSC_j^{l'}, RSC_j^{u'}\right]$, respectively. RSR_i' and RSC_i' are calculated through Equation (16), where ρ_{i1}, ρ_{i2}, ρ_{j1} and ρ_{j2} are parameters to denote experts' risk attitude.

$$\begin{cases} RSR_i' = \left[\frac{\left((1-\rho_{i1})\sum_{j=1}^{n} t_{ij}^{ll} + \sum_{j=1}^{n} t_{ij}^{lm} + \rho_{i1}\sum_{j=1}^{n} t_{ij}^{lu}\right)}{2}, \frac{\left((1-\rho_{i2})\sum_{j=1}^{n} t_{ij}^{ul} + \sum_{j=1}^{n} t_{ij}^{um} + \rho_{i2}\sum_{j=1}^{n} t_{ij}^{uu}\right)}{2}\right] \\ RSC_j' = \left[\frac{\left((1-\rho_{j1})\sum_{i=1}^{n} t_{ij}^{ll} + \sum_{i=1}^{n} t_{ij}^{lm} + \rho_{j1}\sum_{i=1}^{n} t_{ij}^{lu}\right)}{2}, \frac{\left((1-\rho_{j2})\sum_{i=1}^{n} t_{ij}^{ul} + \sum_{i=1}^{n} t_{ij}^{um} + \rho_{j2}\sum_{i=1}^{n} t_{ij}^{uu}\right)}{2}\right] \end{cases} \tag{16}$$

Then, rough numbers RSR_i' and RSC_j' are converted into crisp numbers. The method of converting a rough number $RN = [C^l, C^u]$ to a crisp number C is given in Equation (17) (Song, et al., 2013), where θ is the indicator of risk attitude.

$$C = (1-\theta)C^l + \theta C^u \tag{17}$$

If experts are optimistic about their assessment of θ, then they can select a value bigger than 0.5. If decision makers are neutral about their assessment, then they can choose the value of 0.5. Otherwise, they can select a value smaller than 0.5 for θ.

With Equation (17), the crisp sum of i^{th} row CSR_i and crisp sum of j^{th} column CSC_j are calculated through Equation (18), where θ_{Ri} and θ_{Cj} are indicators of risk attitude.

$$\begin{aligned} CSR_i &= (1-\theta_{Ri})RSR_i^{l'} + \theta_{Ri}RSR_i^{u'} \\ CSC_j &= \left(1-\theta_{Cj}\right)RSC_j^{l'} + \theta_{Cj}RSC_j^{u'} \end{aligned} \tag{18}$$

Then, the crisp prominence CP_i and the crisp relation CR_i are calculated with Equation (19).

$$\begin{cases} CP_i = CSR_i + CSC_i \\ CR_i = CSR_i - CSC_i \end{cases} \tag{19}$$

CP_i indicates the total influence degree that is given by and received by X_i, while CR_i indicates the net effect that X_i contributes to other requirements. CR_i is applied to classify requirements into cause and effect groups. If CR_i is positive, then X_i belongs to the cause group. Otherwise, X_i belongs to the effect group.

(5) Determine weights of PSS requirements

The normalized weight of the i^{th} requirement w_i is calculated with Equation (20).

$$w_i = \frac{\sqrt{(CP_i)^2+(CR_i)^2}}{\sum_{i=1}^{n}\sqrt{(CP_i)^2+(CR_i)^2}} \tag{20}$$

Here, w_i 's are the overall relative importance of PSS requirements, because weights of requirements are determined by considering mutual influence relationships among PSS requirements. Also, w_i 's have the property of $\sum_{i=1}^{n} w_i = 1$. Therefore, w_i calculated from rough-fuzzy DEMATEL is used as the Shapley index $\emptyset_{m_\mu}(X_i)$.

3.2.2 Determine constraints on the interaction indices

According to fuzzy measures, the Shapley value $\emptyset_{m_\mu}(X_i)$ is in general different from the fuzzy measure $\mu(X_i)$. $\emptyset_{m_\mu}(X_i)$ can be interpreted as overall importance of X_i while $\mu(X_i)$ is interpreted as importance of X_i. The reason of the difference is that there are interactions between X_i and the other requirements. Consider any two different requirements X_i and X_j, their interaction index $I_{m_\mu}(\{X_i, X_j\})$ can be modelled by Equation (21).

$$\begin{cases} 0 < I_{m_\mu}(\{X_i, X_j\}) \leq 1, \mu(X_i \cup X_j) > \mu(X_i) + \mu(X_j) \\ I_{m_\mu}(\{X_i, X_j\}) = 0, \mu(X_i \cup X_j) = \mu(X_i) + \mu(X_j) \\ -1 \leq I_{m_\mu}(\{X_i, X_j\}) < 0, \mu(X_i \cup X_j) < \mu(X_i) + \mu(X_j) \end{cases} \tag{21}$$

If $\mu(X_i \cup X_j) > \mu(X_i) + \mu(X_j)$, then there is complementarity between X_i and X_j, hence simultaneous satisfaction of both requirements should be favored. The requirement interactions are then positive with $I_{m_\mu}(\{X_i, X_j\}) \in (0,1)$. The larger the $I_{m_\mu}(\{X_i, X_j\})$, the larger the complementarity. In particular, if $I_{m_\mu}(\{X_i, X_j\}) = 1$, then there is perfect complementarity. If $\mu(X_i \cup X_j) = \mu(X_i) + \mu(X_j)$, then X_i and X_j are mutual independent and $I_{m_\mu}(\{X_i, X_j\}) = 0$. If $\mu(X_i \cup X_j) < \mu(X_i) + \mu(X_j)$, then there is substitutability or some overlap between X_i and X_j. The requirement interactions are then negative with $I_{m_\mu}(\{X_i, X_j\}) \in [-1,0]$. The smaller the $I_{m_\mu}(\{X_i, X_j\})$, the larger the substitutability. In particular, if $I_{m_\mu}(\{X_i, X_j\}) = -1$, then there is perfect substitutability.

The assessment of constrains on interaction indices includes three steps. First, the type of a specific interaction index is assessed, which can be either positive, negative or independent. Second, quantitative constraints on interaction indices are determined according to the conditions to be satisfied by the 2-additive fuzzy measures. With respect to the conditions to be satisfied in the Equation (3), constraints on degree of interaction between X_i and X_j are derived and defined in Equation (22) (Wu & Zhang, 2010).

$$\begin{cases} -\frac{2\emptyset_{m_\mu}(X_i)}{n-1} \leq I_{m_\mu}(\{X_i, X_j\}) \leq \frac{2\emptyset_{m_\mu}(X_i)}{n-1} \\ -\frac{2\emptyset_{m_\mu}(X_j)}{n-1} \leq I_{m_\mu}(\{X_j, X_i\}) \leq \frac{2\emptyset_{m_\mu}(X_j)}{n-1} \end{cases} \tag{22}$$

Let $I_{ij} = \min\left\{\frac{2\emptyset_{m_\mu}(X_i)}{n-1}, \frac{2\emptyset_{m_\mu}(X_j)}{n-1}\right\}$. Because of $I_{m_\mu}(\{X_i, X_j\}) = I_{m_\mu}(\{X_j, X_i\})$, there is the following constraint on $I_{m_\mu}(\{X_i, X_j\})$ as defined in Equation (23).

$$\left|I_{m_\mu}(\{X_i, X_j\})\right| \leq I_{ij} \tag{23}$$

Third, for the sake of describing interactions more intuitively, the degree of interaction is elicited and falls into certain subinterval of $[-I_{ij}, I_{ij}]$. $[-I_{ij}, I_{ij}]$ is divided into five subintervals, including $[-I_{ij}, -\frac{3}{5}I_{ij}]$, $[-\frac{3}{5}I_{ij}, -\frac{1}{5}I_{ij}]$, $[-\frac{1}{5}I_{ij}, \frac{1}{5}I_{ij}]$, $[\frac{1}{5}I_{ij}, \frac{3}{5}I_{ij}]$, $[\frac{3}{5}I_{ij}, I_{ij}]$, representing significant negative interaction, negative interaction, independence, positive interaction and significant positive interaction, respectively. $I_{m_\mu}(\{X_i, X_j\})$ should lie in certain subinterval I'_{ij} $(i, j = 1, 2, \ldots, n$ and $i \neq j)$. This yields:

$$I_{m_\mu}(\{X_i, X_j\}) \in I'_{ij} \tag{24}$$

Furthermore, other preference information may be elicited depending on the particular context, such as overall utilities of alternatives, rank of alternatives and interactions. Comparatively, the overall utilities of alternatives cannot always be obtained in the early stage of the PSS development while the burden to obtain the rank of alternatives or interactions is lighter.

3.2.3 Determine 2-additive fuzzy measures and their Möbius transform

Several approaches are available in the literature for identifying fuzzy measures, such as least-squares based method, maximum split method, minimum variance method, and supervised method with and without regularization (Grabisch, Kojadinovic, & Meyer, 2008; Kojadinovic, 2007; Pelegrina, Duarte, Grabisch, & Romano, 2020). The minimum variance method is used to identify the “least specific” fuzzy measures conditioning the initial preference being satisfied (Kojadinovic, 2007). It has the advantage of finding a unique solution, because of the mathematical form of the objective function. Compared with the least-squares based method, this method does not require preference information about overall utility assessment of alternatives. The requirements’ weights, constraints on interaction indices, and other available information are used as constraints in the minimum variance method. Therefore, the minimum variance method is applied here to determine 2-additive fuzzy measures and their Möbius transform. The objective function and its constraints are given in Equation (25).

$$\min \quad \frac{1}{n}\sum_{X_i \in X}\sum_{Q \subseteq X \setminus \{X_i\}} \frac{(|X|-|Q|-1)!\,|Q|!}{|X|!}\left(\sum_{S \subseteq Q} m_\mu(S \cup X_i) - \frac{1}{n}\right)^2 \tag{25}$$

$$s.t. \begin{cases} w_i = \emptyset_{m_\mu}(X_i) = I_{m_\mu}(\{X_i, X_j\}), i = j = 1, \ldots, n \\ I_{m_\mu}(\{X_i, X_j\}) \in I'_{ij} \\ \ldots \end{cases}$$

The first constraint is obtained from relative weight of the requirement X_i. The second constraint gives information about the interaction indices when 2-additive fuzzy measures are used. More constraints can be added when they are available. In fact, Möbius transform m_μ’s are identified through the optimization process. Then, 2-additive fuzzy measures are identified using Equation (2).

3.2.4 Aggregate PSS requirements

Although weights of PSS requirements take requirement interactions into consideration, the weighted arithmetic mean remains an unattractive aggregation operator, which is unsuitable when additive independence is violated. The fuzzy measures are introduced to replace the weights vector in the weighted arithmetic mean. They can express not only the importance of each requirement but also the importance of each subset of requirements. A suitable extension that generalizes the weighted arithmetic mean is the Choquet integral with regards to fuzzy measures.

Assume the marginal utility function of the requirement X_i has already been determined and been denoted by $u_i(x_i) \in [0,1]$ with utility theory (Keeney & Raiffa, 1993) or MACBETH approach (Bana E Costa & Chagas, 2004). Those marginal utility functions should be commensurable as required by application of the Choquet integral (Grabisch, et al., 2008). For example, if $u_i(x_i)$ and $u_j(x_j)$ are commensurable, then all scales of $u_i(x_i)$ can be represented by the same scale of $u_j(x_j)$. They represent the same degree of satisfaction when $u_i(x_i) = u_j(x_j)$. Let $u = \{u_1, u_2, \ldots, u_n\}$ denote the set of marginal utility functions.

The PSS requirements are aggregated with the Choquet integral. In case of 2-additive fuzzy measures, the Choquet integral of u with respect to μ can be expressed by the interaction indices and the Shapley values as defined in Equation (26) (Grabisch & Labreuche, 2010), where $\wedge$ and $\vee$ denote min and max, respectively.

$$C_\mu(u) = \sum_{I_{m_\mu}(\{X_i,X_j\})>0} [u_i \wedge u_j]\, I_{m_\mu}(\{X_i,X_j\}) + \sum_{I_{m_\mu}(\{X_i,X_j\})<0} [u_i \vee u_j] \left| I_{m_\mu}(\{X_i,X_j\}) \right| + \sum_{i=1}^{n} u_i \left[\emptyset_{m_\mu}(X_i) - 0.5 \sum_{i \neq j} \left| I_{m_\mu}(\{X_i,X_j\}) \right| \right] \tag{26}$$

4 Illustrative application

In this section, the proposed method is applied to evaluate requirement interactions for developing a smart wearable medical system in Company A. Company A is a recently established business focusing on developing smart wearable medical systems for families and hospitals. They have already successfully launched a smart wearable medical device into market for monitoring body temperatures of patients. In order to extend their product line, they are developing a new smart wearable medical system that will provide sophisticated capabilities for monitoring patients' vital signs, such as their pulse, blood pressure and temperature, and for medical services/professionals. This new system is a kind of smart PSS. The framework of the system is shown in Fig. 2.

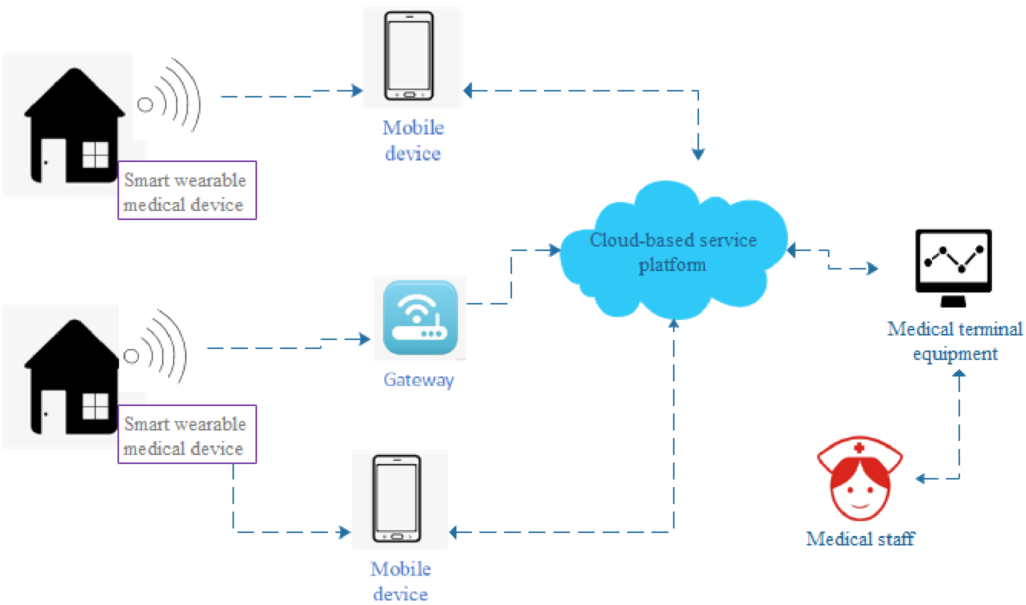

Fig. 2. The framework of smart wearable medical system.

The evaluation of requirement interactions is conducted by a decision group of five members, including two customer representatives, one software engineer, one hardware engineer and one product manager. After several iterations in the decision group, a set of nine high-level system requirements has been identified as given in Table 3.

Table 3 The set of requirements of the smart wearable medical system

Requirement	Description
X_1	The system should measure patient's vital signs accurately
X_2	The system should be waterproof to resist sweat from patient's body
X_3	The system should be comfortable when attached to patient's body
X_4	The system should be easy to use
X_5	The system should be used repeatedly
X_6	The system should monitor patient's vital signs remotely and continuously
X_7	The system should have low lifecycle cost
X_8	The system should provide data storage, analysis, and an emergency alarm
X_9	The system should allow remote medical diagnosis

It is straightforward to detect interaction among requirements. For example, the requirement X_2 will influence X_1 and there is negative interaction between X_1 and X_2. The interactions significantly influence requirements prioritization and aggregation. The objective of evaluating interacting requirements for the smart wearable medical system is to determine weights of requirements and to develop model of aggregated requirements considering interactions. The evaluation provides valuable information for managers and design engineers in Company A, which in turn enables them to focus on more important requirements, to evaluate alternatives, and to optimize their design. The method is compared with the fuzzy DEMATEL method with respect to requirements prioritization, and compared with the weighted arithmetic mean method with respect to requirements aggregation.

4.1 Evaluate requirement interactions for the smart wearable medical system

4.1.1 Determine weights of requirements for the smart wearable medical system

(1) Construct group fuzzy initial direct-relation matrix

For the identified requirements in Table 3, the members in the decision group provide their linguistic assessments. The result with respect to the influence degree from X_i to X_j is $r_{ij} = \{r_{ij}^1, r_{ij}^2, r_{ij}^3, r_{ij}^4, r_{ij}^5\}$. The group fuzzy initial direct-relation matrix IDM in Equation (8) is conveniently represented in Table 4. Each cell of the table is filled with 5 assessments from the 5 members. For example, the cell from X_1 to X_2 denotes that four members give "no influence" and that one member give "low influence" of X_1 to X_2.

Table 4 The table form of the group fuzzy initial direct-relation matrix

DMs	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9
X_1	N,N,N,N,N	N,N,L,N,N	M,L,M,M,M	L,L,M,L,L	M,L,L,M,M	N,N,N,N,N	M,H,M,H,H	N,N,N,N,N	N,N,N,N,N
X_2	H,M,M,M,M	N,N,N,N,N	M,H,V,H,M	N,N,N,N,N	M,M,H,M,M	L,N,N,N,N	M,M,L,L,L	N,N,N,N,N	N,N,N,N,N
X_3	L,L,M,M,M	L,N,M,L,N	N,N,N,N,N	N,N,N,L,N	L,N,L,N,N	N,N,L,N,L	M,M,M,M,M	N,N,N,N,N	N,N,N,N,N
X_4	L,N,L,N,M	N,N,N,N,N	N,N,N,L,N	N,N,N,N,N	N,N,N,N,N	N,N,N,L,N	L,L,L,M,L	N,N,N,N,N	N,N,N,N,N
X_5	M,L,N,L,N	L,L,L,L,L	L,N,N,N,N	N,N,L,N,N	N,N,N,N,N	M,L,M,L,M	H,M,M,M,M	N,N,N,N,N	N,N,N,N,N
X_6	N,N,N,L,N	N,N,N,N,N	M,M,H,H,M	M,L,L,M,M	M,M,L,M,M	N,N,N,N,N	M,H,M,M,M	M,M,H,H,V	M,M,M,M,M
X_7	M,L,M,L,L	N,N,L,N,N	L,L,M,M,L	N,N,L,N,L	M,L,M,H,M	L,L,L,L,L	N,N,N,N,N	M,M,L,M,M	M,M,L,M,M
X_8	N,N,N,N,N	N,N,N,N,N	N,N,N,N,N	H,H,H,M,M	N,N,N,N,N	N,N,N,N,N	H,M,M,H,H	N,N,N,N,N	H,H,H,M,M

X_9	N,N,N,N,N	N,N,N,N,N	N,N,N,N,N	H,M,M,L,M	M,M,L,L,L	N,N,N,N,N	M,H,M,M,H	N,N,N,N,N	N,N,N,N,N

(2) Calculate rough-fuzzy direct-relation matrix and its normalized matrix

By using Equation (9), the r_{ij}'s are converted into rough-fuzzy numbers $\overline{r_{ij}}$'s. Taking the group assessments of r_{32} as an example, the five linguistic assessments are L, N, M, L and N, and their corresponding fuzzy numbers are (0, 0.25, 0.5), (0, 0, 0), (0.25, 0.5, 0.75), (0, 0.25, 0.5) and (0, 0, 0). The ranking order of elements in r_{32} is N, N, L, L and M. The lower approximation and upper approximation of N are $LA(N) = \{N, N\}$ and $UA(N) = \{N, N, L, L, M\}$, respectively. The lower limit of N is calculated through averaging TFNs in $LA(N)$. The upper limit of N is calculated through averaging TFNs in $UA(N)$. The lower limit and upper limit of N are (0, 0, 0) and (0.05,0.2,0.35), respectively. The lower approximation and upper approximation of L are $LA(L) = \{N, N, L, L\}$ and $UA(L) = \{L, L, M\}$, respectively. The lower limit and upper limit of N is (0, 0.125, 0.25) and (0.083,0.333,0.583). The lower approximation and upper approximation of M are $LA(M) = \{N, N, L, L, M\}$ and $UA(M) = \{M\}$, respectively. The lower limit and upper limit of M is (0.05,0.2,0.35) and (0.25,0.50,0.75). The rough-fuzzy number $\overline{r_{32}} = \left[\overline{r_{32}}^{l}, \overline{r_{32}}^{u}\right]$ is [(0.01, 0.09, 0.17), (0.10, 0.31, 0.52)]. The calculation process is repeated for all the r_{ij}'s and the rough-fuzzy direct-relation matrix RDM in Equation (10) is then obtained. The subset of the full RDM is presented in Table 5.

Table 5 The rough-fuzzy direct-relation matrix

DMs	X_1	X_2	X_3	…	X_9
X_1	[(0.00,0.00,0.00), (0.00,0.00,0.00)]	[(0.00,0.01,0.02), (0.00,0.09,0.18)]	[(0.16,0.41,0.66), (0.24,0.49,0.74)]	….	[(0.00,0.00,0.00), (0.00,0.00,0.00)]
X_2	[(0.26,0.51,0.76), (0.34,0.59,0.84)]	[(0.00,0.00,0.00), (0.00,0.00,0.00)]	[(0.34,0.59,0.83), (0.56,0.81,0.96)]	…	[(0.00,0.00,0.00), (0.00,0.00,0.00)]
X_3	[(0.09,0.34,0.59), (0.21,0.46,0.71)]	[(0.01,0.09,0.17), (0.10,0.31,0.52)]	[(0.00,0.00,0.00), (0.00,0.00,0.00)]	…	[(0.00,0.00,0.00), (0.00,0.00,0.00)]
…	…	…	…	…	…
X_9	[(0.00,0.00,0.00), (0.00,0.00,0.00)]	[(0.00,0.00,0.00), (0.00,0.00,0.00)]	[(0.00,0.00,0.00), (0.00,0.00,0.00)]	…	[(0.00,0.00,0.00), (0.00,0.00,0.00)]

The normalized rough-fuzzy direct-relation matrix $NRDM$ is then obtained through dividing each element in the matrix RDM by a rough number $RN(r)$. $RN(r)$ is calculated by Equation (11) and is $[4.4, 5.09]$. The calculated $NRDM$ is given in Table 6.

Table 6 The normalized rough-fuzzy direct-relation matrix

DMs	X_1	X_2	X_3	…	X_9
X_1	[(0.000,0.000,0.000), (0.000,0.000,0.000)]	[(0.000,0.002,0.005), (0.000,0.018,0.035)]	[(0.036,0.093,0.150), (0.047,0.096,0.145)]	…	[(0.000,0.000,0.0000), (0.000,0.000,0.000)]
X_2	[(0.059,0.116,0.172), (0.067,0.116,0.165)]	[(0.000,0.000,0.000), (0.000,0.000,0.000)]	[(0.077,0.134,0.1890), (0.110,0.159,0.189)]	…	[(0.000,0.000,0.000), (0.000,0.000,0.000)]
X_3	[(0.020,0.077,0.134), (0.041,0.090,0.139)]	[(0.002,0.020,0.039), (0.020,0.061,0.102)]	[(0.000,0.000,0.000), (0.000,0.000,0.000)]	…	[(0.000,0.000,0.000), (0.000,0.000,0.000)]
…	…	…	…	…	…
X_9	[(0.000,0.000,0.000), (0.000,0.000,0.000)]	[(0.000,0.000,0.000), (0.000,0.000,0.000)]	[(0.000,0.000,0.000), (0.000,0.000,0.000)]	…	[(0.000,0.000,0.000), (0.000,0.000,0.000)]

(3) Calculate rough-fuzzy total-relation matrix

By applying Equations (12) and (13), the rough-fuzzy total-relation matrix RTM is calculated. The resulting RTM is given in Table 7.

Table 7 The rough-fuzzy total-relation matrix

DMs	X_1	X_2	X_3	…	X_9
X_1	[(0.002,0.025,0.098), (0.007,0.045,0.166)]	[(8.454e-05,0.011,0.042), (9.983e-04,0.036,0.112)]	[(0.037,0.111,0.232), (0.051,0.129,0.280)]	…	[(3.218e-03,0.021,0.079), (0.005,0.024,0.089)]
X_2	[(0.061,0.141,0.277), (0.075,0.163,0.335)]	[(1.813e-04,0.012,0.048), (2.271e-03,0.026,0.095)]	[(0.080,0.160,0.298), (0.116,0.201,0.350)]	…	[(9.471e-04,0.016,0.078), (0.003,0.023,0.095,)]
X_3	[(0.021,092,0.020), (0.045,0.123,0.279)]	[(2.276e-03,0.023,0.058), (1.976e-02,0.072,0.163)]	[(0.001,0.023,0.090), (0.006,0.043,0.158)]	…	[(2.316e-03,0.017,0.067), (0.003,0.022,0.089)]
…	…	…	…	…	…
X_9	[(0.001,0.015,0.065), (0.005,0.032,0.116)]	[(1.484e-06,0.005,0.027), (6.003e-05,0.010,0.049)]	[(0.001,0.014,0.064), (0.003,0.025,0.100)]	…	[(2.645e-03,0.018,0.066), (0.004,0.021,0.081)]

(4) Calculate crisp prominence and crisp relation

For the RTM, the rough-fuzzy sum of rows and the rough-fuzzy sum of columns are calculated with Equation (14), and the results are given in the 2nd column and 5th column of Table 8, respectively. If the decision group is neutral about the TFNs, then ρ equals 0.5 in Equation (15). According to Equation (16), the rough sum of rows and rough sum of columns are calculated when ρ equals 0.5. The acquired results are shown in the 3rd column and 6th column of Table 8, respectively. For other possible risk attitude of the decision group about the TFNs, the calculation is straightforward. Furthermore, if the decision group is neutral about the rough number, then θ equals 0.5 in Equation (17). The crisp sum of row and crisp sum of column when θ equals 0.5 are calculated by applying Equation (18), and the results are shown in in the 4th column and 7th column of Table 8, respectively.

Table 8 Crisp sum of row and column when ρ equals 0.5 and θ equals 0.5

	Rough-fuzzy sum of row	Rough sum of row	Crisp sum of row	rough-fuzzy sum of column	Rough sum of column	Crisp sum of column
X_1	[(0.153,0.548,1.354), (0.235,0.695,1.748)]	[0.651,0.843]	0.747	[(0.102,0.474,1.251), (0.223,0.757,1.982)]	[0.576,0.930]	0.753
X_2	[(0.228,0.656,1.564), (0.326,0.838,1.988)]	[0.776,0.998]	0.887	[(0.003,0.137,0.432), (0.026,0.278,0.876)]	[0.177,0.365]	0.271
X_3	[(0.092,0.385,1.020), (0.140,0.599,1.662)]	[0.470,0.750]	0.610	[(0.198,0.604,1.439), (0.306,0.816,1.957)]	[0.711,0.973]	0.842
…	…	…	…	…	…	…
X_9	[(0.122,0.417,1.029), (0.209,0.534,1.280)]	[0.497,0.639]	0.568	[(0.199,0.542,1.266), (0.235,0.576,1.336)]	[0.637,0.680]	0.659

According to Equation (19), by adding the crisp sum of row to crisp sum of column, the crisp prominence is obtained and the results when ρ equals 0.5 are shown in the 2nd column of Table 8. By subtracting the crisp sum of row to crisp sum of column, the crisp relation is obtained and the results when ρ equals 0.5 are shown in the 5th column of Table 8. The relation values enable to separate these 9 requirements into cause and effect groups. The relation values of X_2, X_6 and X_8 are positive, and they are classified in the cause group. The relation values of other requirements are negative, and they belong to the effect group. The crisp prominence and crisp relation when ρ equals 0 and 1 respectively are also calculated and shown in Table 9.

Table 9 Crisp prominence, crisp relation and relative weight

	crisp prominence			crisp relation			Relative weight		
	$\rho = 0.5$	$\rho = 0$	$\rho = 1$	$\rho = 0.5$	$\rho = 0$	$\rho = 1$	$\rho = 0.5$	$\rho = 0$	$\rho = 1$
X_1	1.500	0.797	2.202	-0.006	0.019	-0.030	0.106	0.100	0.109
X_2	1.158	0.623	1.693	0.616	0.401	0.831	0.093	0.093	0.093
X_3	1.452	0.785	2.121	-0.232	-0.177	-0.287	0.104	0.101	0.105
X_4	1.068	0.554	1.581	-0.496	-0.307	-0.684	0.083	0.079	0.085
X_5	1.669	0.878	2.459	-0.243	-0.169	-0.318	0.119	0.112	0.122
X_6	1.679	0.933	2.424	0.795	0.552	1.037	0.132	0.136	0.130
X_7	2.590	1.164	3.715	-0.560	-0.415	-0.705	0.188	0.191	0.186
X_8	1.211	0.744	1.678	0.217	0.163	0.271	0.087	0.096	0.084
X_9	1.227	0.708	1.745	-0.091	-0.067	-0.114	0.087	0.090	0.086

(5) Determine relative weights of requirements for the smart wearable medical system

The relative weight of the requirement X_i is calculated by applying Equation (20). The results are provided in Table 9. The rank of the requirements for the smart wearable medical system is presented as follows: $w_7(0.188) > w_6(0.132) > w_5(0.119) > w_1(0.106) > w_3(0.104) > w_2(0.093) > w_8(0.087) = w_9(0.087) > w_4(0.083)$. The top five requirements are X_7 (Low lifecycle cost), X_6 (Monitor vital signs remotely and continuously), X_5 (Be used repeatedly), X_1 (Accuracy), and X_3 (Comfort). By adjusting the value of ρ, relative weights of requirements change accordingly as shown in Table 8. This change of relative weights is due to the fuzzy assessment of influence degree and different risk attitudes of the decision group.

4.1.2 Determine constraints on the interaction indices

The degree of interaction between any two requirements is determined by verifying the type and strength of their interaction. For example, the decision group believes that there is a negative interaction between the requirement X_1 (Accuracy) and the requirement X_2 (Be waterproof to resist sweat), because there is somewhat overlapping effect between them or double counting in terms of preference. At the same time, there is positive interaction between requirements X_1 and X_3 (Comfort), and simultaneous satisfaction of them is favored. After repeatedly verifying the interactions between any two requirements, the type and the strength of interaction are determined. Furthermore, the constrains on the interaction indices are calculated by applying Equation (24). The results are given in Table 10.

Table 10 constraints on the interaction indices

Requirements	Constraints of interaction	Requirements	Constraints of interaction
X_1, X_2	[-0.01395, -0.00465]	X_2, X_4	[-0.00415, 0.00415]
X_1, X_3	[0.0052, 0.0156]	X_2, X_5	[-0.01395, -0.00465]
X_1, X_4	[0.00415, 0.01245]	X_2, X_6	[-0.00465, 0.00465]
X_1, X_5	[0.00595, 0.01785]	X_2, X_7	[-0.01395, -0.00465]
X_1, X_6	[0.0066, 0.0198]	X_2, X_8	[-0.00435, 0.00435]
X_1, X_7	[0.0282, 0.047]	X_2, X_9	[-0.00435, 0.00435]
X_1, X_8	[0.00435, 0.01305]	X_3, X_4	[0.00415, 0.01245]

X_1, X_9	[0.00435, 0.01305]	…	…
X_2, X_3	[-0.01395, -0.00465]	X_8, X_9	[-0.02175, -0.01305]

4.1.3 Determine 2-additive fuzzy measures and their Möbius transform

The above determined information is used as constraints of the optimization model based on Equation (25). The optimization model is then solved by applying the Kappalab R package (Grabisch, et al., 2008). The value of the objective function is 0.122. The 2-additive fuzzy measures and their Möbius transform are shown in Table 11.

Table 11 The 2-additive fuzzy measures and their Möbius transform

Requirement	μ	m_μ	Requirement	μ	m_μ	Requirement	μ	m_μ
X_1	0.081	0.081	X_1, X_2	0.177	-0.007	X_2, X_4	0.182	0.002
X_2	0.104	0.104	X_1, X_3	0.181	0.005	X_2, X_5	0.205	-0.005
X_3	0.095	0.095	X_1, X_4	0.161	0.004	X_2, X_6	0.218	-0.002
X_4	0.076	0.076	X_1, X_5	0.193	0.006	X_2, X_7	0.243	-0.013
X_5	0.106	0.106	X_1, X_6	0.204	0.007	X_2, X_8	0.202	0.004
X_6	0.116	0.116	X_1, X_7	0.261	0.028	X_2, X_9	0.202	0.004
X_7	0.152	0.152	X_1, X_8	0.179	0.004	X_3, X_4	0.175	0.004
X_8	0.094	0.094	X_1, X_9	0.179	0.004	…	…	…
X_9	0.094	0.094	X_2, X_3	0.194	-0.005	$X_1, \ldots, X_9$	1	0

4.1.4 Aggregate requirements for the smart wearable medical system

In case of 2-additive fuzzy measures, there is a property that $m_\mu\{X_i, X_j\}$ equals $I_{m_\mu}(\{X_i, X_j\})$, so the values of $m_\mu\{X_i, X_j\}$'s are used in Equation (26). Let u_i denote the marginal utility function of X_i, the aggregation function of the smart wearable medical system requirements is built in Equation (27).

$$\begin{aligned} C_\mu(u) = \ & 0.074u_1 + 0.072u_2 + 0.089u_3 + 0.068u_4 + 0.093u_5 + 0.106u_6 + 0.14u_7 \\ & + 0.068u_8 + 0.068u_9 + 0.007(u_1 \vee u_2) + 0.005(u_1 \wedge u_3) \\ & + 0.004(u_1 \wedge u_4) + 0.006(u_1 \wedge u_5) + 0.007(u_1 \wedge u_6) + 0.028(u_1 \wedge u_7) \\ & + 0.004(u_1 \wedge u_8) + 0.004(u_1 \wedge u_9) + \cdots + 0.013(u_8 \vee u_9) \end{aligned} \tag{27}$$

4.2 Comparisons and discussions

To demonstrate the feasibility and advantages of the proposed method, two comparative studies are conducted based on the same assessment data. One comparison is conducted between rough DEMATEL and rough-fuzzy DEMATEL with respect to requirements prioritization. Another comparison is conducted between the weighted arithmetic mean and the Choquet integral with respect to requirements aggregation.

The values used in rough DEMATEL are obtained by selecting middle values of the linguistic assessments from the five members and calculating their rough number. For example, about r_{14}={L, L, M, L, L}, its corresponding middle values of the linguistic assessments is {0.25, 0.25, 0.5, 0.25, 0.25}, and the calculated rough number is [0.27, 0.34]. The relative weights of requirements are then calculated and compared with the results from the rough-fuzzy DEMATEL. To demonstrate the effect of fuzzy assessments on final weighting result, three cases when ρ equals 0, 0.5 and 1 respectively are analyzed. The comparative results are shown in Fig. 3.

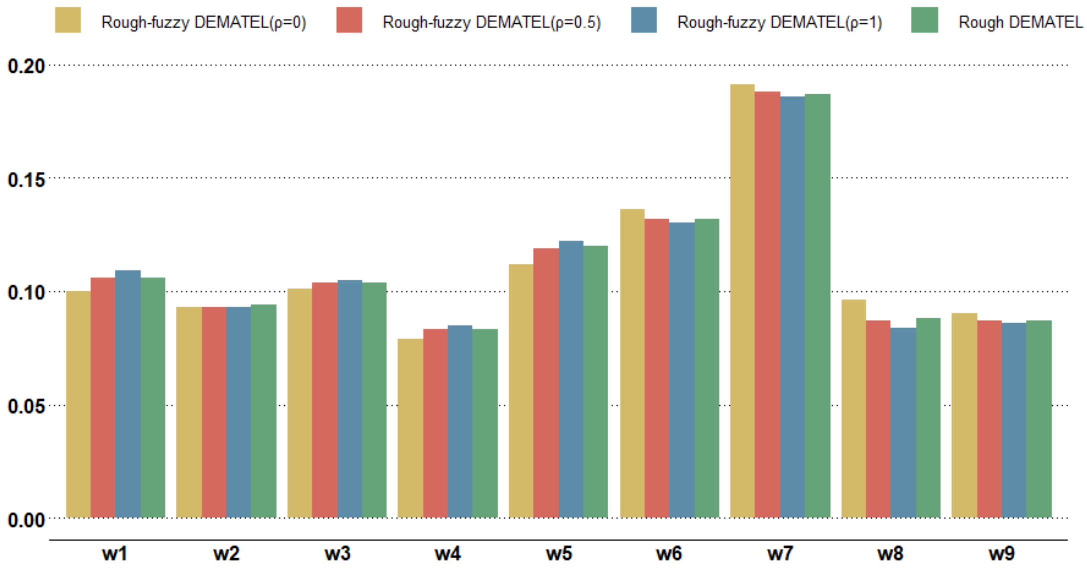

Fig. 3. Weights of requirements with different evaluation methods.

In general, four prioritizations of requirements are similar in these four different cases, except some minor differences. The top three ranked requirements are the same in the four different cases, namely the requirement X_7, X_6 and X_5. There are different ranks for other requirements, but the fluctuations of their ranking positions are very slight. For example, the ranks of the requirement X_1 and X_2 are {4, 5, 4, 4} and {6, 7, 6, 6} in all the four cases. At the same time, there are two interesting phenomena. One is that the weights of requirements calculated by rough DEMATEL are almost the same with those weights calculated by rough-fuzzy DEMATEL when ρ equals 0.5. The other is that the weights of requirements calculated by rough DEMATEL fall into the ranges of weights calculated by rough-fuzzy DEMATEL when $\rho \in [0,1]$. The reason of the first phenomenon is that the group linguistic assessment r_{ij} in the rough-fuzzy DEMATEL when $\rho = 0.5$ is converted into the same rough number as in the rough DEMATEL. For example, about r_{14}={L, L, M, L, L}, the corresponding crisp value set is {0.25, 0.25, 0.5, 0.25, 0.25} when ρ equals 0.5, which results in the rough number [0.27, 0.34]. The reason of the second phenomenon is that rough DEMATEL is a special case of rough-fuzzy DEMATEL, and special middle values of the linguistic assessments are selected for assessment. Therefore, rough-fuzzy DEMATEL is more appropriate model for capturing linguistic assessment and group diversity simultaneously.

The proposed method is then compared with the weighted arithmetic mean method in terms of requirements aggregation. The weighted arithmetic mean is a Shapley integral in nature, and it is not suitable to aggregate requirements when there are interactions. When ρ equals 0.5 and θ equals 0.5, the weighted arithmetic mean of requirements can be expressed by Equation (28). Obviously, there are no interactions among different marginal utility functions u_i's.

$$WAM = 0.106\mathrm{u}_1 + 0.093\mathrm{u}_2 + 0.104\mathrm{u}_3 + 0.083\mathrm{u}_4 + 0.119\mathrm{u}_5 + 0.132\mathrm{u}_6 + 0.188\mathrm{u}_7 + 0.087\mathrm{u}_8 + 0.087\mathrm{u}_9 \tag{28}$$

However, the proposed method explicitly recognizes requirements interactions and it can model the positive and negative interactions between any two requirements during requirements aggregation. For example, as shown in Equation (27), there is a negative interaction between X_1 and X_2, and the influence of their interaction on total preference is modeled by $0.007(u_1 \vee u_2)$.

When these two aggregation methods are used for evaluating design alternatives, they will result in different ranked alternatives for some cases. A simulation procedure is introduced to check the inconsistency ratio between the weighted arithmetic mean method and the proposed method in terms of the recommended design alternatives. It includes the following steps:

1. Assume there are two different alternatives with n attributes. The n samples u_{1i} $(i = 1, \ldots, n)$ are generated for the 1st alternative and the n samples u_{2i} $(i = 1, \ldots, n)$ are generated for the 2nd alternative from a uniform [0,1] distribution, respectively.
2. The values of the 1st alternative and the 2nd alternative are calculated and then ranked according to the weighted arithmetic mean method.
3. The values of the 1st alternative and the 2nd alternative are calculated and then ranked according to the proposed method.
4. Compare the ranking result obtained from the Step 2 and that from the Step 3.
5. Repeat m times (m is the iteration number).
6. Calculate the fraction of times a difference in the recommended design alternatives occurs between these two methods.

With Equation (27) and (28), the simulation results of this application are shown in Fig. 4-a.

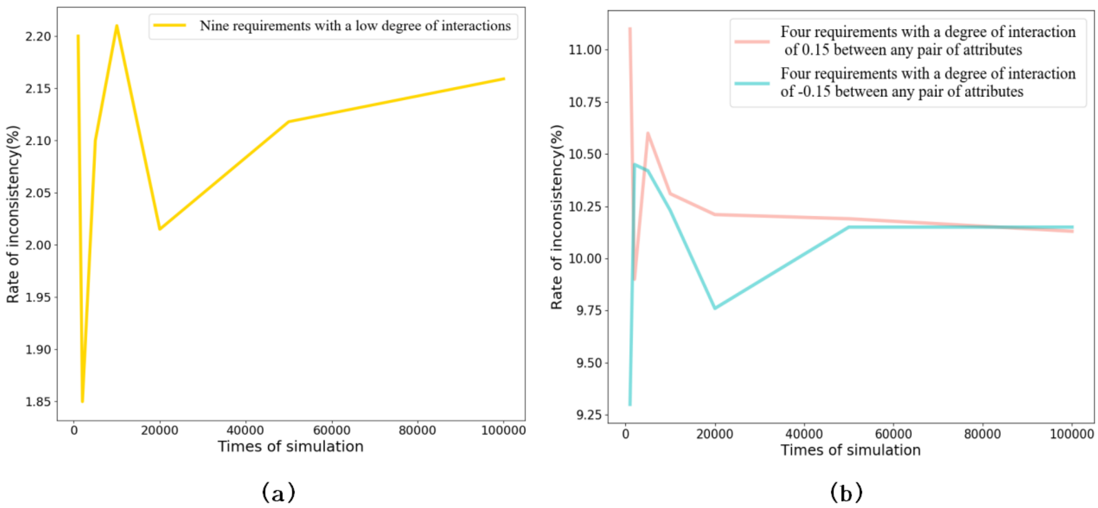

Fig. 4. Rate of inconsistency between the two different methods

The inconsistency ratio is 2.16% with 100,000 iterations. The underlying reason of this inconsistency level is that the identified degree of interactions in Equation (27) and Table 11 is small. With low levels of interaction degree between the requirements, there is a high level of consistency between the weighted arithmetic mean method and the proposed method in terms of the recommended design alternatives. According to Equation (23) and (24), the identified interaction degree is closely related to the number of requirements and assessed subinterval of interactions. When the number of requirements increases, the degree of interactions between any pair of requirements will lessen. If the assessed subinterval of interactions falls into the negative interaction, independence or positive interaction, the interaction degree is lower than significant negative interactions or significant positive interactions.

Consider another example with four attributes of equal relative importance of 0.25 and two different degrees of interaction. One case has a degree of interaction of 0.15 between any pair of attributes, and the other has a degree of interaction of -0.15 between any pair of attributes. Using the same simulation procedure, the ratio of inconsistency is 10.07% and 10.2%, respectively, as shown in Fig. 4-b. This example shows that the advantage of the proposed method is more significant when the number of requirements decreases and when requirement interactions are becoming stronger. Therefore, the proposed requirements aggregation method has the potential to better identify the alternatives that are judged as worse alternatives by the weighted arithmetic mean when there are strong interactions between requirements.

5 Theoretical and practical implications

Interactions are very common among PSS requirements, and they have significant influence on requirements prioritization and aggregation. Evaluation of requirement interactions is still an emerging research field, and it deserves more attention from both academia and practice.

Theoretically, this study contributes to proposing a novel method for evaluating interacting PSS requirements in a group linguistic environment. First, rough-fuzzy DEMATEL is applied to determine relative weights of interacting PSS requirements when a group of experts provide their linguistic judgement of influence degree from one requirement to another. Compared with crisp DEMATEL, rough DEMATEL and fuzzy DEMATEL, rough-fuzzy DEMATEL is more flexible and capable method for dealing with judgement vagueness and group diversity simultaneously. Crisp DEMATEL, rough DEMATEL and fuzzy DEMATEL can be derived from rough-fuzzy DEMATEL through certain conversions of fuzzy and/or rough numbers. Second, the non-additive aggregation operator (i.e. the Choquet integral with respect to 2-additive fuzzy measures) is applied to aggregate PSS requirements. Compared with the weighted arithmetic mean that assumes mutual independence among requirements, the proposed method can explicitly identify, quantify and incorporate interactions into requirements aggregation, which enables building a non-additive aggregation function. Hence, the paper can fill the gap on non-additive requirements aggregation in PSS research. Third, the relative weights determined from rough-fuzzy DEMATEL and constrains on interaction indices are used to identify 2-additive fuzzy measures with the minimum variance method.

Practically, the study has the following characteristics. First, the cognitive burden required from the group of experts is lightweight. Compared with giving crisp assessment of influence degree, it is more realistic for a group of experts to provide their linguistic assessment. The required information for identifying 2-additive fuzzy measures is also lightweight, such as the type of interaction and strength of interaction. Second, the effects of positive or negative interactions on aggregation function are apparent, giving clear demonstration of the result of requirement interactions evaluation. Third, building the non-additive function form is more precise and it can help managers and engineers to make better decisions in PSS development.

6 Conclusions

In this paper, an effective method based on rough-fuzzy DEMATEL, 2-additive fuzzy measures and the Choquet integral is proposed to evaluate requirements interactions of PSS. The main scientific contribution of the proposed method is that it can aggregate interacting PSS requirements non-additively by considering second order requirement interactions between any two requirements besides requirements prioritization. This method includes four steps. Firstly, the rough-fuzzy DEMATEL is applied to determine relative weights of interacting PSS requirements, which has merits of dealing with individual linguistic judgement and group diversity simultaneously. Then, the constrains on interaction indices are determined by deriving information on degree of interaction from relative weights and by eliciting strength of interaction. Furthermore, 2-additive fuzzy measures and their Möbius transform are identified with minimum variance method. Consequently, the interacting PSS requirements are aggregated non-additively by applying the Choquet integral with respect to 2-additive fuzzy measures, which explicitly model the contribution of requirement interactions on preference aggregation. The method can evaluate interacting PSS requirements and conduct requirements prioritization and aggregation together, which contribute to building more precise requirement-based objective functions that can be used in alternative evaluation and design optimization in the PSS.

The proposed method is applied to evaluate requirement interactions of a smart wearable medical system that provides sophisticated capabilities for monitoring vital signs of patients. The application shows that the method enables requirements prioritization and aggregation in the group linguistic environment. The comparison analysis between rough DEMATEL and rough-fuzzy DEMATEL shows that rough-fuzzy DEMATEL is more flexible than rough DEMATEL that is a specific case of rough-fuzzy DEMATEL. Furthermore, the Choquet integral with respect to 2-additive fuzzy measures can aggregate interacting requirements non-additively while additive independence is assumed in the weighted arithmetic mean.

In terms of future research, two research directions are identified. Firstly, although 2-additive fuzzy measures are a reasonable trade-off between modeling accuracy and complexity, k-additive fuzzy measures will enable modeling requirement interactions more flexibly and precisely. Second, the method is preferred to be implemented by a computer software or a module in a requirements management software to reduce the time and calculation burden in the evaluation process.

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