



# A hybrid framework integrating rough-fuzzy best-worst method to identify and evaluate user activity-oriented service requirement for smart product service system

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## ABSTRACT

With the wide application of the smart technologies in the field of product service system, the delivery scope of product-extension service can be expanded from the conventional product operation lifecycle to broader user activity cycle. The identification and evaluation of user activity-oriented service requirements are critical to successful design of smart technology-enabled product service offering. The evaluation process of service requirement generally involves the intrapersonal and interpersonal uncertainties that may lead to inaccurate evaluation results, since the evaluation needs to collect linguistic judgements from multiple stakeholders. However, most the existing research contains scant study of the systematic approach to elicitation and evaluation of the smart service requirement under an environment of multiple uncertainties. Therefore, this paper proposes a hybrid framework to identify and prioritize the user activity-oriented service requirements. The proposed identification method is used to map the key activity elements with the smart capabilities for purpose of eliciting the service requirements in user activity cycle. Moreover, a novel rough-fuzzy best-worst method is proposed to prioritize the identified requirements, simultaneously manipulating the intrapersonal and interpersonal uncertainties. The case study results of smart vehicle service system show that sixteen smart service requirements are identified in the self-driving tour with the smart vehicle, and the requirement “alerting the driver's unsafe behavior using informative diagnostic capability” emerges as the most important one in the proposed rough-fuzzy best-worst method. Moreover, the obtained evaluation results present more accuracy and objectivity compared with the crisp-based, fuzzy-based and rough-based best-worst method.

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## 1. Introduction

The revolutionary development of the advanced smart technologies (e.g. smart sensing, Internet of Things, cyber-physical systems (CPS), virtual-/augmented-reality (VR/AR), artificial intelligence (AI)) enable the manufacturers to transform their value propositions towards smart product service system (PSS) (Zheng et al., 2019). This transformation aims to achieve higher market competition and customer loyalty in today's rapid changing global market (Chowdhury et al., 2018; Rymaszewska et al., 2017). In the context of smart PSS, the smart products can communicate with

each other, and also can connect to the users, environment and technological infrastructures via the IoT technology (Ardolino et al., 2018; Li et al., 2017). A large amount of data generated from the smart connected products (SCPs) is converted into smart data (knowledge or wisdom), thus providing intelligent service for improvement of product operation and user experience (Rymaszewska et al., 2017). The delivery scope of product-extension service can be thus expanded from the conventional product use lifecycle to broader user activity cycle (Chen et al., 2020). The user activity cycle refers to the cycle of an experience journey of users with using the SCP as a critical tool or facility. The SCP could also be used as an interactive interface that can collect raw activity data and deliver valuable service to users. Orienting to the user activity cycle, various services can be created to satisfy the individualized need of customers in a smart manner, based on the application of smart technologies. For instances, the smart service of diagnosing user's behavior (e.g. analyze the driver's

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inappropriate behavior that may cause high energy consumption) (Willke et al., 2009), and predicting user's states (e.g. predict the driver's physical status and driving behavior) (Lim et al., 2018). These smart services have high potential to deliver more added benefit and excellent experience in various activity scenarios of customers (Chen et al., 2020). Although this potential can trigger more value opportunities and service business, it also brings with new challenges towards development, implementation and operation of smart PSS (Zheng et al., 2019).

Requirement identification is acknowledged as a critical step in the development of smart PSS, since its implementation can highly affect the quality of the developed product-extension service and the users' satisfaction (Song, 2017). The task of service requirement identification is to recognize the key customers' concerns and elicit rational requirements from the service-dominant logic (Z. Liu et al., 2019). A successful identification of service requirement orienting to the user activity can provide accurate application scenarios for the smart technologies with objective of delivering prosperous benefits to the users. Some research has been conducted to focus on the requirement identification in the context of smart PSS, such as identification of the co-creative value requirement (Liu and Ming, 2019; Z. Liu et al., 2019) and elicitation of the product-related service requirement (Wang et al., 2019). However, most of the existing research contains scant study of the specific elicitation of user activity-oriented service requirement (UAO-SSRs) for smart PSS. Therefore, it is necessary to develop a feasible method to appropriately elicit the service requirement specified for the user activity while considering the effect of the smart technologies. The first research issue for this paper is thus identified as follows:

*Research issue I: How to appropriately and accurately identify UAO-SSRs for smart PSS based on the application scenario of smart capability in user activity cycle?*

After eliciting the service requirement, the subsequent task is to invite multiple experts (e.g. user representatives, service designers, data analytic experts, marketing experts) to prioritize these requirements using the multi-attribute decision-making (MADM) methods. Requirement prioritization or evaluation is acknowledged as a critical activity, since its results can provide critical foundation for the resource allocation and concept configuration in the later design phase (Song, 2017). Among the frequently used methods, the recently proposed vector-based best-worst method (BWM) (Rezaei, 2015) presents some advantages compared with the matrix-based methods (e.g. analytic hierarchy process (AHP), analytic network process (ANP), DEMATEL) (Rezaei, 2015, 2016; Rezaei et al., 2016), such as, requesting less comparisons and performing high reliability. Therefore, this study proposes a requirement evaluation method based on the BWM. In addition, the requirement evaluation process involves two types of uncertainty (Wu and Mendel, 2010): intrapersonal linguistic vagueness and the interpersonal preference diversity. However, the traditional crisp BWM cannot handle these uncertainties, which may lead to inaccurate evaluation results of the smart service requirement. Although some previous research have attempted to integrate the fuzzy logic or rough set theory into the crisp BWM to singly handle the intrapersonal or interpersonal uncertainty (Guo and Zhao, 2017; H. C. Liu et al., 2019; Stević et al., 2017), most of them cannot simultaneously manipulate these two types of uncertainty. Thus, it is necessary to modify the BWM method to fully handle these uncertainties to provide more accurate and realistic evaluation results. The second research issue is identified as follows:

*Research issue II: How to simultaneously manipulate the intrapersonal and interpersonal uncertainty when using BWM to evaluate and prioritize UAO-SSRs for smart PSS under group decision environment?*

Therefore, to solve these issues, an integrated framework is

proposed to systematically elicit and prioritize the UAO-SSRs under environment of intrapersonal and interpersonal uncertainties. The framework consists of identification stage and evaluation stage. In the identification stage, a conceptual framework is proposed to map the smart data analytic capability with the key activity elements for the purpose of identifying the application scenarios. In addition, an implementation roadmap is developed to provide detailed guidance for the elicitation of service requirement. In the evaluation stage, the identified UAO-SSRs are prioritized using the proposed rough-fuzzy BWM. This method integrates the rough set theory and fuzzy logic into the BWM, which combines the advantages of fuzzy set theory in dealing with intrapersonal linguistic vagueness, the merits of rough set theory in coping with interpersonal preference diversity, and the superiority of BWM method in quickly determining the final weight with high decision consistency. The validity and feasibility of the proposed framework is demonstrated through the framework's application in a case study of smart vehicle service system (SVSS) and comparisons with other methods.

The remainder of this paper is arranged like this: Section 2 reviews some literatures concerning smart PSS, UAO-SSRs, and requirement identification and evaluation methods in PSS field. Section 3 describes the proposed integrated framework for eliciting and evaluating UAO-SSRs. Section 4 presents a case study of application of the proposed framework in SVSS. Section 5 discuss the case study results and the comparisons with some related methods. Finally, the theoretical and practical implications are separately analyzed in Section 6.1 and 6.2. Finally, the conclusions and limitations are summarized in Section 6.3.

## 2. Literature review

### 2.1. Smart PSS and UAO-SSRs

Smart PSS has gained increasing attention from cross-disciplinary domains due to its high potential for delivering economic, environmental and social benefits. The definition, architecture, key elements have been continuously developed from the realm of academia and practice (Zheng et al., 2019). A concept of "smart service based on existing product" was first proposed in the technical report of National Academy of Science and Engineering of German (Kagermann et al., 2014). The report claimed that smart service is created by transforming the raw data generated in the product operation to smart data (knowledge or wisdom). These smart data can be able to deliver added benefits to stakeholders, such as improvement of product performance and user experience. Then, the initial specific definition of smart PSS from academia was derived (Valencia et al., 2015) by leveraging SCP as a media and tool, to produce prosperous e-services as a bundle delivered to meet the individualized needs of customers. Meanwhile, Lerch and Gotsch (2015) identified smart PSS as an integrated package of physical products, intangible services and digital architecture, which is implemented to satisfy customer's personalized requirements. Kühlenkötter et al. (2017) indicated that smart PSS is an socio-technical PSS integrating SCPs and smart service systems for the purpose of providing new functionalities. Zheng et al. (2018) refined smart PSS as a digital-twin-enabled service innovation once the real-time interaction between the product's physical space and cyber space is constructed.

In the context of smart PSS, smart products are connected to each other via the technological infrastructure with forming networked physical platforms (Li et al., 2017; Porter and Heppelmann, 2014). A large amount of data generated from the operation of SCPs is converted to smart data (knowledge or wisdom) using big data analytic tool and artificial intelligence (Ding et al., 2019;

Rymaszewska et al., 2017). These smart data can provide insightful description, diagnosis, prediction and decision-making to optimize the operation of relevant goods, stakeholders, and business (Siow et al., 2018). In this respect, the SCPs can be regarded as interactive interfaces set between SCPs and SCPs, SCPs and users, SCPs and environment, SCPs and infrastructure (Ardolino et al., 2018; Siegel et al., 2018). Therefore, the delivery scope of service in the context of smart PSS has expanded from the conventional product operation lifecycle to broader user activity cycle (Chen et al., 2020). Smart PSS enables the key activity elements (e.g., activity resources and user action) to be perceptible, diagnosable, predictable, controllable and optimizable with the application of smart technologies (Ding et al., 2020; Siow et al., 2018). Prosperous scenarios can be identified for applying these technologies to create smart service, such as the smart service of helping the user to efficiently make a activity plan (e.g. smart driving route plan service for SCVs) (Baines and Lightfoot, 2014; Zheng et al., 2016), the smart service of optimizing user behavior (e.g. recommend proper driving action for reducing oil consumption) (Caveney and Dunbar, 2012) and the smart service of dynamic resource supply (e.g. reserve a fuel filling service proactively) (He et al., 2014).

From the previous research, the potential of smart PSS in delivering added benefit and excellent experience to customers in various activity scenarios have been widely acknowledged. Although this potential has triggered more value opportunities and service business, it also has brought with new challenges towards the development, implementation and operation of smart PSS (Zheng et al., 2019). For specific PSS development, requirement is acknowledged as a critical success factor (Song, 2017). From the service-dominant logic (Z. Liu et al., 2019), smart service requirement orienting to the user activity can be defined as a request that the service fulfills certain smart analytic capabilities or functions to make the key activity elements be smarter and present better performance (Chen et al., 2020). The degree of the designed product-extension service to the customers satisfaction depends on the implementation results of the identification and evaluation of service requirements (Song and Cao, 2017). Chang et al. (2019) stated that the user-centric requirement is a critical driving force for the development of user experience-oriented smart PSS. In the proposed design framework for the IoT-based smart PSS of route optimization system (Shao et al., 2019), the user requirements were considered as the value source of the system development. Thus, the appropriate identification, accurate evaluation and effective mapping of UAO-SSRs are critical to acquire a feasible design solution of UAO-SS concept (Wang et al., 2019).

## 2.2. Service requirement identification for smart PSS

Service requirement identification plays a key role in successful service concept design for a smart PSS (Liu and Ming, 2019). The identification task is to recognize the requirements' source and capture the requirements based on some mapping tool or elicitation model (Song and Cao, 2017). The previous research mainly focuses on the traditional PSS while not considering the context of smart PSS (Qu et al., 2016). Most the existing research contains scant study of the requirement elicitation for smart PSS (Wang et al., 2019). In this section, the literature review concerning requirement elicitation in both the context of traditional PSS and smart PSS are separately introduced as follows.

For the traditional PSS requirement, Hussain et al. (2012) developed a framework in utilization of system-in-use (rather than just product-in-use) data from in-service records to generate deeper customer requirement without considering the involvement of the other stakeholders. Ota et al. (2013) proposed a service planning method to extract customers' potential requirements for a

traditional physical PSS. Long et al. (2013) presented a qualitative method to collect customers' vague functional and perceptual needs. Song et al. (2013) elicited the customers' requirements through developing an industrial customer activity cycle model for physical industrial PSS, without considering the impact of smart technologies on the customer activity content. Moreover, Yang et al. (2017) developed a sustainability-based value requirement elicitation framework from a value uncaptured perspective to help firms recognize the sustainable value factors of PSS business model. Furtherly, Chen et al. (2019) proposed a Product Value State Model (PVSM) which incorporates five value forms: value captured, value failed, value missed, value deteriorated and value surplus, to elicit the value requirement of product use lifecycle for sustainable PSS. These methods are mainly applied for the traditional PSS, while not considering the context of smart PSS.

For the smart PSS requirement, Liu and Ming (2019) modified a value stream mapping tool that is adaptive to the environment of various interaction between smart services and users, and used it to capture the smart PSS requirement. Furtherly, Z. Liu et al. (2019) developed a conceptual model of SVFN in order to identify the co-creative value propositions for smart PSS. Moreover, Wang et al. (2019) proposed a data-driven graph-based requirement elicitation framework for the smart PSS, in which the context-product-service information is linking with the edges and nodes in-between them. In addition, Chang et al. (2019) proposed a user-centric analysis model for requirement identification in development of smart PSS. However, in the previous literatures regarding the smart PSS, the requirement identification methods rarely consider application and effect of the advanced smart technologies. Since the smartness level of product-extension service depends on the used smart capability (Siow et al., 2018), the identification of service requirement for user activity should take the activity elements and required smart capability into an appropriate mapping relationship.

## 2.3. Service requirement evaluation for smart PSS

Requirement evaluation provides critical guidance for designers to make optimal decision for subsequent business model planning and service modules configuration (Song and Sakao, 2017). It is thus crucial to use proper approach to prioritizing the identified service requirement (Sakao and Lindahl, 2012). The evaluation process of service requirement for smart PSS can be regarded a group MADM process, in which 5–10 experts are usually invited to complete the designed questionnaires due to scanty data and short timeframe (Gordijn and Akkermans, 2003). Some typical MADM methods have been widely used in PSS requirement evaluation. For instance, De Felice and Petrillo (2010) applied AHP approach to rank customers' requirements in a well-organized structure. Zhou et al. (2008) utilized ANP method to consider the interrelationship between PSS requirements. Hu et al. (2012) prioritized the PSS sustainability evaluation criteria by using fuzzy Delphi and AHP method. Shimomura and Sakao (2007) used the classical DEMATEL method for PSS requirement evaluation in terms of the dependence of function parameters. Pan and Nguyen (2015) developed a DEMATEL approach for prioritizing the PSS evaluation criteria. Tian et al. (2018) adopted a fuzzy BWM method that is proposed by (Guo and Zhao, 2017; Rezaei, 2015) to evaluate the customers' requirement of smart bike sharing service concept. Compared with the widely used matrix-based methods AHP, ANP and DEMATEL, the recently proposed vector-based method BWM presents several advantages (Rezaei, 2015, 2016): (1) requires fewer comparisons; for BWM, only  $2n-3$  comparisons are needed ( $n$  denotes the number of criteria), while for AHP  $n(n-1)/2$  comparisons are needed, for DEMATEL  $n(n-1)$  comparisons are required. (2) The final weights

with BWM present higher consistency compared to AHP. (3) It can be easy for BWM to be combined with other methods for purpose of handling the decision uncertainty. After the birth of BWM, its feasibility has been verified in many fields (Gupta, 2018; Gupta and Barua, 2017; Hafezalkotob and Hafezalkotob, 2017; H. C. Liu et al., 2019; Rezaei et al., 2016). For example, Rezaei et al. (2016) integrated the BWM to develop a supplier selection life cycle approach. Gupta and Barua (2017) applied the BWM for supplier selection among SMEs based on the green innovation ability.

However, the crisp BWM cannot be capable to manipulate the vagueness of the linguistic expression and the diversity of the group preferences which are involved in the group evaluation process for service requirements. Some research has attempted to integrate the fuzzy logic or rough set theory into the crisp method to handle the evaluation uncertainty. For instances, Guo and Zhao (2017) integrated the triangular fuzzy set into the BWM to handle the experts' linguistic ambiguousness so as to obtain more realistic results. Tian et al. (2018) applied the triangular fuzzy BWM to prioritize the customers' requirements of smart bike sharing service system while considering the qualitative judgements. H. C. Liu et al. (2019) integrated the interval-valued intuitionistic fuzzy set into the BWM for criteria prioritization of sustainable supplier selection under environment of linguistic uncertainty. These applications of fuzzy logic in BWM has demonstrated the feasibility of fuzzy set in handling the intrapersonal linguistic vagueness. However, the fuzzy logic cannot be capable of manipulating the interpersonal randomness and diversity. Thus, Stević et al. (2017) combined the rough set with BWM to handle the group preference diversity under group decision environment for the wagons selection. The rough set has also been used in many other MCDM methods to obtain more objective and realistic results, such as rough DEMATEL (Song and Cao, 2017), rough AHP (Song et al., 2013), rough TOPSIS (Li et al., 2018), etc. Nevertheless, rough set is not feasible for handling the intrapersonal linguistic vagueness, while most the DMs' judgements are ambiguous and qualitative. Moreover, the previous research concerning BWM rarely consider the intrapersonal vagueness and interpersonal variances at the same time.

Therefore, to fill these gaps, this study integrates the fuzzy set, rough set, and BWM into a hybrid approach to prioritizing the UAO-SSRs for smart PSS, with objective of obtaining accurate and reliable results under the intrapersonal and interpersonal uncertain environment.

### 3. The proposed framework for identifying and evaluating UAO-SSRs of smart PSS

#### 3.1. Overview of the proposed framework

This paper proposes an integrated framework that involves identification method and evaluation method for the smart service requirements of smart PSS. As shown in Fig. 1, the whole framework includes two stages: Stage I: Identification method of UAO-SSRs for smart PSS, and Stage II: Evaluation method of UAO-SSRs for smart PSS based on the proposed rough-fuzzy BWM. The detailed description for the proposed identification method and evaluation approach are presented in below.

#### 3.2. Identification method of UAO-SSRs for smart PSS

Identification of UAO-SSRs for smart PSS is regarded as an essential starting step of concept development and business model design of UAO-SPSS. This section firstly introduces a conceptual framework for identifying the UAO-SSRs. Based on the proposed framework, the elicitation and mapping roadmap of UAO-SSRs is

described.

##### 3.2.1. Framework for identifying UAO-SSRs

This section proposes a conceptual framework to systematically identify the UAO-SSRs. As shown in Fig. 2, the proposed cubic framework consists of three critical dimensional axis. The three axis separately denotes the key elements of user activity, user activity cycle and smart data analytic capability. The detailed descriptions about the components of the framework are presented as follows:

**User activity cycle:** In the proposed framework, the user activity cycle consists of three phases: beginning of cycle (BOC), middle of cycle (MOC) and end of cycle (EOC), in which the SCPs can be regarded as an interactive interface. This interface can be used to collect raw activity data, and deliver valuable service to users. In the BOC phase, since users mainly focus on making an activity plan or schedule, this phase is named as schedule. In the MOC phase, i.e. the execution phase of a specific activity, all related activities are undertaking, such as the resource supply, user action and process implementation. In the EOC phase, the activity process is approaching to an end. In the three phases, the data, information and knowledge relevant with the activity elements (resources, process, environment and behavior) can be converted into smart service for purpose of enabling the activity to be more perceptible, controllable, optimizable and improvable. These service requirements lead to a strong need of the smart data analytic capabilities that can provide description, diagnosis, discovery, prediction and prescription of user's activity.

**Four key activity elements:** Orienting to the user activity cycle, four constituted essential elements are identified as: environment, resources, process and action. Environment refers to the circumstance around which the activity take place. Users always expect the environment to be less influential towards their activity, and the activity has slight impact on the environment as possible. Resources are the requested tangible and intangible resources for completing the user activity. Users always expect to have a more efficient supply, higher utilization efficiency and lower resource consumption. Process can be described as a set of actions or steps taken to achieve a particular end. A flexible and convenient activity process can create better experience for users and contribute to a higher activity efficiency. In addition, action mainly represents the user's behavior or fact that is done for a specific aim. User's action or behavior in the activity process has a determined effect on the final activity result. The smarter the action is, the better achievements the activity can acquire.

**Smart data analytic capability hierarchy and smart data value chain:** Fig. 2 depicts how the smart data analytic capability match within the smart data value chain (Bernstein, 2011), which is a general framework used to describe the roadmap from original data to smartness. The seven leveled classification (Siow et al., 2018) of the analytic capability provides foundation to clarify the capability required for acquiring data value. Such classification make it easy to understand what the aim of each data analysis is. The smart data value chain starts with the raw data. These data is perceived and collected through the sensors and communicators installed in the SCPs, examples of which are physical signals, video pictures, and devices' voice. The collection of raw data require the smart capabilities of real-time perception and interactive connection. These capabilities help the users to digitalize what happened to the actual SCPs and the key elements in the activity cycle. They support to transform the realistic facts to meaningful data. Information presents interpreted data with related context, which are obtained from descriptive analysis. For instance, the environmental temperature is real-time monitored and represented by descriptive analytics: an average over a month. In the context of smart PSS, it



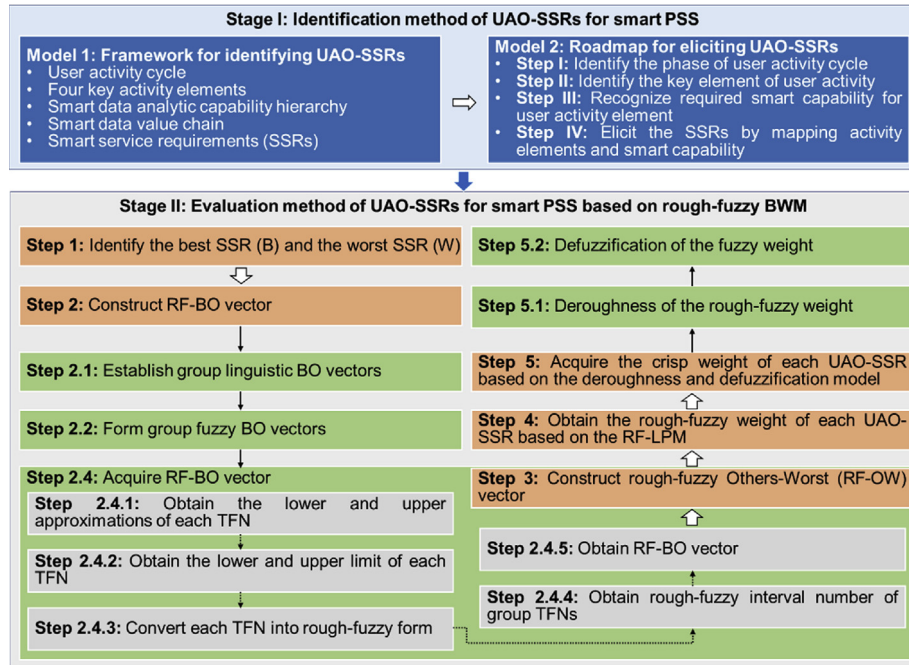


Fig. 1. The proposed framework for identifying and evaluating UAO-SSRs of smart PSS.

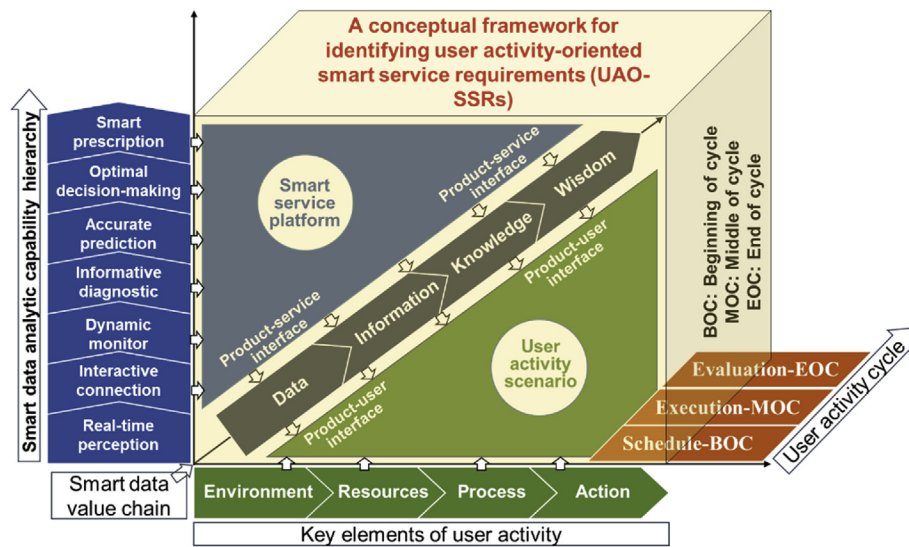


Fig. 2. The proposed conceptual framework for identifying UAO-SSRs.

requests the capability of descriptive analytics and dynamic monitor to acquire information of the activity elements. These capabilities help us to visualize what happened to the key elements in user activity and understand the real states of the elements. In addition, knowledge is information with more understanding about the hidden reason for the perceived facts of the user activity. To obtain the knowledge about the user activity, the smart capabilities of informative diagnostic and insightful discovery are requested. These capabilities can be used to illustrate why something has happened and find out the root cause and explanation for the perceived data. Moreover, wisdom is more like knowledge with insight or foresight, for example, discovering a specific trend of traffic status in the driving route of vehicle and projecting it across future months while providing dynamic route scheduling solutions for a diary driving based on these predictions. In order to obtain

wisdom regarding the key elements of user activity, the capabilities of accurate prediction, optimal decision-making and smart prescription are needed to answer the questions: “what is likely to happen” and “what should be to do”. These capabilities realize the aims based on the predictive and prescriptive analytics of the past data and knowledge.

**Smart service requirements (SSRs):** As mentioned above, the identified four key elements, i.e., environment, resources, process and action, co-constitute the user activity. Smart analytic capabilities can deliver users the value of data, information, knowledge and wisdom in the context of user activity. Such value is transferred through interactive interfaces between the product and service, and between the product and user. The interfaces are formed by leveraging SCPs as media and communicators. Using the smart capabilities transformed from the smart technologies (e.g. IoT, big

data analytics and AI) (Rymaszewska et al., 2017), the key activity elements are enabled to be perceptible, diagnosable, interpretable and predictable (Li et al., 2017). Thus, smart service can be understood like a value proposition for providing the smart analytic capabilities to users, with objective of obtaining more customer value, such as higher efficiency of resource supply, reduction of resource consumption, more flexible activity process and higher adaptiveness to the environment. In this respect, the smart service requirement can be defined as a request that the service fulfills certain smart analytic capabilities or functions to make the key elements be smarter and present better performance. The smart service requirements in different activity phases are identified by mapping the key elements with the smart data analytic capability hierarchy.

### 3.2.2. Roadmap for eliciting UAO-SSRs

Based on the conceptual framework proposed in Section 3.2.2, an implementation roadmap can be developed to elicit the new smart service requirements orienting to each activity element. As shown in Fig. 3, the proposed roadmap for eliciting UAO-SSRs consists of four steps, i.e., identify the phase of user activity cycle, identify the key element of user activity, recognize required smart capability for user activity element and map the smart service requirements. In the first step, the task is to determine the activity phase and the scope for requirement elicitation. Generally, the smart data analytic capability required for the elements in different phase differ with each other. The second step is to determine the target element that will be mapped within the smart capability hierarchy. Then, the third step is to recognize the expected smart capability for the target element from the seven types of capability. Finally, the smart capability and target element can be combined to express one specific service requirement. Some examples are described as follows:

Fig. 3 takes three SSRs, i.e. SSR1: predict user behavior states, SSR2: monitoring real-time user activity resources need and SSR3: smart sensing network reformation of user action, as examples to describe the elicitation process of SSRs. It can be seen that, the phase of MOC are considered as the service scope of the three SSRs. SSR1 and SSR3 are elicited from the element of activity action, with SSR2 from the resource element. The capability corresponding to SSR1 is accurate prediction that can be used to explain what will

happen to the user's behavior. SSR2 is identified by mapping the dynamic monitor capability to the supply need of activity resources. This service requirement is a request that aims to proactively perceive the users' resource need, and thus provide the resources in a flexible and agile manner. SSR3 is derived from the request of real-time perception of user action, and then converted into a need of reformatting a smart sensing network. For instance, the facial status and driving behavior can be perceived by an AI-based smart cameras installed in the smart vehicle. During the elicitation process, some methods are used to gather and collect the information from the users. These methods include, such as interview, questionnaires, focus groups and brainstorming.

Analogously, other SSRs can be elicited by using the similar mapping roadmap described as above. After all the SSRs are completely identified, they will be evaluated and prioritized using the proposed rough-fuzzy BWM method. The acquired prioritization of each SSR can provide critical basis for the designers and managers to configure the smart PSS scheme and allocate the resources for the smart service modules.

### 3.3. Evaluation method of UAO-SSRs for smart PSS based on rough-fuzzy BWM

In this section, an integrated method combining fuzzy set, rough set and BWM (Rezaei, 2015) is proposed to evaluate and prioritize the UAO-SSRs for smart PSS in group decision environment. The computational steps of the proposed model are presented as follows:

#### 3.3.1. Step 1: Identify the best SSR (B) and the worst SSR (W)

A decision-making group consisting of  $R$  DMs is invited to evaluate  $n$  UAO-SSRs. First, the DM group should select the best (most influential) and worst (least significant) SSR based on their common preferences. In case two or more SSRs are recognized as the best, or worst, the target best and worst SSR can be sorted arbitrarily.

#### 3.3.2. Step 2: Construct rough-fuzzy best-others (RF-BO) vector

**3.3.2.1. Step 2.1: Establish group linguistic BO vectors.** The  $s$ th ( $s = 1, 2, \dots, R$ ) DM is asked to use a linguistic variable to express the preference degree of the best service requirement  $SSR_B$  over the

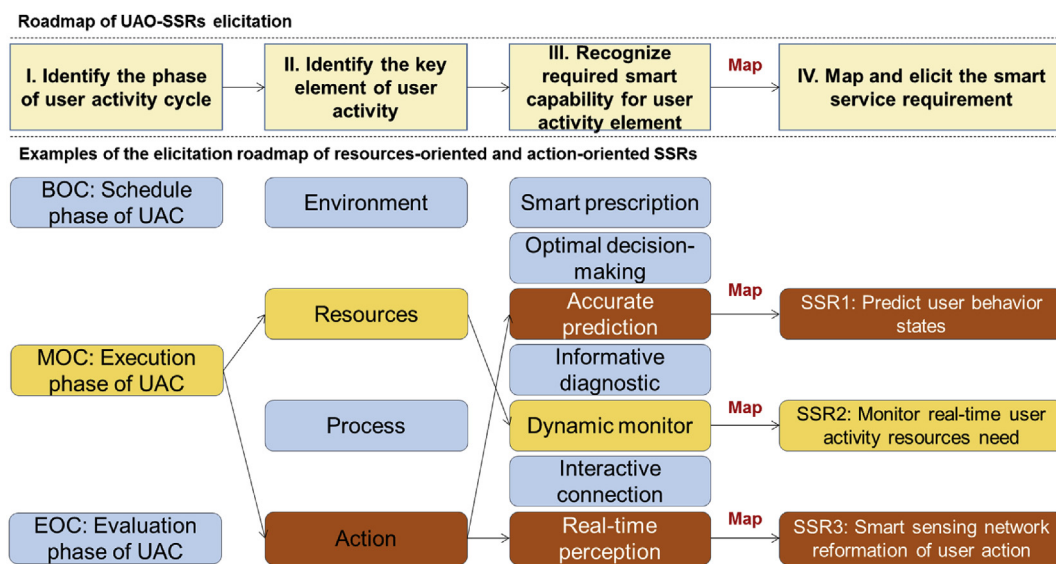


Fig. 3. Roadmap of UAO-SSRs elicitation.

other service requirement  $SSR_j$  ( $j = 1, 2, \dots, n$ ). The comparison judgement is denoted by  $a_{Bj}^s$ . Then the individual linguistic BO vector  $A_{BO}^s$  is formed as follows:

$$A_{BO}^s = [a_{B1}^s, a_{B2}^s, \dots, a_{Bj}^s, \dots, a_{Bn}^s]. \quad (1)$$

Through putting  $R$  linguistic BO vectors that are constructed by  $R$  DMs into one  $R \times n$  matrix, the group linguistic BO vectors  $A_{BO}$  can be formed as follows:

$$A_{BO} = \begin{matrix} A_{BO}^1 \\ A_{BO}^2 \\ \vdots \\ A_{BO}^R \end{matrix} \begin{bmatrix} SSR_1 & SSR_2 & \dots & SSR_n \\ a_{B1}^1 & a_{B2}^1 & \dots & a_{Bn}^1 \\ a_{B1}^2 & a_{B2}^2 & \dots & a_{Bn}^2 \\ \vdots & \vdots & \ddots & \vdots \\ a_{B1}^R & a_{B2}^R & \dots & a_{Bn}^R \end{bmatrix}. \quad (2)$$

**3.3.2.2. Step 2.2: Form group fuzzy BO vectors.** According to Pamučar et al. (2018), the linguistic variables “Equally (E)”, “Low (L)”, “Medium (M)”, “High (H)” and “Very high (VH)” can be respectively converted to triangular fuzzy number: (1, 1, 1), (0.5, 1, 1.5), (1.5, 2, 2.5), (2.5, 3, 3.5) and (3.5, 4, 4). Following this fuzzy scale, the element  $a_{Bj}^s$  of the linguistic BO vector  $A_{BO}^s$  is transformed to  $\tilde{a}_{Bj}^s = (l_{Bj}^s, m_{Bj}^s, u_{Bj}^s)$ , where  $l_{Bj}^s$ ,  $m_{Bj}^s$  and  $u_{Bj}^s$  separately denotes the low boundary, medium boundary and up boundary of the TFN, and  $\tilde{a}_{BB}^s = (1, 1, 1)$ . Then, the fuzzy individual BO vector  $\tilde{A}_{BO}^s$  can be established as follows:

$$\tilde{A}_{BO}^s = [\tilde{a}_{B1}^s, \tilde{a}_{B2}^s, \dots, \tilde{a}_{Bj}^s, \dots, \tilde{a}_{Bn}^s] \quad (3)$$

By separately convert each linguistic vector  $A_{BO}^s$  within the group linguistic vectors into fuzzy vector, the group fuzzy BO vectors  $\tilde{A}_{BO}$  can be formed as follows:

$$\tilde{A}_{BO} = \begin{matrix} \tilde{A}_{BO}^1 \\ \tilde{A}_{BO}^2 \\ \vdots \\ \tilde{A}_{BO}^R \end{matrix} \begin{bmatrix} SSR_1 & SSR_2 & \dots & SSR_n \\ \tilde{a}_{B1}^1 & \tilde{a}_{B2}^1 & \dots & \tilde{a}_{Bn}^1 \\ \tilde{a}_{B1}^2 & \tilde{a}_{B2}^2 & \dots & \tilde{a}_{Bn}^2 \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{a}_{B1}^R & \tilde{a}_{B2}^R & \dots & \tilde{a}_{Bn}^R \end{bmatrix}. \quad (4)$$

Meanwhile, the group BO vectors  $\hat{A}_{BO}$  can be expressed as follows:

$$\hat{A}_{BO} = [\hat{a}_{B1}, \hat{a}_{B2}, \dots, \hat{a}_{Bj}, \dots, \hat{a}_{Bn}] \quad (5)$$

where  $\hat{a}_{Bj} = (\hat{l}_{Bj}, \hat{m}_{Bj}, \hat{u}_{Bj})$ ,  $\hat{l}_{Bj} = \{l_{Bj}^1, \dots, l_{Bj}^R\}$ ,  $\hat{m}_{Bj} = \{m_{Bj}^1, \dots, m_{Bj}^R\}$ ,  $\hat{u}_{Bj} = \{u_{Bj}^1, \dots, u_{Bj}^R\}$ , and the group TFNs can also be expressed as  $\hat{a}_{Bj} = \{\tilde{a}_{Bj}^1, \dots, \tilde{a}_{Bj}^R\}$ .

**3.3.2.3. Step 2.3: Acquire RF-BO vector.** In this step, the group fuzzy vectors formed by  $R$  DMs will be converted into a rough-fuzzy vector based on the rough-fuzzy number proposed by Chen et al. (2020). The rough-fuzzy operation approach is applied to transform the group TFNs  $\hat{a}_{Bj} = (\hat{l}_{Bj}, \hat{m}_{Bj}, \hat{u}_{Bj})$  to rough-fuzzy number form  $RF(\hat{a}_{Bj})$ . The operation procedure are presented as follows:

(1) Step 2.3.1: Obtain the lower and upper approximations of each TFN

For the group TFNs  $\hat{a}_{Bj} = \{\tilde{a}_{Bj}^1, \dots, \tilde{a}_{Bj}^R\}$ , the lower and upper

approximations of the sth TFN  $\tilde{a}_{Bj}^s$  can be obtained as follows:

Lower approximation:

$$\underline{Apr}(\tilde{a}_{Bj}^s) = \cup \{ \tilde{a}_{Bj}^t \in \hat{a}_{Bj} / \tilde{a}_{Bj}^t \leq \tilde{a}_{Bj}^s \} \quad (6)$$

Upper approximation:

$$\overline{Apr}(\tilde{a}_{Bj}^s) = \cup \{ \tilde{a}_{Bj}^t \in \hat{a}_{Bj} / \tilde{a}_{Bj}^t \geq \tilde{a}_{Bj}^s \} \quad (7)$$

where  $\underline{Apr}(\tilde{a}_{Bj}^s)$  and  $\overline{Apr}(\tilde{a}_{Bj}^s)$  are respectively the lower and the upper approximation of the TFN  $\tilde{a}_{Bj}^s$ .

(2) Step 2.3.2: Obtain the lower and upper limit of each TFN

The lower and upper limit of  $\tilde{a}_{Bj}^s$  are separately denoted by  $\underline{Lim}(\tilde{a}_{Bj}^s)$  and  $\overline{Lim}(\tilde{a}_{Bj}^s)$  as follows:

$$\begin{aligned} \underline{Lim}(\tilde{a}_{Bj}^s) &= (\underline{Lim}(l_{Bj}^s), \underline{Lim}(m_{Bj}^s), \underline{Lim}(u_{Bj}^s)) \\ &= \left( \frac{1}{N_s^L} \sum_{k=1}^{N_s^L} x_k^l, \frac{1}{N_s^L} \sum_{k=1}^{N_s^L} x_k^m, \frac{1}{N_s^L} \sum_{k=1}^{N_s^L} x_k^u \right) \end{aligned} \quad (8)$$

$$\begin{aligned} \overline{Lim}(\tilde{a}_{Bj}^s) &= (\overline{Lim}(l_{Bj}^s), \overline{Lim}(m_{Bj}^s), \overline{Lim}(u_{Bj}^s)) \\ &= \left( \frac{1}{N_s^U} \sum_{k=1}^{N_s^U} y_k^l, \frac{1}{N_s^U} \sum_{k=1}^{N_s^U} y_k^m, \frac{1}{N_s^U} \sum_{k=1}^{N_s^U} y_k^u \right) \end{aligned} \quad (9)$$

where  $x_k^l$ ,  $x_k^m$ , and  $x_k^u$  are respectively the elements of lower approximation for low boundary, medium boundary, and up boundary of TFN  $\tilde{a}_{Bj}^s$ ,  $y_k^l$ ,  $y_k^m$ , and  $y_k^u$  are respectively the elements of upper approximation for low boundary, medium boundary, and up boundary of TFN  $\tilde{a}_{Bj}^s$ ,  $N_s^L$  and  $N_s^U$  are the number of objects included in the lower approximation and upper approximation of TFN  $\tilde{a}_{Bj}^s$ .

(3) Step 2.3.3: Convert each TFN into rough-fuzzy form

The rough-fuzzy number form  $RF(\tilde{a}_{Bj}^s)$  of  $\tilde{a}_{Bj}^s$  can be described as follows:

$$\begin{aligned} RF(\tilde{a}_{Bj}^s) &= [\tilde{a}_{Bj}^{sL}, \tilde{a}_{Bj}^{sU}] \\ &= \left[ (l_{Bj}^{sL}, m_{Bj}^{sL}, u_{Bj}^{sL}), (l_{Bj}^{sU}, m_{Bj}^{sU}, u_{Bj}^{sU}) \right]. \end{aligned} \quad (10)$$

Also, the rough-fuzzy number  $RF(\tilde{a}_{Bj}^s)$  can be written as follows:

$$\begin{aligned} RF(\tilde{a}_{Bj}^s) &= (RN(l_{Bj}^s), RN(m_{Bj}^s), RN(u_{Bj}^s)) \\ &= \left( [l_{Bj}^{sL}, l_{Bj}^{sU}], [m_{Bj}^{sL}, m_{Bj}^{sU}], [u_{Bj}^{sL}, u_{Bj}^{sU}] \right). \end{aligned} \quad (11)$$

$$[\tilde{a}_{Bj}^{sL}, \tilde{a}_{Bj}^{sU}] = [\underline{Lim}(\tilde{a}_{Bj}^s), \overline{Lim}(\tilde{a}_{Bj}^s)]. \quad (12)$$

$$(l_{Bj}^{sL}, m_{Bj}^{sL}, u_{Bj}^{sL}) = (\underline{Lim}(l_{Bj}^s), \underline{Lim}(m_{Bj}^s), \underline{Lim}(u_{Bj}^s)). \quad (13)$$

$$(l_{Bj}^{sU}, m_{Bj}^{sU}, u_{Bj}^{sU}) = (\overline{Lim}(l_{Bj}^s), \overline{Lim}(m_{Bj}^s), \overline{Lim}(u_{Bj}^s)). \quad (14)$$

where  $\tilde{a}_{Bj}^{sL}$  and  $\tilde{a}_{Bj}^{sU}$  are the lower limit and upper limit of rough-fuzzy number  $RF(\tilde{a}_{Bj}^s)$ ;  $l_{Bj}^{sL}$  and  $l_{Bj}^{sU}$  are the lower limit and upper limit of rough number  $RN(l_{Bj}^s)$ ;  $m_{Bj}^{sL}$  and  $m_{Bj}^{sU}$  are the lower limit and upper limit of rough number  $RN(m_{Bj}^s)$ ;  $u_{Bj}^{sL}$  and  $u_{Bj}^{sU}$  are the lower limit and upper limit of rough number  $RN(u_{Bj}^s)$ .

(4) Step 2.3.4: Obtain rough-fuzzy interval number of group TFNs

The rough-fuzzy interval number  $RF(\hat{a}_{Bj})$  is acquired by aggregating group rough-fuzzy numbers  $RF(\hat{a}_{Bji})$  based on the rough computation principles as follows:

$$RF(\hat{a}_{Bj}) = (RN(\hat{l}_{Bj}), RN(\hat{m}_{Bj}), RN(\hat{u}_{Bj})) \\ = ([l_{Bj}^L, l_{Bj}^U], [m_{Bj}^L, m_{Bj}^U], [u_{Bj}^L, u_{Bj}^U]). \quad (15)$$

$$[l_{Bj}^L, l_{Bj}^U] = \left[ \frac{1}{R} \sum_{s=1}^R l_{Bjs}^L, \frac{1}{R} \sum_{s=1}^R l_{Bjs}^U \right]. \quad (16)$$

$$[m_{Bj}^L, m_{Bj}^U] = \left[ \frac{1}{R} \sum_{s=1}^R m_{Bjs}^L, \frac{1}{R} \sum_{s=1}^R m_{Bjs}^U \right]. \quad (17)$$

$$[u_{Bj}^L, u_{Bj}^U] = \left[ \frac{1}{R} \sum_{s=1}^R u_{Bjs}^L, \frac{1}{R} \sum_{s=1}^R u_{Bjs}^U \right]. \quad (18)$$

where  $l_{Bj}^L$  and  $l_{Bj}^U$  are the lower and upper limit of rough interval  $RN(\hat{l}_{Bj})$ ;  $m_{Bj}^L$  and  $m_{Bj}^U$  are the lower and upper limit of rough interval  $RN(\hat{m}_{Bj})$ ;  $u_{Bj}^L$  and  $u_{Bj}^U$  are the lower and upper limit of rough interval  $RN(\hat{u}_{Bj})$ .

The operation principles for the rough-fuzzy number are derived by integrating the operation principles of triangular fuzzy number (Chen et al., 2019) and rough number (Zhai et al., 2008), presented as follows:

Addition or subtraction of the rough-fuzzy numbers:

$$RF(\hat{a}_1) \pm RF(\hat{a}_2) = (RN(\hat{l}_1) \pm RN(\hat{l}_2), RN(\hat{m}_1) \pm RN(\hat{m}_2), RN(\hat{u}_1) \pm RN(\hat{u}_2)) \\ = ([l_1^L \pm l_2^L, l_1^U \pm l_2^U], [m_1^L \pm m_2^L, m_1^U \pm m_2^U], [u_1^L \pm u_2^L, u_1^U \pm u_2^U]). \quad (19)$$

Multiplication of the rough-fuzzy numbers:

$$RF(\hat{a}_1) \times RF(\hat{a}_2) = (RN(\hat{l}_1) \times RN(\hat{l}_2), RN(\hat{m}_1) \times RN(\hat{m}_2), RN(\hat{u}_1) \times RN(\hat{u}_2)) \\ = ([l_1^L \times l_2^L, l_1^U \times l_2^U], [m_1^L \times m_2^L, m_1^U \times m_2^U], [u_1^L \times u_2^L, u_1^U \times u_2^U]). \quad (20)$$

Division of the rough-fuzzy numbers:

$$RF(\hat{a}_1) \div RF(\hat{a}_2) = (RN(\hat{l}_1) \div RN(\hat{l}_2), RN(\hat{m}_1) \div RN(\hat{m}_2), RN(\hat{u}_1) \div RN(\hat{u}_2)) \\ = ([l_1^L \div l_2^L, l_1^U \div l_2^U], [m_1^L \div m_2^L, m_1^U \div m_2^U], [u_1^L \div u_2^L, u_1^U \div u_2^U]). \quad (21)$$

(5) Step 2.3.5: Obtain RF-BO vector

After the group fuzzy TFNs  $\hat{a}_{Bj} = (\hat{l}_{Bj}, \hat{m}_{Bj}, \hat{u}_{Bj})$  are converted to rough-fuzzy number form  $RF(\hat{a}_{Bj})$ , the group fuzzy BO vectors  $\hat{A}_{BO}$  can be converted to rough-fuzzy BO (RF-BO) vector  $RF(\hat{A}_{BO})$  as

follows:

$$RF(\hat{A}_{BO}) = [RF(\hat{a}_{B1}), RF(\hat{a}_{B2}), \dots, RF(\hat{a}_{Bj}), \dots, RF(\hat{a}_{Bn})]_{1 \times n}. \quad (22)$$

### 3.3.3. Step 3: Construct rough-fuzzy Others-Worst (RF-OW) vector

Besides, the decision-making group is also asked to use linguistic variables to express the preference degree of the other service requirement  $SSR_j$  ( $j = 1, 2, \dots, n$ ) over the worst service requirement  $SSR_B$ . Following the procedures described in Step 2, the group linguistic Others-Worst vectors can be converted to the rough-fuzzy Others-Worst (RF-OW) vector, shown as follows:

$$RF(\hat{A}_{OW}) = [RF(\hat{a}_{1W}), RF(\hat{a}_{2W}), \dots, RF(\hat{a}_{jW}), \dots, RF(\hat{a}_{nW})]_{1 \times n}. \quad (23)$$

where

$$RF(\hat{a}_{jW}) = ([l_{jW}^L, l_{jW}^U], [m_{jW}^L, m_{jW}^U], [u_{jW}^L, u_{jW}^U]). \quad (24)$$

### 3.3.4. Step 4: obtain the rough-fuzzy weight of each UAO-SSR based on the RF-LPM

This step is aiming to determine the optimal weights of the UAO-SSRs in terms of rough-fuzzy interval number form, which should be in line with the case that the difference in the maximum absolute values for each  $SSR_j$  is minimum. It is expressed as follows:

$$\min \max_j \left\{ \left| \frac{RF(w_B)}{RF(w_j)} - RF(\hat{a}_{Bj}) \right|, \left| \frac{RF(w_j)}{RF(w_W)} - RF(\hat{a}_{jW}) \right| \right\}. \quad (25)$$

where  $RF(w_j)$ ,  $RF(w_B)$  and  $RF(w_W)$  respectively denotes the optimal



rough-fuzzy weight of the  $j$ th, best and worst service requirement  $SSR_j$ ,  $SSR_B$  and  $SSR_W$ . In addition, the rough-fuzzy weight is expressed in rough-fuzzy form:

$$RF(w_j) = ([l_j^{wL}, l_j^{wU}], [m_j^{wL}, m_j^{wU}], [u_j^{wL}, u_j^{wU}]). \quad (26)$$

For all the element of the rough-fuzzy weights of  $SSR_j$ , it can be seen that the lower limit of each boundary is always less than or equal to the corresponding upper limit, and the low boundary, medium boundary and up boundary are always ordered in ascending sequence. Therefore, some of the constraints for the rough-fuzzy weight can be described as follows:

$$\begin{cases} l_j^{wL} \leq l_j^{wU}, m_j^{wL} \leq m_j^{wU}, u_j^{wL} \leq u_j^{wU} \\ l_j^{wL} \leq m_j^{wL} \leq u_j^{wL}, l_j^{wU} \leq m_j^{wU} \leq u_j^{wU} \\ 0 \leq l_j^{wL}, l_j^{wU}, m_j^{wL}, m_j^{wU}, u_j^{wL}, u_j^{wU} \leq 1 \end{cases} \quad (27)$$

In addition, the corresponding crisp value  $w_j$  for each rough-fuzzy weight  $RF(w_j)$  generally drop in the interval of  $[m_j^{wL}, m_j^{wU}]$ . That is to say,  $l_j^{wL} \leq m_j^{wL} \leq w_j \leq m_j^{wU} \leq u_j^{wU}$ . Moreover, since the sum of all crisp weights  $\sum_{j=1}^n w_j = 1$ , it can be thus found that  $\sum_{j=1}^n l_j^{wL} \leq \sum_{j=1}^n m_j^{wL} \leq 1$  and  $1 \leq \sum_{j=1}^n m_j^{wU} \leq \sum_{j=1}^n u_j^{wU}$ . Also, the sum of all components within the rough-fuzzy weight of each SSR (except the best SSR) is less than or equal to the one of best SSR, and the one of each SSR is more than or equal to the one of worst SSR. That can be expressed as:  $sum(RF(w_j)) \leq sum(RF(w_B))$  and  $sum(RF(w_j)) \geq sum(RF(w_W))$ , where  $sum(RF(w_j)) = l_j^{wL} + l_j^{wU} + m_j^{wL} + m_j^{wU} + u_j^{wL} + u_j^{wU}$ .

Based on the identified conditions and constraints for the rough-fuzzy weights, the RF-LPM is constructed to determine the optimal weights for the service requirements, presented as follows:

$$\min \max_j \left\{ \left| \frac{RF(w_B)}{RF(w_j)} - RF(\hat{a}_{Bj}) \right|, \left| \frac{RF(w_j)}{RF(w_W)} - RF(\hat{a}_{jW}) \right| \right\}$$

s.t.

$$\begin{cases} l_j^{wL} \leq l_j^{wU}, m_j^{wL} \leq m_j^{wU}, u_j^{wL} \leq u_j^{wU}; \\ l_j^{wL} \leq m_j^{wL} \leq u_j^{wL}, l_j^{wU} \leq m_j^{wU} \leq u_j^{wU}; \\ 0 \leq l_j^{wL}, l_j^{wU}, m_j^{wL}, m_j^{wU}, u_j^{wL}, u_j^{wU} \leq 1; \\ sum(RF(w_j)) \leq sum(RF(w_B)); \\ sum(RF(w_j)) \geq sum(RF(w_W)); \\ \sum_{j=1}^n l_j^{wL} \leq \sum_{j=1}^n m_j^{wL} \leq 1; \\ \sum_{j=1}^n m_j^{wU} \geq \sum_{j=1}^n u_j^{wU} \geq 1; \\ 1 \leq j \leq n. \end{cases} \quad (28)$$

Through combining Eqs. (15), (21), (24) and (26), Model (28) can be rewritten as follows:

$\min \delta$

s.t.

$$\begin{cases} \left| \frac{l_B^{wL}}{u_j^{wU}} - l_{Bj}^L \right| \leq \delta; \left| \frac{l_B^{wU}}{u_j^{wL}} - l_{Bj}^U \right| \leq \delta; \left| \frac{m_B^{wL}}{m_j^{wU}} - m_{Bj}^L \right| \leq \delta; \\ \left| \frac{s_B^{wU}}{m_j^{wL}} - m_{Bj}^U \right| \leq \delta; \left| \frac{u_B^{wL}}{l_j^{wU}} - u_{Bj}^L \right| \leq \delta; \left| \frac{u_B^{wU}}{l_j^{wL}} - u_{Bj}^U \right| \leq \delta; \\ \left| \frac{l_j^{wL}}{u_W^{wU}} - l_{jW}^L \right| \leq \delta; \left| \frac{l_j^{wU}}{u_W^{wL}} - l_{jW}^U \right| \leq \delta; \left| \frac{m_j^{wL}}{m_W^{wU}} - m_{jW}^L \right| \leq \delta; \\ \left| \frac{s_j^{wU}}{m_W^{wL}} - m_{jW}^U \right| \leq \delta; \left| \frac{u_j^{wL}}{l_W^{wU}} - u_{jW}^L \right| \leq \delta; \left| \frac{u_j^{wU}}{l_W^{wL}} - u_{jW}^U \right| \leq \delta; \\ l_j^{wL} \leq l_j^{wU}; m_j^{wL} \leq m_j^{wU}; u_j^{wL} \leq u_j^{wU}; \\ l_j^{wL} \leq m_j^{wL} \leq u_j^{wL}; l_j^{wU} \leq m_j^{wU} \leq u_j^{wU}; \\ 0 \leq l_j^{wL}, l_j^{wU}, m_j^{wL}, m_j^{wU}, u_j^{wL}, u_j^{wU} \leq 1; \\ sum(RF(w_j)) \leq sum(RF(w_B)); \\ sum(RF(w_j)) \geq sum(RF(w_W)); \\ \sum_{j=1}^n l_j^{wL}, \sum_{j=1}^n m_j^{wL} \leq 1; \\ \sum_{j=1}^n m_j^{wU}, \sum_{j=1}^n u_j^{wU} \geq 1; \\ 1 \leq j \leq n. \end{cases} \quad (29)$$

By solving Model (29), the optimal rough-fuzzy weights set of the UAO-SSRs  $RF(W) = [RF(w_1), RF(w_2), \dots, RF(w_j), \dots, RF(w_n)]_{1 \times n}$  and the optimal value  $\delta^*$  are obtained. The consistency of the obtained results will be checked based on [Pamućar et al. \(2018\)](#). If the consistency ratio do not satisfy the requirement, the original decision-making data will be modified to meet the requested consistency.

### 3.3.5. Step 5: acquire the crisp weight of each UAO-SSR based on the deroughness and defuzzification model

In order to prioritize the UAO-SSRs, it is necessary to obtain the crisp value from the determined rough-fuzzy weight of each service requirement. Since  $RF(w_j)$  is an interval-valued rough-fuzzy number, the process for obtaining crisp value includes two steps: deroughness and defuzzification. Therefore, in this section two models are introduced respectively for deroughness and defuzzification of  $RF(w_j)$ . The first model is proposed by [Song and Cao \(2017\)](#) to conduct deroughness of rough number, called as "deroughness model". The second model is CFCS (Converting Fuzzy data into Crisp Scores) defuzzification model ([Chang et al., 2011](#)).

**Table 1**

The codes and specific SSRs orienting to the activity cycle of self-driving tour for SVSS.

Codes	UAO-SSRs	Phase of UAC	Key element	Corresponding smart capability
SSR1	Service requirement of preliminary weather prediction along the tour route	BOC: Tour scheduling	Environment	The capability of accurate prediction
SSR2	Service requirement of automatically ordering hotel and tourist sites ticket	BOC: Tour scheduling	Resources	The capability of interactive connection
SSR3	Service requirement of preliminary route planning	BOC: Tour scheduling	Process	The capability of optimal decision-making
SSR4	Service requirement of grouping a driver partners team	BOC: Tour scheduling	Action	The capability of interactive connection
SSR5	Service requirement of monitoring the accidents in driving route	MOC: Tour execution	Environment	The capability of dynamic interactive connection
SSR6	Service requirement of predicting the traffic status in driving route	MOC: Tour execution	Environment	The capability of accurate prediction
SSR7	Service requirement of monitoring the refueling need	MOC: Tour execution	Resources	The capability of dynamic monitor
SSR8	Service requirement of recommending the refueling station	MOC: Tour execution	Resources	The capability of optimal decision-making
SSR9	Service requirement of dynamic predicting route change	MOC: Tour execution	Process	The capability of accurate prediction
SSR10	Service requirement of diagnosis of driver's behavior	MOC: Tour execution	Action	The capability of informative diagnostic
SSR11	Service requirement of monitoring drivers' mental status	MOC: Tour execution	Action	The capability of dynamic monitor
SSR12	Service requirement of alerting driver's unsafe behavior	MOC: Tour execution	Action	The capability of informative diagnostic
SSR13	Service requirement of predicting driver's behavior and status	MOC: Tour execution	Action	The capability of accurate prediction
SSR14	Service requirement of recommending optimal driving behavior	MOC: Tour execution	Action	The capability of optimal decision-making
SSR15	Service requirement of automatic guidance for parking	MOC: Tour execution	Action	The capability of interactive connection
SSR16	Service requirement of smart making tour photo album	EOC: Tour summary	Resources	The capability of interactive connection

**3.3.5.1. Step 5.1: Deroughness of the rough-fuzzy weight.** The rough-fuzzy weight can be expressed as  $RF(w_j) = (RN(l_j^w), RN(m_j^w), RN(u_j^w))$ , the crisp value of  $l_j^w, m_j^w, u_j^w$  can be obtained based on the following computing procedure which is described by taking the rough low boundary  $RN(l_j^w) = [l_j^{wL}, l_j^{wU}]$  as examples.

First, normalize the lower limit  $l_j^{wL}$  and upper limit  $l_j^{wU}$  of the rough low boundary  $RN(l_j^w)$  as follows:

$$\bar{l}_j^{wL} = (l_j^{wL} - \min_j l_j^{wL}) / \Delta_{\min}^{\max} \quad (30)$$

$$\bar{l}_j^{wU} = (l_j^{wU} - \min_j l_j^{wL}) / \Delta_{\min}^{\max} \quad (31)$$

$$\Delta_{\min}^{\max} = \max_j l_j^{wU} - \min_j l_j^{wL} \quad (32)$$

where  $\bar{l}_j^{wL}$  and  $\bar{l}_j^{wU}$  are the normalized form of the  $l_j^{wL}$  and  $l_j^{wU}$ , respectively.

Then, determine a total normal crisp value as follows:

$$\alpha_j = \frac{\bar{l}_j^{wL} \times (1 - \bar{l}_j^{wL}) + \bar{l}_j^{wU} \times \bar{l}_j^{wU}}{1 - \bar{l}_j^{wL} + \bar{l}_j^{wU}} \quad (33)$$

Finally, obtain the crisp value  $l_j^w$  for rough low boundary  $RN(l_j^w)$  as follows:

$$l_j^w = \min_j l_j^{wL} + \alpha_j \Delta_{\min}^{\max} \quad (34)$$

Analogously, the crisp value  $m_j^w$  and  $u_j^w$  for rough medium and up boundary can be acquired through the procedure above. The rough-fuzzy weight of each service requirement is thus converted to a fuzzy weight  $F(w_j) = (l_j^w, m_j^w, u_j^w)$ .

**3.3.5.2. Step 5.2: Defuzzification of the fuzzy weight.** The fuzzy weight  $F(w_j)$  can be defuzzified to a crisp value  $w_j$  by using the CFCS method as follows:

First, normalize the low boundary, medium boundary and up boundary as follows:

$$\bar{l}_j^w = (l_j^w - \min_j l_j^w) / \sigma_{\min}^{\max} \quad (35)$$

$$\bar{m}_j^w = (m_j^w - \min_j l_j^w) / \sigma_{\min}^{\max} \quad (36)$$

**Table 2**

The 8 DMs' linguistic BO and OW vectors.

BO	SSR1	SSR2	SSR3	SSR4	SSR5	SSR6	...	SSR13	SSR14	SSR15	SSR16
DM1	M	VH	L	H	M	M	...	M	E	M	H
DM2	L	H	E	H	H	H	...	E	L	M	M
DM3	M	H	M	H	H	H	...	M	M	H	H
DM4	L	VH	M	H	M	VH	...	E	L	L	M
DM5	M	H	H	H	M	VH	...	L	L	M	H
DM6	H	VH	H	M	L	H	...	M	E	M	H
DM7	L	H	M	H	H	VH	...	L	L	H	M
DM8	M	H	E	M	L	M	...	L	L	M	M
OW	SSR1	SSR3	SSR4	SSR5	SSR6	SSR7	...	SSR13	SSR14	SSR15	SSR16
DM1	M	H	L	M	M	H	...	M	VH	M	L
DM2	H	H	L	L	L	H	...	H	H	M	M
DM3	M	M	L	L	L	M	...	M	M	L	L
DM4	H	M	L	M	E	L	...	VH	VH	H	M
DM5	M	L	L	M	E	L	...	H	H	M	L
DM6	L	L	M	H	L	H	...	M	H	M	L
DM7	H	M	L	L	E	H	...	H	H	L	M
DM8	M	H	M	H	M	M	...	H	H	M	M

**Table 3**  
The group fuzzy BO and OW vectors.

BO	SSR1	SSR2	SSR3	SSR4	SSR5	SSR6	...	SSR13	SSR14	SSR15	SSR16
DM1	(1.5, 2, 2.5)	(3.5, 4, 4)	(0.5, 1, 1.5)	(2.5, 3, 3.5)	(1.5, 2, 2.5)	(1.5, 2, 2.5)	...	(1.5, 2, 2.5)	(1, 1, 1)	(1.5, 2, 2.5)	(2.5, 3, 3.5)
DM2	(0.5, 1, 1.5)	(2.5, 3, 3.5)	(1, 1, 1)	(2.5, 3, 3.5)	(2.5, 3, 3.5)	(2.5, 3, 3.5)	...	(1, 1, 1)	(0.5, 1, 1.5)	(1.5, 2, 2.5)	(1.5, 2, 2.5)
DM3	(1.5, 2, 2.5)	(2.5, 3, 3.5)	(1.5, 2, 2.5)	(2.5, 3, 3.5)	(2.5, 3, 3.5)	(2.5, 3, 3.5)	...	(1.5, 2, 2.5)	(1.5, 2, 2.5)	(2.5, 3, 3.5)	(2.5, 3, 3.5)
DM4	(0.5, 1, 1.5)	(3.5, 4, 4)	(1.5, 2, 2.5)	(2.5, 3, 3.5)	(1.5, 2, 2.5)	(3.5, 4, 4)	...	(1, 1, 1)	(0.5, 1, 1.5)	(0.5, 1, 1.5)	(1.5, 2, 2.5)
DM5	(1.5, 2, 2.5)	(2.5, 3, 3.5)	(2.5, 3, 3.5)	(2.5, 3, 3.5)	(1.5, 2, 2.5)	(3.5, 4, 4)	...	(0.5, 1, 1.5)	(0.5, 1, 1.5)	(1.5, 2, 2.5)	(2.5, 3, 3.5)
DM6	(2.5, 3, 3.5)	(3.5, 4, 4)	(2.5, 3, 3.5)	(1.5, 2, 2.5)	(0.5, 1, 1.5)	(2.5, 3, 3.5)	...	(1.5, 2, 2.5)	(1, 1, 1)	(1.5, 2, 2.5)	(2.5, 3, 3.5)
DM7	(0.5, 1, 1.5)	(2.5, 3, 3.5)	(1.5, 2, 2.5)	(2.5, 3, 3.5)	(2.5, 3, 3.5)	(3.5, 4, 4)	...	(0.5, 1, 1.5)	(0.5, 1, 1.5)	(2.5, 3, 3.5)	(1.5, 2, 2.5)
DM8	(1.5, 2, 2.5)	(2.5, 3, 3.5)	(1, 1, 1)	(1.5, 2, 2.5)	(0.5, 1, 1.5)	(1.5, 2, 2.5)	...	(0.5, 1, 1.5)	(0.5, 1, 1.5)	(1.5, 2, 2.5)	(1.5, 2, 2.5)
OW	SSR1	SSR3	SSR4	SSR5	SSR6	SSR7	...	SSR13	SSR14	SSR15	SSR16
DM1	(1.5, 2, 2.5)	(2.5, 3, 3.5)	(0.5, 1, 1.5)	(1.5, 2, 2.5)	(1.5, 2, 2.5)	(2.5, 3, 3.5)	...	(1.5, 2, 2.5)	(3.5, 4, 4)	(1.5, 2, 2.5)	(0.5, 1, 1.5)
DM2	(2.5, 3, 3.5)	(2.5, 3, 3.5)	(0.5, 1, 1.5)	(0.5, 1, 1.5)	(0.5, 1, 1.5)	(2.5, 3, 3.5)	...	(2.5, 3, 3.5)	(2.5, 3, 3.5)	(1.5, 2, 2.5)	(1.5, 2, 2.5)
DM3	(1.5, 2, 2.5)	(1.5, 2, 2.5)	(0.5, 1, 1.5)	(0.5, 1, 1.5)	(0.5, 1, 1.5)	(1.5, 2, 2.5)	...	(1.5, 2, 2.5)	(1.5, 2, 2.5)	(0.5, 1, 1.5)	(0.5, 1, 1.5)
DM4	(2.5, 3, 3.5)	(1.5, 2, 2.5)	(0.5, 1, 1.5)	(1.5, 2, 2.5)	(1, 1, 1)	(0.5, 1, 1.5)	...	(3.5, 4, 4)	(3.5, 4, 4)	(2.5, 3, 3.5)	(1.5, 2, 2.5)
DM5	(1.5, 2, 2.5)	(0.5, 1, 1.5)	(0.5, 1, 1.5)	(1.5, 2, 2.5)	(1, 1, 1)	(0.5, 1, 1.5)	...	(2.5, 3, 3.5)	(2.5, 3, 3.5)	(1.5, 2, 2.5)	(0.5, 1, 1.5)
DM6	(0.5, 1, 1.5)	(0.5, 1, 1.5)	(1.5, 2, 2.5)	(2.5, 3, 3.5)	(0.5, 1, 1.5)	(2.5, 3, 3.5)	...	(1.5, 2, 2.5)	(2.5, 3, 3.5)	(1.5, 2, 2.5)	(0.5, 1, 1.5)
DM7	(2.5, 3, 3.5)	(1.5, 2, 2.5)	(0.5, 1, 1.5)	(0.5, 1, 1.5)	(1, 1, 1)	(2.5, 3, 3.5)	...	(2.5, 3, 3.5)	(2.5, 3, 3.5)	(0.5, 1, 1.5)	(1.5, 2, 2.5)
DM8	(1.5, 2, 2.5)	(2.5, 3, 3.5)	(1.5, 2, 2.5)	(2.5, 3, 3.5)	(1.5, 2, 2.5)	(1.5, 2, 2.5)	...	(2.5, 3, 3.5)	(2.5, 3, 3.5)	(1.5, 2, 2.5)	(1.5, 2, 2.5)

$$\bar{u}_j^w = (u_j^w - \min_j^w) / \sigma_{\min}^{\max} \quad (37) \quad w_j = \min_j^w + \beta_j \sigma_{\min}^{\max} \quad (41)$$

where  $\sigma_{\min}^{\max} = \max_j^w - \min_j^w$ .

Then, compute right  $\bar{L}_j^w$  and left  $\bar{R}_j^w$  normalized values:

$$\bar{L}_j^w = \bar{m}_j^w / (1 + \bar{m}_j^w - \bar{l}_j^w) \quad (38)$$

$$\bar{R}_j^w = \bar{u}_j^w / (1 + \bar{u}_j^w - \bar{m}_j^w) \quad (39)$$

Moreover, the total normalized crisp values are computed as follows:

$$\beta_j = \frac{\bar{L}_j^w \times (1 - \bar{L}_j^w) + \bar{R}_j^w \times \bar{R}_j^w}{1 - \bar{L}_j^w + \bar{R}_j^w} \quad (40)$$

Finally, the crisp weight  $w_j$  for the  $j$ th service requirement is computed as follows:

#### 4. Case study

In this section, the elicitation and evaluation of UAO-SSRs for smart vehicle service system (SVSS) is taken as an example to validate the feasibility and effectiveness of the proposed framework. A SVSS manufacturer M, a world class vehicle company, is committed to providing customers with various types of passenger vehicles and related services. The rapid development of advanced smart technologies and new business patterns have accelerated the mainstream of automotive product strategy towards a trend of driving-unmanned, smart-connected, power-electrified, usage-shared and service-oriented (Kuang et al., 2018). This emerging trend has boosted the company M to transform its value propositions from product-centric to customer-centric, product-sold to service-sold, and function-based to experience-based. In this respect, the company is endeavoring to discover more service opportunities in the user (driver) activity cycle, which delivers more added value to the customers and creates better user experience. The company has

**Table 4**  
The rough-fuzzy BO and OW vectors.

SSRs	Rough-fuzzy BO vector	Rough-fuzzy OW vector
SSR1	([0.879, 1.631], [1.379, 2.131], [1.879, 2.631])	([1.369, 2.121], [1.869, 2.621], [2.369, 3.121])
SSR2	([2.641, 3.109], [3.141, 3.609], [3.570, 3.805])	([1.000, 1.000], [1.000, 1.000], [1.000, 1.000])
SSR3	([1.083, 1.936], [1.406, 2.353], [1.646, 2.858])	([1.147, 2.094], [1.647, 2.594], [2.147, 3.094])
SSR4	([2.063, 2.438], [2.563, 2.938], [3.063, 3.438])	([0.563, 0.938], [1.063, 1.438], [1.563, 1.938])
SSR5	([1.147, 2.094], [1.647, 2.594], [2.147, 3.094])	([0.906, 1.853], [1.406, 2.353], [1.906, 2.853])
SSR6	([2.147, 3.094], [2.647, 3.594], [3.077, 3.766])	([0.703, 1.177], [1.063, 1.438], [1.234, 1.923])
SSR7	([0.771, 1.750], [1.271, 2.250], [1.771, 2.750])	([1.250, 2.229], [1.750, 2.729], [2.250, 3.229])
SSR8	([0.771, 1.750], [1.271, 2.250], [1.771, 2.750])	([1.250, 2.229], [1.750, 2.729], [2.250, 3.229])
SSR9	([0.951, 1.411], [1.391, 1.859], [1.747, 2.374])	([1.641, 2.109], [2.141, 2.609], [2.641, 3.109])
SSR10	([0.703, 1.177], [1.063, 1.438], [1.234, 1.923])	([2.056, 2.698], [2.556, 3.198], [3.048, 3.568])
SSR11	([0.750, 1.250], [1.250, 1.750], [1.750, 2.250])	([1.750, 2.250], [2.250, 2.750], [2.750, 3.250])
SSR12	([1.000, 1.000], [1.000, 1.000], [1.000, 1.000])	([3.500, 3.500], [4.000, 4.000], [4.000, 4.000])
SSR13	([0.738, 1.263], [1.141, 1.609], [1.394, 2.125])	([1.879, 2.631], [2.379, 3.131], [2.872, 3.495])
SSR14	([0.567, 0.948], [1.016, 1.234], [1.286, 1.729])	([2.302, 2.944], [2.802, 3.444], [3.271, 3.714])
SSR15	([1.302, 1.944], [1.802, 2.444], [2.302, 2.944])	([1.056, 1.698], [1.556, 2.198], [2.056, 2.698])
SSR16	([1.750, 2.250], [2.250, 2.750], [2.750, 3.250])	([0.750, 1.250], [1.250, 1.750], [1.750, 2.250])

established a Smart Connected Vehicle Platform to connect majority of the sold smart connected vehicles (SCVs). A SCV is defined as a new generation of vehicle installed with the advanced sensors and human-machine interactors. A SCV can be used as an interactive interface to perceive drivers' service requirement and deliver the expected smart service, as well as build connection between the vehicle to users, vehicle to vehicle, vehicle to infrastructure, vehicle to environment, and vehicle to platform. Based on this network foundation, the company tend to pay more attention on developing smart vehicle service orienting to the user activity cycle.

Self-driving tour is regarded as a frequent driving activity of vehicle user. During the activity cycle of self-driving process, the users would have large amount of requirements for each key activity elements. For instance, the SVSS can deliver some smart service, such as monitor driver's behavior, alert driver's unsafe behavior, perceive the refueling need of vehicle, and automatically order the hotel and tourist ticket. Therefore, the purpose of UAO-SSRs elicitation and evaluation in this case study is to recognize the vital customer concerns in the self-driving activity cycle, providing basis of concept design of the SVSS. Moreover, the proposed rough-fuzzy BWM is compared with the crisp BWM, fuzzy BWM, and rough BWM, to verify its feasibility and effectiveness.

#### 4.1. Identify UAO-SSRs of SVSS

A survey based on the proposed framework in section 3.2.1 and the presented roadmap in section 3.2.2 is applied among the company M to identify the possible SSRs for the vehicle users' self-driving tour. The identified SSRs for the user activity cycle of self-driving tour for a new SVSS are presented in Table 1, and the experts confirm that they are appropriate. The detailed description on these SSRs are also shown in Table 1.

#### 4.2. Evaluate UAO-SSRs of SVSS

The proposed rough-fuzzy BWM is used to assess and prioritize the identified SVSS SSRs among a group that consists of 8 DMs: 3 experienced self-driving tourists, 1 vehicle expert, 2 service experts, and 2 data experts. The three self-driving tourists are experienced end users who have more than 10 years' driving experience. The vehicle expert has more than 5 years of professional experience in SCVs design. The two service experts are smart vehicle service designers with more than 8 years' experience in their respective fields. The two data experts have focused on developing the analysis of SCVs' operational data for 6 years. We named these DMs respectively as DM1–8. This case study applies questionnaire to collect the preferences from the DMs group, and then implements the evaluation procedure according to the below description.

##### 4.2.1. Step 1: Identify the best SSR (B) and the worst SSR (W) for SVSS

Among the identified SSRs of self-driving activity cycle for SVSS shown in Table 1, the DMs team of 8 experts separately choose SSR12 and SSR2 as the best SSR and worst SSR.

##### 4.2.2. Step 2: Construct RF-BO and RF-OW vectors for SVSS

**4.2.2.1. Step 2.1: Establish group linguistic BO and OW vectors.** For the selected SSRs in Table 1, the DMs team respectively give linguistic preferences degree of the best service requirement SSR12 over the other service requirement  $SSR_j$  ( $j = 1, 2, \dots, 16$ ), and of the other service requirement  $SSR_j$  over the worst service requirement SSR2. The group linguistic BO and OW vectors are formed as Table 2.

**4.2.2.2. Step 2.2: Establish group fuzzy BO and OW vectors.** Then, the group linguistic BO and OW vectors in Table 2 are respectively converted to the group fuzzy BO and OW vectors presented in Table 3, by using the fuzz scale mentioned in section 3.3.2.2 and adopting Eqs. (3) and (4).

**4.2.2.3. Step 2.3: Establish RF-BO and RF-OW vectors.** First, the group TFNs in each BO and OW vectors are respectively converted to rough numbers by following the Eqs. (6)–(18). Here, the group TFNs judgement of the preference degree of the best service requirement SSR12 over the service requirement SSR3, i.e.  $\hat{a}_{B3}$  are taken as an example to illustrate the transformation from group TFNs  $\hat{a}_{B3}$  to rough-fuzzy number  $RF(\hat{a}_{B3})$ . As shown in Table 3, the corresponding fuzzy number of  $\hat{a}_{B3}$  are respectively as: (0.5, 1, 1.5), (1, 1, 1), (1.5, 2, 2.5), (1.5, 2, 2.5), (2.5, 3, 3.5), (2.5, 3, 3.5), (1.5, 2, 2.5), and (1, 1, 1). The group fuzzy number can be obtained as  $\hat{a}_{B3} = (\hat{l}_{B3}, \hat{m}_{B3}, \hat{u}_{B3})$ , where:

$$\hat{l}_{B3} = \{0.5, 1, 1.5, 1.5, 2.5, 2.5, 1.5, 1\},$$

$$\hat{m}_{B3} = \{1, 1, 2, 2, 3, 3, 2, 1\}, \hat{u}_{B3} = \{1.5, 1, 2.5, 2.5, 3.5, 3.5, 2.5, 1\}$$

Take the transformation of group fuzzy medium boundary number  $\hat{m}_{B3}$  as examples:

$$\underline{Lim}(1) = 1, \overline{Lim}(1) = (1 + 1 + 2 + 2 + 3 + 3 + 2 + 1) / 8 = 1.875;$$

$$\underline{Lim}(2) = (1 + 1 + 1 + 2 + 2 + 2) / 6 = 1.5, \overline{Lim}(2) = (2 + 2 + 2 + 3 + 3) / 5 = 2.4;$$

$$\underline{Lim}(3) = (1 + 1 + 1 + 2 + 2 + 2 + 3 + 3) / 8 = 1.875, \overline{Lim}(3) = 3;$$

$$RN(m_{B3}^1) = RN(m_{B3}^2) = RN(m_{B3}^8) = [\underline{Lim}(1), \overline{Lim}(1)] = [1, 1.875],$$

$$RN(m_{B3}^3) = RN(m_{B3}^4) = RN(m_{B3}^7) = [\underline{Lim}(2), \overline{Lim}(2)] = [1.5, 2.4],$$

$$RN(m_{B3}^5) = RN(m_{B3}^6) = [\underline{Lim}(3), \overline{Lim}(3)] = [1.875, 3].$$

Then, by aggregating those rough numbers following Eq. (15)–(18), the rough average number  $RN(\hat{m}_{B3}) = [1.406, 2.353]$ . By adopting the same computing procedures, the rough number form of  $\hat{l}_{B3}$  and  $\hat{u}_{B3}$  can be acquired as  $RN(\hat{l}_{B3}) = [1.083, 1.936]$  and  $RN(\hat{u}_{B3}) = [1.646, 2.858]$ . Finally, the group fuzzy judgements are converted to rough-fuzzy number  $RF(\hat{a}_{B3}) = ([1.083, 1.936], [1.406, 2.353], [1.646, 2.858])$ . Similarly, the other group TFNs in the group fuzzy BO and OW vectors can be converted to rough-fuzzy number by taking same procedures. Moreover, by using Eq. (22), the RF-BO and RF-OW vector is respectively constructed in Table 4.

##### 4.2.3. Step 3: Compute the rough-fuzzy weight of each SSR for SVSS

Based on the acquired RF-BO and RF-OW vectors in Table 4, the RF-LPM Model (29) is used for calculating the optimal values of the rough-fuzzy weight of each SSR. Due to the length limitation, this section only describes part of the model, in case of  $j = 1$ , i.e. the first service requirement SSR, as follows:



$\min \delta$ 
 $s.t.$ 

$$\begin{cases}
 j = 1 : \left\{ \begin{array}{l}
 \left| \frac{l_B^{wL}}{u_1^{wU}} - l_{B1}^L \right| \leq \delta; \left| \frac{l_B^{wU}}{u_1^{wL}} - l_{B1}^U \right| \leq \delta; \left| \frac{m_B^{wL}}{m_1^{wU}} - m_{B1}^L \right| \leq \delta; \\
 \left| \frac{s_B^{wU}}{m_1^{wL}} - m_{B1}^U \right| \leq \delta; \left| \frac{u_B^{wL}}{l_1^{wU}} - u_{B1}^L \right| \leq \delta; \left| \frac{u_B^{wU}}{l_1^{wL}} - u_{B1}^U \right| \leq \delta; \\
 \left| \frac{l_1^{wL}}{u_W^{wU}} - l_{1W}^L \right| \leq \delta; \left| \frac{l_1^{wU}}{u_W^{wL}} - l_{1W}^U \right| \leq \delta; \left| \frac{m_1^{wL}}{m_W^{wU}} - m_{1W}^L \right| \leq \delta; \\
 \left| \frac{s_1^{wU}}{m_W^{wL}} - m_{1W}^U \right| \leq \delta; \left| \frac{u_1^{wL}}{l_W^{wU}} - u_{1W}^L \right| \leq \delta; \left| \frac{u_1^{wU}}{l_W^{wL}} - u_{1W}^U \right| \leq \delta; \\
 l_1^{wL} \leq l_1^{wU}; m_1^{wL} \leq m_1^{wU}; u_1^{wL} \leq u_1^{wU}; \\
 l_1^{wL} \leq m_1^{wL} \leq u_1^{wL}; l_1^{wU} \leq m_1^{wU} \leq u_1^{wU}; \\
 0 \leq l_1^{wL}, l_1^{wU}, m_1^{wL}, m_1^{wU}, u_1^{wL}, u_1^{wU} \leq 1; \\
 sum(RF(w_1)) \leq sum(RF(w_B)); \\
 sum(RF(w_1)) \geq sum(RF(w_W));
 \end{array} \right. \\
 j = 2 \cdots; \\
 \vdots \\
 j = 16 \cdots; \\
 \sum_{j=1}^{16} l_j^{wL}, \sum_{j=1}^{16} m_j^{wL} \leq 1, 1 \leq j \leq 16; \\
 \sum_{j=1}^{16} m_j^{wU}, \sum_{j=1}^{16} u_j^{wU} \geq 1, 1 \leq j \leq 16.
 \end{cases}$$

Then, enter the corresponding value in Table 4 into the model above and thus obtain the expanded model as follows:

 $\min \delta$ 
 $s.t.$ 

$$\begin{cases}
 j = 1 : \left\{ \begin{array}{l}
 \left| \frac{l_B^{wL}}{u_1^{wU}} - 0.879 \right| \leq \delta; \left| \frac{l_B^{wU}}{u_1^{wL}} - 1.631 \right| \leq \delta; \left| \frac{m_B^{wL}}{m_1^{wU}} - 1.379 \right| \leq \delta; \\
 \left| \frac{s_B^{wU}}{m_1^{wL}} - 2.131 \right| \leq \delta; \left| \frac{u_B^{wL}}{l_1^{wU}} - 1.879 \right| \leq \delta; \left| \frac{u_B^{wU}}{l_1^{wL}} - 2.631 \right| \leq \delta; \\
 \left| \frac{l_1^{wL}}{u_W^{wU}} - 1.369 \right| \leq \delta; \left| \frac{l_1^{wU}}{u_W^{wL}} - 2.121 \right| \leq \delta; \left| \frac{m_1^{wL}}{m_W^{wU}} - 1.869 \right| \leq \delta; \\
 \left| \frac{s_1^{wU}}{m_W^{wL}} - 2.621 \right| \leq \delta; \left| \frac{u_1^{wL}}{l_W^{wU}} - 2.369 \right| \leq \delta; \left| \frac{u_1^{wU}}{l_W^{wL}} - 3.121 \right| \leq \delta; \\
 l_1^{wL} \leq l_1^{wU}; m_1^{wL} \leq m_1^{wU}; u_1^{wL} \leq u_1^{wU}; \\
 l_1^{wL} \leq m_1^{wL} \leq u_1^{wL}; l_1^{wU} \leq m_1^{wU} \leq u_1^{wU}; \\
 0 \leq l_1^{wL}, l_1^{wU}, m_1^{wL}, m_1^{wU}, u_1^{wL}, u_1^{wU} \leq 1; \\
 sum(RF(w_1)) \leq sum(RF(w_B)); \\
 sum(RF(w_1)) \geq sum(RF(w_W));
 \end{array} \right. \\
 j = 2 \cdots; \\
 \vdots \\
 j = 16 \cdots; \\
 \sum_{j=1}^{16} l_j^{wL}, \sum_{j=1}^{16} m_j^{wL} \leq 1, 1 \leq j \leq 16; \\
 \sum_{j=1}^{16} m_j^{wU}, \sum_{j=1}^{16} u_j^{wU} \geq 1, 1 \leq j \leq 16.
 \end{cases}$$

By solving the model above, the optimal rough-fuzzy weights for the SSRs of SVSS are obtained as presented in Table 5. It can be seen that, the obtained rough-fuzzy weights are in the fulfilment of the constraints that:  $\sum_{j=1}^{16} l_j^{wL}, \sum_{j=1}^{16} m_j^{wL} \leq 1$ , and  $\sum_{j=1}^{16} m_j^{wU}, \sum_{j=1}^{16} u_j^{wU} \geq 1$ , since  $\sum_{j=1}^{16} l_j^{wL} = 0.778$ ,  $\sum_{j=1}^{16} m_j^{wL} = 0.976$ ,

**Table 5**

The rough-fuzzy, fuzzy, and crisp weights of each SSR.

	Rough-fuzzy weights	Fuzzy weights	Crisp weights
SSR1	([0.044, 0.071], [0.058, 0.088], [0.083, 0.110])	(0.054, 0.072, 0.099)	0.063
SSR2	([0.033, 0.033], [0.034, 0.034], [0.035, 0.036])	(0.033, 0.034, 0.035)	0.029
SSR3	([0.041, 0.075], [0.053, 0.087], [0.069, 0.105])	(0.053, 0.067, 0.088)	0.060
SSR4	([0.034, 0.041], [0.041, 0.049], [0.052, 0.064])	(0.034, 0.042, 0.055)	0.037
SSR5	([0.038, 0.058], [0.048, 0.079], [0.059, 0.097])	(0.043, 0.059, 0.076)	0.052
SSR6	([0.031, 0.041], [0.035, 0.048], [0.041, 0.061])	(0.032, 0.037, 0.045)	0.032
SSR7	([0.043, 0.075], [0.055, 0.093], [0.074, 0.113])	(0.054, 0.073, 0.097)	0.064
SSR8	([0.043, 0.075], [0.055, 0.093], [0.074, 0.113])	(0.054, 0.073, 0.097)	0.064
SSR9	([0.049, 0.071], [0.067, 0.088], [0.091, 0.110])	(0.057, 0.077, 0.104)	0.068
SSR10	([0.061, 0.094], [0.082, 0.111], [0.102, 0.126])	(0.078, 0.101, 0.120)	0.085
SSR11	([0.052, 0.076], [0.071, 0.095], [0.096, 0.115])	(0.061, 0.084, 0.109)	0.072
SSR12	([0.110, 0.121], [0.122, 0.124], [0.124, 0.126])	(0.119, 0.124, 0.126)	0.107
SSR13	([0.056, 0.090], [0.075, 0.107], [0.092, 0.123])	(0.072, 0.094, 0.113)	0.080
SSR14	([0.069, 0.100], [0.087, 0.118], [0.119, 0.132])	(0.087, 0.109, 0.130)	0.092
SSR15	([0.039, 0.058], [0.051, 0.074], [0.067, 0.092])	(0.044, 0.059, 0.079)	0.052
SSR16	([0.036, 0.045], [0.043, 0.059], [0.054, 0.074])	(0.037, 0.047, 0.061)	0.042

$\sum_{j=1}^{16} m_j^{wU} = 1.348$ , and  $\sum_{j=1}^{16} u_j^{wU} = 1.597$ . The optimal value  $\delta^*$  of  $\delta$  is acquired as 0.436. Through using the consistency checking method proposed by Pamučar et al. (2018), the consistency ratio satisfies the requirement.

#### 4.2.4. Step 4: acquire the crisp weight of each SSR for SVSS

By using the Eqs. (30)–(34), the rough-fuzzy weight of each SSR can be converted to fuzzy weights in the form of deroughness as shown in Table 5. Then, the crisp value of importance weight of each SSR is obtained by applying the Eqs. (35)–(41) (Table 5). The importance of the UAO-SSRs for the SVSS are ranking in following order:

SSR12 (0.107) > SSR14 (0.092) > SSR10 (0.085) > SSR13 (0.080) > SSR11 (0.072) > SSR09 (0.068) > SSR07 (0.064) > SSR08 (0.064) > SSR01 (0.063) > SSR03 (0.060) > SSR15 (0.052) > SSR05 (0.052) > SSR16 (0.042) > SSR04 (0.037) > SSR06 (0.032) > SSR02 (0.029).

The top five important SSRs of the activity cycle of self-driving tour for SVSS are respectively SSR12 (alerting driver's unsafe behavior), SSR14 (recommending optimal driving behavior), SSR10 (diagnosis of driver's behavior), SSR13 (predicting driver's behavior and status) and SSR11 (monitoring drivers' mental

status). These service requirements deserve more priority and resources when configure user activity-oriented smart service modules. SSR12 and SSR14 are regarded as the top two important SSRs by the DMs team, because driving safety has been always considered as the most important issue in a long-term self-driving tour. With the application of smart technologies, the driving safety can be effectively enhanced through alerting the driver's unsafe behaviors (e.g. calling, abnormal driving behavior) or states (e.g. drunk, sleepy), and recommending optimal driving behavior (e.g. proper brake timing). In this respect, the service requirements of ensuring safety with the application of advanced technology have significant influence on the design and planning of the SVSS concept and also have huge potential for obtaining high user satisfaction. In addition, the acquired relative weight of each SSR can be entered into the configuration of SVSS, which is aiming to select the best service module portfolios with respect to meet customers' satisfaction.

## 5. Comparisons and discussions

In order to demonstrate the feasibility and effectiveness of the proposed method, we conduct comparisons of SSRs prioritization of SVSS among the crisp BWM, fuzzy BWM, rough BWM, and the

**Table 6**

The BO vectors of crisp BWM, fuzzy BWM and rough BWM.

	Crisp BO	Fuzzy BO	Rough BO
SSR1	1.750	(1.250, 1.750, 2.250)	[1.379, 2.131]
SSR2	3.375	(2.875, 3.375, 3.688)	[3.141, 3.609]
SSR3	1.750	(1.500, 1.875, 2.250)	[1.146, 2.358]
SSR4	2.750	(2.250, 2.750, 3.250)	[2.563, 2.938]
SSR5	2.125	(1.625, 2.125, 2.625)	[1.647, 2.594]
SSR6	3.125	(2.625, 3.125, 3.438)	[2.647, 3.594]
SSR7	1.750	(1.250, 1.750, 2.250)	[1.271, 2.250]
SSR8	1.750	(1.250, 1.750, 2.250)	[1.271, 2.250]
SSR9	1.563	(1.188, 1.625, 2.063)	[1.247, 1.874]
SSR10	1.063	(0.938, 1.250, 1.563)	[0.734, 1.423]
SSR11	1.500	(1.000, 1.500, 2.000)	[1.250, 1.750]
SSR12	1.000	(1.000, 1.000, 1.000)	[1.000, 1.000]
SSR13	1.250	(1.000, 1.375, 1.750)	[0.894, 1.625]
SSR14	1.000	(0.750, 1.125, 1.500)	[0.786, 1.229]
SSR15	2.125	(1.625, 2.125, 2.625)	[1.802, 2.444]
SSR16	2.500	(2.000, 2.500, 3.000)	[2.250, 2.750]

**Table 7**

The OW vectors of crisp BWM, fuzzy BWM and rough BWM.

	Crisp OW	Fuzzy OW	Rough OW
SSR1	2.250	(2.625, 3.125, 3.438)	[1.869, 2.621]
SSR2	1.000	(1.000, 1.000, 1.000)	[1.000, 1.000]
SSR3	2.125	(1.250, 1.750, 2.250)	[1.647, 2.594]
SSR4	1.250	(1.250, 1.750, 2.250)	[1.063, 1.438]
SSR5	1.875	(1.188, 1.625, 2.063)	[1.406, 2.353]
SSR6	1.063	(0.938, 1.250, 1.563)	[0.734, 1.423]
SSR7	2.250	(1.000, 1.500, 2.000)	[1.750, 2.729]
SSR8	2.250	(1.000, 1.375, 1.750)	[1.750, 2.729]
SSR9	2.375	(0.750, 1.125, 1.500)	[2.141, 2.609]
SSR10	2.875	(1.625, 2.125, 2.625)	[2.556, 3.198]
SSR11	2.500	(2.000, 2.500, 3.000)	[2.250, 2.750]
SSR12	4.000	(1.750, 2.250, 2.750)	[4.000, 4.000]
SSR13	2.750	(1.625, 2.125, 2.625)	[2.379, 3.131]
SSR14	3.125	(0.750, 1.250, 1.750)	[2.802, 3.444]
SSR15	1.875	(1.375, 1.875, 2.375)	[1.556, 2.198]
SSR16	1.500	(0.938, 1.250, 1.563)	[1.250, 1.750]

proposed rough-fuzzy BWM. The same linguistic judgement data from the DMs group are inputted the four methods by respectively transforming them into average crisp number, triangular fuzzy number, rough number, and rough-fuzzy number. For the crisp BWM, the input BO and OW vectors are obtained by taking the arithmetical means of the 8 DMs' initial scores. Fuzzy crisp BWM obtains the group average fuzzy intervals number through arithmetically meaning the group fuzzy judgements. In rough BWM, the rough interval number is acquired by aggregating the group crisp judgements according to the arithmetical operation of rough number. By using these methods, the group linguistic BO vectors in Table 2 are respectively converted to the average group crisp BO, average group fuzzy BO and rough BO vectors (Table 6). Similarly, the OW vectors for the crisp BWM, fuzzy BWM and rough BWM are obtained as shown in Table 7.

The main linear programming model (LPM) for the crisp-based, fuzzy-based and rough-based BWM are respectively referring Rezaei (2015), Guo and Zhao (2017), and Stević et al. (2017). The linear programming model of crisp BWM (CLPM), fuzzy BWM (FLPM), and rough BWM (RLPM) are written as follows:

CLPM:

$$\begin{aligned}
 & \min \delta^C \\
 & \text{s.t.} \\
 & \left\{ \begin{aligned} & \left| \frac{w_B}{w_1} - 1.75 \right| \leq \delta^C; \left| \frac{w_B}{w_2} - 3.375 \right| \leq \delta^C; \\ & \dots \left| \frac{w_B}{w_j} - a_{Bj} \right| \leq \delta^C \dots \left| \frac{w_B}{w_{16}} - 2.5 \right| \leq \delta^C; \\ & \left\{ \begin{aligned} & \left| \frac{w_1}{w_W} - 2.25 \right| \leq \delta^C; \left| \frac{w_2}{w_W} - 1 \right| \leq \delta^C; \\ & \dots \left| \frac{w_j}{w_W} - a_{jW} \right| \leq \delta^C \dots \left| \frac{w_{16}}{w_W} - 1.5 \right| \leq \delta^C; \end{aligned} \right. \\ & \sum_{j=1}^n w_j = 1; \\ & w_j \leq w_B; \\ & w_j \geq w_W; \end{aligned} \right. \quad (42) \\
 & 1 \leq j \leq 16.
 \end{aligned}$$

where  $w_j$ ,  $w_B$ , and  $w_W$  separately denotes the obtained optimal weigh of the  $j$ th SSR, the best SSR (i.e. SSR12) and the worst SSR (i.e. SSR2),  $a_{Bj}$  and  $a_{jW}$  respectively represents the  $j$ th element of crisp BO and OW vector.

FLPM:

$\min \delta^F$

s.t.

$$\begin{aligned}
 & \left\{ \begin{aligned} & \left| \frac{l_B^W}{u_1^W} - 1.25 \right| \leq \delta^F; \left| \frac{m_B^W}{m_1^W} - 1.75 \right| \leq \delta^F; \left| \frac{u_B^W}{l_1^W} - 2.25 \right| \leq \delta^F; \\ & \left| \frac{l_1^W}{u_W^W} - 2.625 \right| \leq \delta^F; \left| \frac{m_1^W}{m_W^W} - 3.125 \right| \leq \delta^F; \left| \frac{u_1^W}{l_W^W} - 3.438 \right| \leq \delta^F; \\ & \vdots \\ & \left\{ \begin{aligned} & \left| \frac{l_B^W}{u_j^W} - l_{Bj} \right| \leq \delta^F; \left| \frac{m_B^W}{m_j^W} - m_{Bj} \right| \leq \delta^F; \left| \frac{u_B^W}{l_j^W} - u_{Bj} \right| \leq \delta^F; \\ & \left| \frac{l_j^W}{u_W^W} - l_{jW} \right| \leq \delta^F; \left| \frac{m_j^W}{m_W^W} - m_{jW} \right| \leq \delta^F; \left| \frac{u_j^W}{l_W^W} - u_{jW} \right| \leq \delta^F; \end{aligned} \right. \\ & \vdots \\ & \left\{ \begin{aligned} & \left| \frac{l_B^W}{u_{16}^W} - 2 \right| \leq \delta^F; \left| \frac{m_B^W}{m_{16}^W} - 2.5 \right| \leq \delta^F; \left| \frac{u_B^W}{l_{16}^W} - 3 \right| \leq \delta^F; \\ & \left| \frac{l_{16}^W}{u_W^W} - 0.938 \right| \leq \delta^F; \left| \frac{m_{16}^W}{m_W^W} - 1.25 \right| \leq \delta^F; \left| \frac{u_{16}^W}{l_W^W} - 1.563 \right| \leq \delta^F; \end{aligned} \right. \\ & 0 \leq l_j^W \leq m_j^W \leq u_j^W \leq 1; \\ & l_j^W + m_j^W + u_j^W \leq l_B^W + m_B^W + u_B^W; \\ & l_j^W + m_j^W + u_j^W \geq l_W^W + m_W^W + u_W^W; \\ & \sum_{j=1}^{16} l_j^W \leq 1, \sum_{j=1}^{16} u_j^W \geq 1; \\ & 1 \leq j \leq 16. \end{aligned} \right. \quad (43)
 \end{aligned}$$

where  $l_j^W$ ,  $m_j^W$ , and  $u_j^W$  separately represents the low boundary, medium boundary and up boundary of the fuzzy interval weight for the  $j$ th SSR; the subscript B and W denotes the best SSR and worst SSR; the subscript Bj and jW respectively denotes the  $j$ th element of the fuzzy BO and OW vector.

RLPM:

$$\begin{aligned}
& \min \delta^R \\
& s.t. \\
& \left\{ \begin{aligned}
& j = 1 : \begin{cases} \left| \frac{L_B^w}{U_1^w} - 1.379 \right| \leq \delta^R; \left| \frac{U_B^w}{L_1^w} - 2.131 \right| \leq \delta^R; \\ \left| \frac{L_1^w}{U_W^w} - 1.869 \right| \leq \delta^R; \left| \frac{U_1^w}{L_W^w} - 2.621 \right| \leq \delta^R; \end{cases} \\
& \vdots \\
& j = j : \begin{cases} \left| \frac{L_B^w}{U_j^w} - L_{Bj} \right| \leq \delta^R; \left| \frac{U_B^w}{L_j^w} - U_{Bj} \right| \leq \delta^R; \\ \left| \frac{L_j^w}{U_W^w} - L_{jW} \right| \leq \delta^R; \left| \frac{U_j^w}{L_W^w} - U_{jW} \right| \leq \delta^R; \end{cases} \\
& \vdots \\
& j = 16 : \begin{cases} \left| \frac{L_B^w}{U_{16}^w} - 2.25 \right| \leq \delta^R; \left| \frac{U_B^w}{L_{16}^w} - 2.75 \right| \leq \delta^R; \\ \left| \frac{L_{16}^w}{U_W^w} - 1.25 \right| \leq \delta^R; \left| \frac{U_{16}^w}{L_W^w} - 1.75 \right| \leq \delta^R; \end{cases} \\
& 0 \leq L_j^w \leq U_j^w \leq 1; \\
& L_j^w + U_j^w \leq L_B^w + U_B^w; \\
& L_j^w + U_j^w \geq L_W^w + U_W^w; \\
& \sum_{j=1}^{16} L_j^w \leq 1, \sum_{j=1}^{16} U_j^w \geq 1; \\
& 1 \leq j \leq 16.
\end{aligned} \right. \quad (44)
\end{aligned}$$

where  $L_j^w$  and  $U_j^w$  separately represents the lower boundary and upper boundary of the rough interval weight for the  $j$ th SSR; the subscript  $B$  and  $W$  denotes the best SSR and worst SSR; the subscript  $Bj$  and  $jW$  respectively denotes the  $j$ th element of the rough BO and OW vector.

By separately solving the Models (42), (43) and (44), the optimal weight vectors for crisp BWM, fuzzy BWM and rough BWM are obtained (Table 8), and the corresponding optimal value  $\delta^{C*} = 0.975$ ,  $\delta^{F*} = 0.676$ , and  $\delta^{R*} = 0.479$ .

Then, the crisp weights with the fuzzy BWM are obtained by using the defuzzification method proposed in section 3.3.5.2 to compute the fuzzy weights in Table 8. The crisp weights with the rough BWM are acquired by using the deroughness method proposed in section 3.3.5.1 to calculate the rough weights in Table 8. Finally, the relative weights and rank of the UAO-SSRs for SVSS with

**Table 8**

The weight vectors of crisp BWM, fuzzy BWM and rough BWM.

	Crisp weight	Fuzzy weight	Rough weight
SSR1	0.064	(0.092, 0.118, 0.144)	[0.058, 0.088]
SSR2	0.038	(0.044, 0.046, 0.047)	[0.033, 0.034]
SSR3	0.092	(0.057, 0.074, 0.098)	[0.053, 0.092]
SSR4	0.045	(0.044, 0.057, 0.071)	[0.041, 0.050]
SSR5	0.072	(0.052, 0.072, 0.090)	[0.048, 0.078]
SSR6	0.043	(0.041, 0.048, 0.055)	[0.040, 0.048]
SSR7	0.086	(0.053, 0.069, 0.091)	[0.055, 0.093]
SSR8	0.057	(0.053, 0.072, 0.091)	[0.055, 0.093]
SSR9	0.060	(0.057, 0.071, 0.086)	[0.066, 0.092]
SSR10	0.061	(0.073, 0.099, 0.117)	[0.082, 0.113]
SSR11	0.055	(0.073, 0.107, 0.131)	[0.071, 0.095]
SSR12	0.093	(0.113, 0.133, 0.146)	[0.121, 0.124]
SSR13	0.058	(0.068, 0.091, 0.117)	[0.076, 0.107]
SSR14	0.058	(0.067, 0.082, 0.097)	[0.089, 0.117]
SSR15	0.058	(0.054, 0.081, 0.104)	[0.051, 0.073]
SSR16	0.059	(0.049, 0.058, 0.070)	[0.044, 0.058]

the crisp, fuzzy, rough and proposed rough-fuzzy methods are presented in Fig. 4. The comparative results show that the obtained relative weights and priority of the SSRs with the four methods are almost different with each other. For instances, SSR1 is ranked fifth with the crisp approach, second with the fuzzy method and ninth with both the rough and rough-fuzzy approaches. SSR10 comes in sixth under the crisp approach, fourth under the fuzzy approach and third under both the rough and rough-fuzzy approaches. SSR15 emerges as the tenth important requirement in the crisp approach, seventh in the fuzzy BMW, twelfth in the rough BMW and eleventh in the rough-fuzzy BMW. The other SSRs also have distinctive ranking, such as SSR3, SSR5, SSR7 and SSR14. However, the most important eight SSRs have similar clusters distribution with the fuzzy, rough and rough-fuzzy approach. The significant differences between the four methods are mainly caused by their different judgement manipulation mechanisms in terms of intrapersonal uncertainty (individual linguistic vagueness) and interpersonal uncertainty (group preference diversity).

In order to demonstrate the difference between the manipulation mechanism of group linguistic judgements across the four methods in terms of intrapersonal and interpersonal uncertainty, the comparison between the estimation interval with the four methods are conducted. The group linguistic judgements {L, L, M, H, VH, L, L, M} of the preference degree of the best service requirement SSR12 over SSR7 are used as examples. As shown in Fig. 5, corresponding to each linguistic judgement from the eight DMs, the crisp values are 1, 1, 2, 3, 4, 1, 1 and 2; the fuzzy intervals are [0.5, 1.5], [0.5, 1.5], [1.5, 2.5], [2.5, 3.5], [3.5, 4], [0.5, 1.5], [0.5, 1.5] and [1.5, 2.5]; the rough intervals are [1.000, 1.875], [1.000, 1.875], [1.333, 2.750], [1.571, 3.500], [1.875, 4.000], [1.000, 1.875], [1.000, 1.875] and [1.333, 2.750]; and the rough-fuzzy intervals are [1.000, 1.844], [1.000, 1.844], [1.333, 2.688], [1.571, 3.375], [1.844, 3.750], [1.000, 1.844], [1.000, 1.844] and [1.333, 2.688]. The linguistic variables of DM1 and DM5 are used as examples to illustrate the different uncertainty manipulation mechanism. Their linguistic variables are L and VH, respectively, whose crisp score are the lowest (score as 1) and highest (score as 4) ones.

It can be seen from Fig. 5 that the low boundary (0.5) of DM1's fuzzy interval [0.5, 1.5] is overestimated compared to the low boundary (1.0) of DM1's rough-fuzzy interval [1.000, 1.844], because the fuzzy-based approach only takes the intrapersonal uncertainty (individual linguistic vagueness) into accounting without considering the influence of other higher DMs' score on the total group's judgements, i.e., interpersonal uncertainty (group preference diversity). Analogously, the up boundary (1.5) of DM1's fuzzy interval is underestimated compared with the up boundary



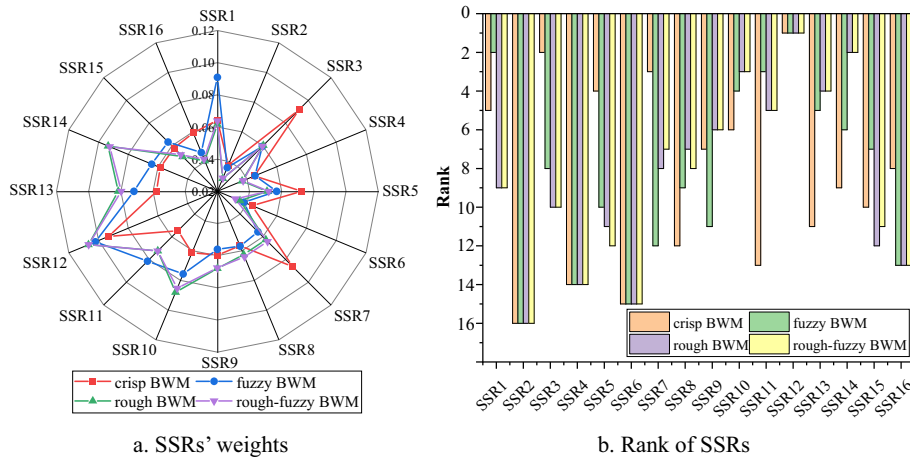


Fig. 4. Comparisons among crisp BWM, fuzzy BWM, rough BWM and rough-fuzzy BWM in terms of a. IVPs' weights and b. Rank of IVPs.

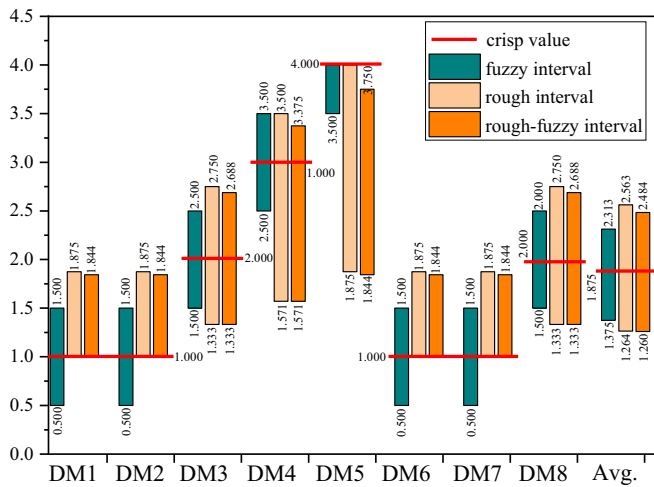


Fig. 5. Comparisons of estimation interval.

(1.844) of DM1's rough-fuzzy interval, due to the ignorance of the impact of the higher scores from other DMs. In addition, the up boundary of DM1's rough interval presents a larger value (1.875) than the one of rough-fuzzy boundary, since it only handles the interpersonal uncertainty (group preference diversity) without considering the individual linguistic vagueness. Moreover, for the DM5's preference degree (the highest score 4), the rough-fuzzy interval presents with a similar feature as the one of the lowest score (score 1). Fig. 5 indicates that the low boundary and up boundary of DM5's rough-fuzzy interval are lower than the corresponding one of DM5's fuzzy interval and rough interval, since both the ambiguous preferences (individual vagueness) and the effect of the lower scores from other DMs (group diversity) are also considered by the rough-fuzzy estimating method.

Besides, the overall average value and average intervals for the crisp scores, fuzzy intervals, rough intervals and rough-fuzzy intervals are respectively calculated as 1.875, [1.375, 2.313], [1.264, 2.563] and [1.260, 2.484]. Fig. 5 states that the up boundary of rough-fuzzy interval is situated between the fuzzy one and rough one, and the low boundary is near to the one of rough interval. This is because of the intrapersonal and interpersonal uncertainties are both considered in the rough-fuzzy estimation interval. Therefore, the integration of rough set and fuzzy set make it feasible to present the realistic situation of the group decision-making. The proposed

method can provide more precise and realistic evaluation results of UAO-SSRs for SVSS.

## 6. Implications and conclusions

### 6.1. Theoretical implications

This study presents a novel systematic framework for identifying and evaluating the UAO-SSRs for smart PSS, with considering the application scenarios of smart technologies and the involved intrapersonal and interpersonal uncertainties.

In the identification stage, a conceptual framework and a general elicitation roadmap are proposed to present the foundation and implementation of UAO-SSRs identification. The conceptual identification framework integrates the data analytic logic, data value chain, user activity cycle and key activity elements. A smart analytic capability hierarchy is first introduced in this framework based on the logic that describes the transition from original data to wisdom, with objective of categorizing the requirement level of smart service and thus providing a theoretical basis for elicitation of the smart service requirements. Moreover, the identification framework offers a clear mapping range between the smart capability and the user activity. In addition, an implementation roadmap for eliciting the UAO-SSRs is developed to provide a feasible procedure for designers to map each smart capability hierarchy with the key activity elements. The proposed identification method can help to recognize the SSRs that can contribute to deliver more sustainability benefit, e.g. increase activity resources utilization efficiency, reduce the user's harm to environment and improve activity flexible.

The evaluation stage mainly proposes a novel rough-fuzzy BWM with simultaneous manipulation of both the intrapersonal and interpersonal uncertainties. First, the proposed rough-fuzzy BWM can provide more realistic and accurate evaluation results, compared with the crisp BWM, fuzzy BWM and rough BWM. This is because that the proposed approach uses the triangular fuzzy set to convert the linguistic judgement into triangular fuzzy number and applies the rough set theory to transform the group triangular fuzzy numbers into rough-fuzzy interval number. This operation integrates the strength of fuzzy set in handling individual linguistic vagueness and the merit of rough set theory in manipulating group preference diversity. Second, a newly proposed model RF-LPM performs well to find the optimal rough-fuzzy weights of SSRs under environment of intrapersonal and interpersonal uncertainty. The model also presents the inherent strength of traditional BWM

in requesting less pairwise judgement data. Moreover, this model helps to reduce the distortion of the initial decision uncertainties throughout the procedure and provides useful guidance for researchers to integrate fuzzy logic and rough set theory into the MCDM methods. Third, the introduced deroughness and defuzzification methods are feasible to accurately transform the rough-fuzzy weight of each SSR into crisp value.

## 6.2. Practical implications

In addition to the theoretical implications, the proposed framework presents some contributions in the practical concept design and business model plan for smart PSS. First, the proposed systematic framework for identifying the smart service requirement provides a logical, understandable and operable approach to recognizing the key concerns of customers in their activity scenarios. The smart capability hierarchy is applied into the practical development of smart PSS with objective of assisting designers to identify their actual capability of smart technologies and thus determine appropriate service innovation direction. The proposed method helps the PSS manufacturers to create more value opportunities by leveraging SCP as the product-service interface and the product-user service interface. The presented method can be implemented as a standardized operating program file in practice to identify the UAO-SSRs with respect to ultimate user experience.

Second, the developed rough-fuzzy BWM can be easily used by the company managers to prioritize the practical SSRs. The individual linguistic ambiguousness and multiple preference variation involved in the group decision process can be easily captured with the proposed rough-fuzzy BWM. The proposed integrating method provides a valuable guidance for the practitioners to combine the uncertainty handling tool and MCDM technique for purpose of solving practically complex issues. By implementing the proposed method as a software, the required time and efforts to gather the judgement data from multiple DMs can be minimized.

## 6.3. Conclusions

This paper proposes an integrated framework to identify and evaluate the UAO-SSRs for smart PSS. The proposed identification method presents a feasible and operable procedure to map the key activity elements within the smart analytic capability hierarchy. The UAO-SSRs obtained from the identification phase are then entered into the evaluation phase. The proposed evaluation method combines the fuzzy set theory, rough set theory and BWM to prioritize the importance weight of the identified UAO-SSRs. A RF-LPM is developed to find the optimal rough-fuzzy weight of each SSR under uncertain environment. Moreover, a deroughness method and a defuzzification model are introduced to obtain accurate crisp weight from the rough-fuzzy weights for the final prioritization of the UAO-SSRs. An illustrated example of identification and evaluation of SSRs for self-driving tour cycle of SVSS and four comparisons between the crisp BWM, fuzzy BWM, rough BWM and the proposed rough-fuzzy BWM have demonstrated the feasibility of the proposed framework. The case results show that SSR12 (alerting driver's unsafe behavior), SSR14 (recommending optimal driving behavior), SSR10 (diagnosis of driver's behavior), SSR13 (predicting driver's behavior and status) and SSR11 (monitoring drivers' mental status) emerge as the top five SSRs. These service requirements should be paid more attention in configuring process of user activity-oriented smart service modules. It is notable that the rough set, fuzzy set and BWM are first integrated for the requirement evaluation of smart PSS field.

Although the proposed integrated framework presents several advantages in identifying and evaluating service requirement of

smart PSS, it still has some limitations. One limitation of the identification method is that more empirical cases should be explored to acquire better validity of the conceptual framework and implementation roadmap. Moreover, one limitation of the proposed evaluation method is that it does not take the individual effect of experts into account. In addition, more research work on integration of other fuzzy set theory (e.g. interval-valued intuitionistic fuzzy set, interval-valued hesitant fuzzy set) and the rough set theory can be conducted to explore handling mechanisms of multiple uncertainty with the BWM method.

## Author contributions

Zhihua Chen and Xinguo Ming conceived of the presented idea. Zhihua Chen developed the theory and performed the computations. Tongtong Zhou and Yuan Chang verified the analytical methods. Xinguo Ming encouraged Zhihua Chen and Zhaohui Sun to investigate the requirement identification methods for smart PSS and the mathematical methods of requirement evaluation and supervised the findings of this work. All authors discussed the results and contributed to the final manuscript.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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