Smart Product Service Requirements Identification and Evaluation: A Hybrid Method

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Abstract - **Identification and evaluation of smart product service requirements (SPSRs) are considered to be the critical steps for smart product service system (smart PSS) designing. However, there are few studies on the SPSRs identification and lack of service evaluation methods that comprehensively consider multiple uncertain factors. Therefore, this paper proposes a framework for SPSRs identification, which innovatively considers the characteristics of smart PSS and helps to elicit SPSRs from the logic of data value creation. Furthermore, considering the effects of individual semantic vagueness and individual subjective preference, a method based on the rough-fuzzy number is proposed, which helps service designers obtain subjective and accurate evaluation results. The case of the smart maintenance service of smart cars is used to prove the flexibility and feasibility of the identification and evaluation method.**

Keywords - **smart product service system, service requirement identification, service requirement evaluation, rough-fuzzy number**

I. INTRODUCTION

The rapid development of the world economy makes the role of services more and more important in providing product value. Manufacturing companies pay more attention to providing users with product derivative services and increasing the added value of products by providing support services. The solution that packages products and services to consumers has become a new profit and value growth point for manufacturing companies. This kind of service-oriented value proposition is called product service system (PSS) [1,2], which plays an important role in the improvement of social production, living standards, the value-added in the product life cycle, and environmental protection [3].

The integrated applications of advanced smart technologies, such as smart sensing, cyber-physical system (CPS), and artificial intelligence (AI), have greatly shortened the distance between manufacturers and consumers. Thanks to the above smart technologies, the manufacturers could conduct information collection, data preprocessing via their products. Then, the information integration platforms, such as the big data platform, could be further established based on the communication capability of the Internet of Things (IoT). Finally, smart service innovation emerges between companies and customers in the form of collaboration [4,5]. A new business form, namely, smart product service system (smart PSS), has become the mainstream strategy adopted by manufacturers to obtain higher market competitiveness, customer satisfaction, and environmental sustainability [6].

Smart PSS was first proposed by Valencia et al. [7]. It uses smart connected products (SCPs) as media and tools to integrate with various smart product services (SPSs), such as smart maintenance services, smart update services, etc., and to deliver them to customers. Generated by processing the data collected and generated by SCPs, the information, knowledge, and wisdom can be used by SPSs to provide an insightful description, diagnosis, prediction, and decision-making capabilities to optimize the performance of physical product service activities [8].

In smart PSS development, the identification and evaluation of smart product service requirements (SPSRs) are the important factors that affect the quality of the service solution delivered to consumers. Through the requirement identification process, manufacturers (usually also service providers) identify the SPSs that users need, which is the foundation of the design of smart PSS. Due to the constraint of resources, manufacturers need to recognize the relative priority of SPSRs through the evaluation process and clarify the services that need to be paid attention to first [9]. However, most research on product service requirements identification aims at traditional PSS, so there is a lack of research on SPSRs identification in smart PSS services. Moreover, the current methods of service requirements evaluation are mostly expert scoring [10]. This process always involves two kinds of uncertainty: the uncertainty caused by the vagueness and multi-meaning of experts' language and the uncertainty caused by experts' subjective preference, both of which may lead to subjective and inaccurate results. The previous evaluation methods mostly only consider one of the two uncertainty factors.

To solve the above problems, a reference framework for SPSRs identification is proposed in Section III, and then an evaluation method based on the rough-fuzzy number is used in Section IV to quantify the importance degree of SPSRs. In Section V, a case study is conducted to verify the feasibility and effectiveness of the identification and evaluation method. The conclusion is summarized in Section VI.

II. LITERATURE REVIEW

There have been many studies on service requirements identification of the traditional PSS. QFD method was widely used to transform user needs into product service requirements [11]. The I-CAC framework was proposed to

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identify the stakeholders appearing in the product life cycle and their interaction activities with users, to derive product service requirements [8]. To extract customers' potential requirements in PSS, a service scenario planning method was applied [12]. However, the characteristics of smart PSS were not considered in these methods. Recently, there are some studies on SPSRs identification, but most of them mainly identify SPSRs by the data-driven method [2,5]. The frameworks which allow manufacturers and service providers to proactively identify SPRSs of smart PSS are lacking.

In terms of requirements evaluation, some evaluation models combined with expert scoring were commonly used [10]. Instead of precise numerical values, experts tend to use some vague words (e.g., a little important, important, very important) to score. Therefore, expert opinions are always ambiguous. Triangular and trapezoidal fuzzy sets were used to handle this kind of uncertainty caused by semantics fuzziness [9]. Moreover, the cognition of the relationship between service requirements and evaluation indicators is usually influenced by individual subjective preferences, which may also affect the scoring results [8,13-15]. This kind of uncertainty cannot be solved by using fuzzy set theory alone, while the rough set theory is an ideal method to obtain objective and realistic results. However, the rough set is not suitable to handle personal semantic fuzziness [16].

III. IDENTIFICATION METHOD OF SPSRs

A. The Proposed Framework for SPSRs Identification

The proposed framework (see Fig. 1) mainly includes three-dimensional axes.

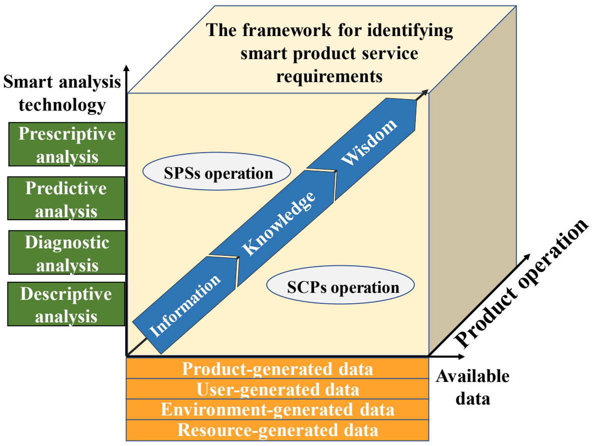

Fig. 1. The reference framework for SPSRs Identification.

These three dimensions represent the product operation, the available data and the smart analysis technology. The detailed descriptions of these three dimensions are as follows.

Product operation dimension: In different operation phases, users usually have different SPSRs. To identify SPSRs clearly and effectively, the operation dimension needs to be divided into various stages. The division methods can be flexibly chosen according to specific demands of SPSRs identification. For example, when identifying coarse-grained types of SPSRs, the SCP operation dimension can be divided into different phases according to the product life cycle, such as design, manufacturing, sales, use, maintenance, and recycling. If identifying SPSRs in a specific business scenario is required, this dimension can also be divided according to the operation states of the SCP. For example, in the maintenance scenario, the operation dimension can be divided into two phases, i.e., the SCP is operating normally and the SCP is malfunctioning.

Available data dimension: The available data refers to the raw data that could be collected and used during the SCP operation. Considering the data source, these data can be classified into four categories: product-generated data, user-generated data, environment-generated data, and resource-generated data. Product-generated data includes the SCP's self-information and the real-time and historical data generated by SCP operations. User-generated data includes user personal data, user behavior data, user status data, etc. The environment-generated data refers to the data generated by the natural environment where the SCP is located and includes temperature data, geographic location data, etc. Because service resources are essential for accomplishing SPSs, resource-generated data needs to be considered. It mainly includes service tool data, service personnel data, etc.

Smart analysis technology dimension: According to the smart level, smart analysis technologies can be classified into four categories, namely, descriptive analysis, diagnostic analysis, predictive analysis, and prescriptive analysis [17]. The available data mentioned above are processed by data analysis technology and then transformed into valuable information, knowledge, and wisdom which realize the expected smart service function. Descriptive analysis is mainly used to summarize what happened. It summarizes and presents past or ongoing events through aggregation and statistics of the raw data in the form of reports or graphs. Diagnostic analysis helps people understand why things happen. After comprehensive consideration of the information related to an event, the diagnostic analysis can help people find the root cause. Predictive analysis can predict what might happen in the future. It uses past data and existing information to predict future results and the likelihood of their occurrence. Prescriptive analysis focuses on giving action recommendations for people and help them make the best decision.

B. Roadmap for Identifying SPSRs

Based on the reference framework in Section III.A, the steps for SPSRs identification are shown in Fig. 2. The first step is to specify the phase of product operation, which determines the types of available data. The second step is to recognize the data that can be obtained and used by SCPs, which can be considered from four aspects. Then, the third step is to recognize the smart analysis technology required in the process of transforming available raw data into high-value information, knowledge, and wisdom. After being

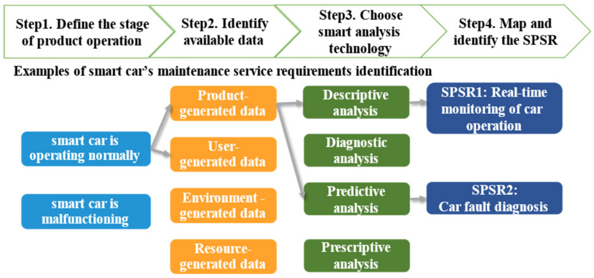

Fig. 2. Roadmap of SPSRs identification.

processed by different kinds of smart analysis technologies, the available data will generate different values. Finally, the SPSRs which are provided by the information, knowledge, and wisdom are elicited. Professional service designers and smart product R&D personnel need to participate in the whole process because their opinions can guarantee the professionalism and technical feasibility of the SPSRs. Moreover, different types of data often cooperate to support the same smart service, so the derived SPSRs are likely to be repeated. For example, through predictive analysis, the real-time product status data and user behavior data can both provide the smart service of product future status prediction. At this time, the final identified SPSRs need to be de-duplicated.

Take the maintenance service requirements identification of the smart car as an example (see Fig. 2). The operation dimension of the car can be divided into two phases: the smart car is operating normally and the smart car is malfunctioning. In the previous phase, based on the data generated by the smart car, two kinds of SPSRs are derived (i.e., SPSR1, SPSR2).

IV. EVALUATION METHOD OF SPSRs

After identifying the SPSRs, the importance degree of the identified SPSRs should be sorted, which can help service designers recognize the priorities in SPSs development. In that way, the effort and resources can be reasonably allocated. In this section, considering both the ambiguity of individual language expression and the individual subjective preference, a method based on the rough-fuzzy number is applied. Through this method, an objective and quantitative evaluation result can be obtained. The calculation steps are as follows:

Step1. Define evaluation indicators, the weight of each indicator, and linguistic evaluation variables and corresponding triangular fuzzy numbers (See Table I). The weights of indicators must satisfy the following restriction:

$$\sum_{n=1}^{q} w_n = 1 \tag{1}$$

where q is the number of evaluation indicators.

TABLE I
FUZZY SCALE OF LINGUISTIC EVALUATION VARIABLES

Linguistic evaluation variable	Triangular Fuzzy number
Very low(VL)	(1, 1, 1.5)
Low(L)	(1.5, 2, 2.5)
Medium(M)	(2.5, 3, 3.5)
High(H)	(3.5, 4, 4.5)
Very high(VH)	(4.5, 5, 5)

Step2. Obtain the linguistic evaluation matrix. Invite R experts to evaluate the importance correlation between p SPSRs and q evaluation indicators. The linguistic evaluation matrix E^{ls} made by the s-th expert is as follows:

$$E^{ls} = \begin{bmatrix} E_{11}^{ls} & E_{12}^{ls} & \cdots & E_{1q}^{ls} \\ E_{21}^{ls} & E_{22}^{ls} & \cdots & E_{2q}^{ls} \\ \vdots & \vdots & \ddots & \vdots \\ E_{p1}^{ls} & E_{p2}^{ls} & \dots & E_{pq}^{ls} \end{bmatrix}, \tag{2}$$

where E_{ij}^{ls} denotes the importance correlation between the i-th SPSR and the j-th evaluation indicator. ($i = 1,2,\dots,p$, $j = 1,2,3,\dots,q$, $s = 1,2,3,\dots,R$).

Step3. Obtain the fuzzy evaluation matrix. Based on the fuzzy scale in Table I, the linguistic evaluation matrix E^{ls} can be transformed into $\tilde{E}^{Ts}$ as follows:

$$\tilde{E}^{Ts} = \begin{bmatrix} \tilde{E}_{11}^{Ts} & \tilde{E}_{12}^{Ts} & \cdots & \tilde{E}_{1q}^{Ts} \\ \tilde{E}_{21}^{Ts} & \tilde{E}_{22}^{Ts} & \cdots & \tilde{E}_{2q}^{Ts} \\ \vdots & \ddots & \ddots & \vdots \\ \tilde{E}_{p1}^{Ts} & \tilde{E}_{p2}^{Ts} & \dots & \tilde{E}_{pq}^{Ts} \end{bmatrix}, \tag{3}$$

where $\tilde{E}_{ij}^{Ts} = (l_{ij}^{Ts}, m_{ij}^{Ts}, u_{ij}^{Ts})$, and l_{ij}^{Ts}, m_{ij}^{Ts} and u_{ij}^{Ts} represent the low, middle, and up boundaries of the triangular fuzzy number respectively.

Step4. Form the group fuzzy evaluation matrix. The group fuzzy evaluation matrix $\hat{E}^{T}$ is constructed by integrating the fuzzy evaluation matrices made by R experts.

$$\hat{E}^{T} = \begin{bmatrix} \hat{E}_{11}^{T} & \hat{E}_{12}^{T} & \cdots & \hat{E}_{1q}^{T} \\ \hat{E}_{21}^{T} & \hat{E}_{22}^{T} & \cdots & \hat{E}_{2q}^{T} \\ \vdots & \ddots & \ddots & \vdots \\ \hat{E}_{p1}^{T} & \hat{E}_{p2}^{T} & \dots & \hat{E}_{pq}^{T} \end{bmatrix} \tag{4}$$

and each element in this matrix can also be described as a group fuzzy evaluation set $\hat{E}_{ij}^{T}$ as follows:

$$\hat{E}_{ij}^{T} = \{\tilde{E}_{ij}^{T1}, \dots, \tilde{E}_{ij}^{Ts}, \dots, \tilde{E}_{ij}^{TR}\}. \tag{5}$$

$\hat{E}_{ij}^{T}$ can also be described as:

$$\hat{E}_{ij}^{T} = \{\hat{l}_{ij}^{T}, \hat{m}_{ij}^{T}, \hat{u}_{ij}^{T}\} = \{(l_{ij}^{T1}, \cdots, l_{ij}^{Ts}, \cdots, l_{ij}^{TR}), (m_{ij}^{T1}, \cdots, m_{ij}^{Ts}, \cdots, m_{ij}^{TR}), (u_{ij}^{T1}, \cdots, u_{ij}^{Ts}, \cdots, u_{ij}^{TR})\}. \tag{6}$$

Step5. Construct the rough-fuzzy evaluation matrix. Each element $\hat{E}_{ij}^{T}$ in the $\hat{E}^{T}$ can be converted to a rough-fuzzy number by the following steps proposed in [16].

Step5.1 Find the lower and upper approximations of each element in $\hat{E}_{ij}^{T}$. Then, the lower approximation $\underline{Apr}(\tilde{E}_{ij}^{Ts})$ and upper approximation $\overline{Apr}(\tilde{E}_{ij}^{Ts})$ of s-th element $\tilde{E}_{ij}^{Ts}$ can be defined as:

$$\overline{Apr}(\tilde{E}_{ij}^{Ts}) = \cup \{\tilde{E}_{ij}^{Tt} \in \hat{E}_{ij}^{T} | \tilde{E}_{ij}^{Tt} \geq \tilde{E}_{ij}^{Ts}\}, \tag{7}$$

$$\underline{Apr}(\tilde{E}_{ij}^{Ts}) = \cup \{\tilde{E}_{ij}^{Tt} \in \hat{E}_{ij}^{T} | \tilde{E}_{ij}^{Tt} \leq \tilde{E}_{ij}^{Ts}\}. \tag{8}$$

Step5.2 Calculate the lower limit number and upper limit number of each element in $\hat{E}_{ij}^{T}$. The lower limit number $\overline{Lim}(\tilde{E}_{ij}^{Ts})$ and upper limit number $\underline{Lim}(\tilde{E}_{ij}^{Ts})$ of s-th element

$\tilde{E}_{ij}^{Ts}$ can be obtained as follows:

$$\overline{Lim}(\tilde{E}_{ij}^{Ts}) = (\overline{Lim}(l_{ij}^{Ts}), \overline{Lim}(m_{ij}^{Ts}), \overline{Lim}(u_{ij}^{Ts}))$$

$$= \left(\frac{1}{N_s^U}\sum_{n=1}^{N_s^U} y_n^l, \frac{1}{N_s^U}\sum_{n=1}^{N_s^U} y_n^m, \frac{1}{N_s^U}\sum_{n=1}^{N_s^U} y_n^u\right), \tag{9}$$

$$\underline{Lim}(\tilde{E}_{ij}^{Ts}) = (\underline{Lim}(l_{ij}^{Ts}), \underline{Lim}(m_{ij}^{Ts}), \underline{Lim}(u_{ij}^{Ts}))$$

$$= \left(\frac{1}{N_s^L}\sum_{n=1}^{N_s^L} x_n^l, \frac{1}{N_s^L}\sum_{n=1}^{N_s^L} x_n^m, \frac{1}{N_s^L}\sum_{n=1}^{N_s^L} x_n^u\right), \tag{10}$$

where N_s^U and N_s^L are the numbers of elements in the upper approximation and lower approximation respectively, and y_n^l, y_n^m, y_n^u represent the low, middle, and up boundaries of the elements in upper approximation, and x_n^l, x_n^m, x_n^u represent the low, middle, and up boundaries of the elements in the lower approximation.

Step5.3 Use the form of rough-fuzzy to represent each fuzzy evaluation. The fuzzy evaluation $\tilde{E}_{ij}^{Ts}$ can be described in the rough-fuzzy form $RF(\tilde{E}_{ij}^{Ts})$ as follows:

$$RF(\tilde{E}_{ij}^{Ts}) = [\underline{Lim}(\tilde{E}_{ij}^{Ts}), \overline{Lim}(\tilde{E}_{ij}^{Ts})], \tag{11}$$

where

$$\underline{Lim}(\tilde{E}_{ij}^{Ts}) = [\left(\underline{Lim}(l_{ij}^{Ts}), \underline{Lim}(m_{ij}^{Ts}), \underline{Lim}(u_{ij}^{Ts})\right),$$

$$\overline{Lim}(\tilde{E}_{ij}^{Ts}) = [\left(\overline{Lim}(l_{ij}^{Ts}), \overline{Lim}(m_{ij}^{Ts}), \overline{Lim}(u_{ij}^{Ts})\right).$$

Step5.4 Calculate the rough-fuzzy interval number of each group fuzzy evaluation set. Then, the group rough-fuzzy interval number $RF(\hat{E}_{ij}^T)$ of the group fuzzy evaluation set $\hat{E}_{ij}^T = \{\tilde{E}_{ij}^{T1}, \dots, \tilde{E}_{ij}^{Ts}, \dots, \tilde{E}_{ij}^{TR}\}$ can be calculated as follows:

$$RF(\hat{E}_{ij}^T) = [(e_{ij}^{Ll}, e_{ij}^{Lm}, e_{ij}^{Lu}), (e_{ij}^{Ul}, e_{ij}^{Um}, e_{ij}^{Uu})]$$

$$= [(\frac{1}{R}\sum_{s=1}^{R} \underline{Lim}(l_{ij}^{Ts}), \frac{1}{R}\sum_{s=1}^{R} \underline{Lim}(m_{ij}^{Ts}), \frac{1}{R}\sum_{s=1}^{R} \underline{Lim}(u_{ij}^{Ts})),$$

$$\frac{1}{R}\sum_{s=1}^{R} \overline{Lim}(l_{ij}^{Ts}), \frac{1}{R}\sum_{s=1}^{R} \overline{Lim}(m_{ij}^{Ts}), \frac{1}{R}\sum_{s=1}^{R} \overline{Lim}(u_{ij}^{Ts}))]. \tag{12}$$

Step5.5 Obtain the rough-fuzzy evaluation matrix. According to (4) and (12), the group fuzzy evaluation matrix $\hat{E}^T$ can be transformed into a rough-fuzzy evaluation matrix $RF(\hat{E}^T)$ as follows:

$$RF(\hat{E}^T) = \begin{bmatrix} RF(\hat{E}_{11}^T) & RF(\hat{E}_{12}^T) & \cdots & RF(\hat{E}_{1q}^T) \\ RF(\hat{E}_{21}^T) & RF(\hat{E}_{22}^T) & \cdots & RF(\hat{E}_{2q}^T) \\ \vdots & & \ddots & \vdots \\ RF(\hat{E}_{p1}^T) & RF(\hat{E}_{p2}^T) & \dots & RF(\hat{E}_{pq}^T) \end{bmatrix}. \tag{13}$$

Step6. The crisp evaluation matrix e can be obtained as follows:

$$e = \begin{bmatrix} e_{11} & e_{12} & \cdots & e_{1q} \\ e_{21} & e_{22} & \cdots & e_{2q} \\ \vdots & \vdots & \ddots & \vdots \\ e_{p1} & e_{p2} & \cdots & e_{pq} \end{bmatrix}, \tag{14}$$

where the crisp evaluation number e_{ij} can be calculated using group rough-fuzzy interval number $RF(\hat{E}_{ij}^T)$ in (12):

$$e_{ij} = (e_{ij}^{Ll} + 4e_{ij}^{Lm} + e_{ij}^{Lu} + e_{ij}^{Ul} + 4e_{ij}^{Um} + e_{ij}^{Uu})/12. \tag{15}$$

Step7. Obtain the comprehensive evaluation number. The crisp comprehensive evaluation number (CEN) of *i*-th SPSR can be obtained as follows:

$$CEN_i = \sum_{n=1}^{p} w_n e_{in}. \tag{16}$$

By comparing the CEN of each SPSR, the importance ranking results can be obtained. Those SPSRs with higher CEN are more important.

TABLE II
THE SMART MAINTENANCE SERVICE REQUIREMENTS OF SMART CARS

Smart Car Operation	Available Data	Smart analysis Tech.	SPSR	Code
Operating normally	Product-generated data	Descriptive analysis	Real-time monitoring of car operation	SPSR1
	Product-generated data	Predictive analysis	Car failure prediction	SPSR2
	Product-generated data	Prescriptive analysis	Optimization of car operation	SPSR3
	User-generated data	Descriptive analysis	Monitoring and warning of unsafe driving behavior	SPSR4
	User-generated data	Prescriptive analysis	Recommendations for safe driving	SPSR5
Malfunctioning	Product-generated data	Descriptive analysis	Early warning and reporting of abnormal car status	SPSR6
	Product-generated data	Diagnostic analysis	Car fault diagnosis	SPSR7
	Product-generated data	Prescriptive analysis	Optimal maintenance plan generation	SPSR8
	User-generated data	Prescriptive analysis	User emergency measures guidance	SPSR9
	Environment-generated data	Descriptive analysis	Reporting of car position	SPSR10
	Environment-generated data	Prescriptive analysis	Recommendations for optimal maintenance path	SPSR11
	Resource-generated data	Descriptive analysis	Monitoring of Maintenance resources	SPSR12
	Resource-generated data	Prescriptive analysis	Intelligent deployment of maintenance resources	SPSR13

V. CASE STUDY

The world-class smart car manufacturer B is committed to providing customers with advanced smart cars and various kinds of related services. Smart maintenance is one of the basic but important services, so company B spends a lot of effort on it. The proposed identification method was applied to the service requirements identification of company B. Thirteen smart maintenance service requirements were obtained (see Table II). Taking customer satisfaction as the goal, the importance evaluation indicators were defined by company B as the safety and reliability during the smart car operation (Ind. 1), the timeliness of the maintenance service (Ind. 2) and the quality of the maintenance service (Ind. 3). The weight of each indicator was 0.3, 0.35 and 0.35, respectively. Three professional experts were invited to score the importance correlations between SPSRs and indicators. According to the calculation steps in Section IV, the comprehensive evaluation number (CEN) could be acquired (see Table III).

The result (see in Table III) shows that the service of early warning and reporting of abnormal car status is considered to be the most important service, followed by

TABLE III
EXPERT SCORES AND EVALUATION RESULTS

SPSR	Ind. 1	Ind. 2	Ind. 3	CEN	Rank
SPSR1	VH, H, H	H, H, H	L, L, L	3.40	7
SPSR2	M, M, M	M, H, H	H, H, H	3.58	5
SPSR3	H, H, H	L, M, L	L, L, M	2.83	9
SPSR4	VH, H, H	VL, VL, L	L, L, L	2.47	11
SPSR5	M, M, M	VL, VL, VL	VL, VL, L	1.72	13
SPSR6	H, H, H	VH, VH, VH	M, M, M	4.00	1
SPSR7	L, L, L	VH, H, H	H, VH, H	3.63	2
SPSR8	VL, VL, VL	VH, VH, VH	H, VH, VH	3.67	3
SPSR9	VH, VH, H	M, M, M	M, M, H	3.62	4
SPSR10	L, L, VL	M, M. H	L, L. L	2.37	12
SPSR11	VL, VL, VL	H, VH, H	M, M, M	2.87	8
SPSR12	L, L, VL	H, H, H	M, M, L	2.83	10
SPSR13	VL, VL, VL	VH, VH, VH	H, H, H	3.45	6

Note: The linguistic scoring results in the second column to fifth column of the table are scored by three experts.

car fault diagnosis service and optimal maintenance plan generation service. Therefore, in the development of smart maintenance services, the service designers in company B are asked to firstly focus on the top-ranked services. In this way, company B quickly identifies the core maintenance service requirements and reasonably arranged development resources, which significantly saves service development costs and improves customer satisfaction.

VI. CONCLUSION

This paper proposes a hybrid method for SPSRs identification and evaluation. Our framework for SPSRs identification innovatively considers the characteristics of smart PSS, which allows service designers to elicit SPSRs from the perspectives of different SCPs operation stages and the data analytic logic. The identification method makes designers identify SPSRs as comprehensively as possible, and reduces the omission of important requirements. As for the evaluation of SPSRs, a method integrating rough set theory and fuzzy set theory is proposed, which successfully resolves two kinds of uncertainty (i.e., the uncertainty caused by the vagueness and multi-meaning of experts' language and the uncertainty caused by experts' subjective preference) in the evaluation process. The case study shows the feasibility of the SPSRs identification and evaluation method. It provides a reference in the design and development processes of the smart maintenance service for smart cars.

In the future, some other elements involved in smart PSS such as relevant stakeholders could also be taken into consideration to improve the comprehensiveness of the reference framework of SPSRs identification, which may help service designers identify SPSRs from more perspectives and more easily.

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