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Design concept evaluation of smart product-service systems considering sustainability: an integrated method

Intelligent products and services are integrated into Smart product-service systems (PSS) through information and communication technology (ICT). Various feasible Smart PSS designs are usually created in the design stage, and the design concept selection directly affects the delivery performance of the Smart PSS. However, existing methods often require more comparisons, omits criteria objective weights, and considers less about the impact of information subjectivity and impreciseness on the Smart PSS design concept selection. To solve the problems, a new integrated method is proposed, which integrates both subjective and objective weights to improve the accuracy of evaluation. Firstly, for criteria weighting, the proposed approach integrates the merits of the Best Worst Method (BWM) in reducing the burden of pair-wise comparisons when determining the subjective weights, and the strengths of the Criteria Importance Though Inter-criteria Correlation (CRITIC) method in considering the correlation and contrast between all criteria when determining the objective weights. Then, Rough Set Theory is used to flexibly deal with the decision-making vagueness without much prior information. Finally, a case study of a smart washing machine is adopted to validate the effectiveness of the proposed method.

Keywords: Smart Product Service System, Sustainability, Rough Set theory, Best Worst Method, Criteria Importance Though Inter-criteria Correlation

Abbreviations

PSS	product-service systems
ICT	information and communication technology
BWM	best worst method
CRITIC	criteria importance though inter-criteria correlation
TOPSIS	technique for order preference by similarity to an ideal solution
AHP	analytic hierarchy process
ANP	analytical network process
PI	physical internet
CC	cloud computing
SCP	smart connected product
MCDM	multi-criteria decision-making
QFD	quality function deployment
DEMATEL	decision making trial and evaluation laboratory
CF	collaborative filtering
FMEA	Failure mode and effects analysis
DEA	data envelopment analysis
DCE	design concept evaluation

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1 Introduction

A PSS is a business model in which a company provides services while selling products (Goedkoop 1999, Mont 2001, Meier 2010). PSS includes tangible products and intangible services, which are combined to meet specific customer demands and strive to achieve sustainable development goals (Tukker, 2004). This model follows the principle of sustainable development and is environmentally friendly. With the development of artificial intelligence and ICT technology, products have become more intelligent by incorporating smart components such as microprocessors and software (Porter and Heppelmann, 2015). The definition of Smart PSS is a combination of intelligent products and electronic services where individual demands of consumers can be satisfied (Valencia 2015). There are a huge number of complex connections and interactions in the entire life cycle of the Smart PSS (Gudergan et al., 2017). The information generated by the users is collected in a large amount during the process of service (Campos et al., 2017). When companies design products or business processes, these data can be used to identify the customers' demands for generating better system designs (Wang et al., 2019; Song and Sakao,2017). The results of the design evaluation will directly affect the subsequent development direction of the Smart PSS, which will affect the subsequent development of systems.

The design concept evaluation of Smart PSS is a typical multi-criteria decision-making (MCDM) problem. The evaluation accuracy depends much on the criteria weighting methods. Some subjective weighting methods, such as Analytic Hierarchy Process (AHP) (Satty, 1988) and Analytical Network Process (ANP) (Satty, 1996), are used to determine the weights of criteria of PSS design (Biju et al., 2017; Lee et al., 2015). However, these subjective weighting methods rely much on the subjective judgments of the decision-makers (Wang and Lee, 2009). Moreover, as the number of criteria increases, decision-makers may not be able to assign precise weights to criteria due to the heavy burden of pair-wise comparisons and the limitation of analytical capabilities of decision-makers (Kahneman et al., 1982). Thus, some objective weighting methods, such as Entropy-based weighting (Hwang and Yoon, 1981) and CRITIC (Diakoulaki et al., 1995) methods, are adopted to reduce the impact of subjective weighting methods(Wang and Lee, 2009). However, the objective weighting methods require sufficient decision-making information, and they do not fully reflect the preferences of the decision-makers on criteria. Beside the criteria weighting methods, the vagueness in the decision-making information can also influence the result accuracy of MCDM (Song and Cao, 2017; Song and Ming 2014). Previous studies often adopt fuzzy set theory to deal with the vagueness of decision making which require much prior information (e.g. pre-set membership function).

To obtain a more accurate result of PSS design evaluation, this paper proposes a Rough BWM-CRITIC-TOPSIS method. Compared with the previous subjective and objective weighting methods, the proposed approach integrates the merits of the BWM method in reducing the burden of pair-wise comparisons when determining the subjective weights, the strengths of the CRITIC in dealing with criteria conflicts when determining the objective weights, the advantages of rough set theory in flexibly coping with the decision-making vagueness without much prior information. Rough number from rough set theory (Pawlak, 1982) are introduced to handle ambiguity and uncertainty in decision making information. The rough intervals can flexibly change to indicate the vagueness in decision making information. The rough number can accurately describe the distribution of the vague evaluation information and retain the decision-making information quality to the greatest extent (Zhai et al., 2009; Song and Cao, 2017; Khoo et al., 1999; Zhu et al., 2015).

The structure of the paper is arranged as follows. Section 2 reviews the related researches of Smart PSS, the evaluation criteria system of Smart PSS designs and the method of PSS design decision-making. Section 3 provides the calculation of the rough CRITIC-BWM-TOPSIS method. In section 4, a case study based on smart washing machine PSS designs is presented. The conclusion of the study is given in Section 5.

2 Literature Review

2.1 Smart Product-Service Systems

In competitive markets, manufacturers offer customized products with value-added services, which are product-service systems (Mont 2002, Song and Chan 2015), to gain more profits and sustained development (Parida et al., 2014). PSS does not regard the products as the primary goal, but emphasizes the service more. The value of the function is realized by products with personalized service.

With the development of ICT and AI technology, it has been challenging to adapt PSS to smart market competition (Chowdhury et al., 2018) until Smart PSS appeared. For the development of Smart PSS, the most powerful support is from intelligent products (Marilungo et al., 2017). Intelligent products are products with a high ability to generate, operate and process information (Rijsdijk and Hultink, 2009). Smart PSS has some features of smart products, but differ in certain aspects. Smart PSS can provide both products and services to meet the demands of consumers, which is a significant difference from intelligent products. When physical space and cyberspace of products are in real-time connection, Smart PSS can accept digital twin-enabled service innovation (Zheng et al., 2018). Most services provide value through electronic products (Stafford, 2003). Smart PSS builds a basic system consisting of embedded electronics, software and so on. This system is used for information and knowledge exchange (Takenaka, 2016). These systems were adapted at the system level autonomously through big data and intelligent algorithms (Lee et al., 2014). Smart PSS can perform engineer change management in a data-driven and digital service manner (Zheng et al., 2019). Zhang et al. (2016) proposed that smart box-enabled PSS consists of physical internet, PSS and cloud computing, which can provide green logistics to reduce the logistic cost and protect the environment.

The characteristics of Smart PSS are summarized by Valencia et al. (2015) as follows: consumer empowerment, services personalization, community feeling, service participation, ownership of products, personal/shared experience and continued growth. For businesses and consumers, the study shows that it is feasible to integrate products and services in an advanced way with the development of technology. Bernd et al. (2017) proposed that Smart

PSS is a value-created ecosystem-based digital technology. The ecosystem is complicated, dynamic and interrelated among stakeholders. Manufacturers occupy the information-intensive market by creating more smart connected products (SCP) (Porter and Heppelmann, 2014). The SCP transmits information to stakeholders through multiple smart tools in an ad-hoc manner (Rymaszewska et al., 2017). Smart PSS is a unique digital service that uses SCP as a medium for generating electronic services (Zheng et al., 2019).

2.2 Evaluation Criteria System of Smart PSS Designs

Evaluating the Smart PSS design during the design stage can reduce the risk (Allen et al., 2012). In previous studies, the evaluation criteria were more focused on economic aspects (Watanabe et al., 2016, Fang and Song, 2018) and environmental aspects (Song and Sakao, 2018). In PSS evaluation, sustainability and customer value are two main perspectives that represent the whole society and the individual customers. Kim et al. (2013) reported an evaluation framework that includes five aspects of profitability, planet, people, quality and cost. The evaluation criteria include cost, working environment, and influence on society, etc. Otherwise, the PSS value is created through its lifecycle (Dreyer et al., 2006). The value of Smart PSS is created together by manufacturers, customers and other points (Liu et al., 2018). Shen et al. (2017) made an assessment to help select the design with the least cost. With the emergence of Smart PSS, the system interacts with the environment, customers, and other aspects more frequently. Seven characteristics of Smart PSS are summarized by Valencia et al. (2015). For the evaluation criteria of products, economic, quality, safety, environmental protection and other aspects should be considered. There are many related qualitative and quantitative criteria. Therefore, the impact on society cannot be ignored.

According to the summary of the literature, ten criteria are selected to construct the evaluation criteria system of Smart PSS designs during the entire life cycle. These ten criteria are divided into economic, environmental and social aspects, where the description of each evaluation criterion is in Table 1.

Table 1. Description of the evaluation criteria

2.3 *The Method of PSS Design Decision-making*

PSS design evaluation is a typical MCDM problem. Different methods may produce different design ranking results with different accuracy. The inaccurate results will directly affect the development direction of the PSS, which will lead to significant failures to the companies, even bankruptcy. Therefore, many researchers have proposed a variety of decision-making methods to obtain better results. Some researchers take subjective assessment methods when calculating weights. For instance, Zhang et al. introduced a method by combining quality function deployment (QFD), fuzzy theory and group decisions to reduce the impact of uncertain factors on program decision-making (Zhang et al. 2009). Geng (2011) proposed a method that includes fuzzy pair-wise comparison and the KANO model to evaluate optimal planning. However, these methods cannot objectively describe and analyze vague information.

To manipulate the vague information in design decision-making, some previous research introduces the rough number concept (Zhai et al., 2009; Khoo et al., 1999) from rough set theory (Pawlak, 1982). Song et al. (2013) improved AHP and TOPSIS with rough number to evaluate the design concepts in subjective environments. Liu et al. (2020) used rough set to evaluate the sustainability of Smart PSS design, which effectively reduced the inconsistency among experts. To reduce the perceived interpersonal uncertainty, a rough-fuzzy data envelopment analysis (DEA) method was proposed for assessing Smart PSS alternatives (Chen et al., 2020). Qi et al. (2020) proposed an integrated rough VIKOR for customer-involved design concept evaluation combining with customers' preferences and designers' perceptions. A Rough DEMATEL-collaborative filtering (CF) model was proposed to solve the PSS alternative recommendation problem under vague environments (Song and Sakao,2017). Although the previous method based on rough number can effectively deal with the vagueness and subjectivity, they do not consider the objective criteria weights when evaluating the PSS designs. This will influence the accuracy of evaluation results.

3 Methodology

To achieve accurate design solution evaluation of smart PSS, a new decision-making method based on Rough BWM-CRITIC-TOPSIS is proposed in this section. The framework of the decision-making method is shown in Figure 1.

Figure 1. The proposed evaluation framework using Rough BWM-CRITIC-TOPSIS

3.1 *Determine the Weight of the Evaluation Index of the Smart PSS Designs*

3.1.1 Determine the subjective weight using Rough BWM

BWM, a method for calculating the subjective weights, is a method that compares some criteria with the best and worst ones. This new structured comparison method simplifies the data and calculation process and makes the results more reliable.

Step 1. Identify the best and worst criterion

The sets of criteria $\mathrm{A} = [a_1, a_2, \cdots, a_n]$ are selected for the Smart PSS design decision evaluation and there are n criteria in the sets.

Then the best criteria A_B and the worst criteria A_W are identified.

Step 2. Construct a comparison vector

The preferences of A_B over other criteria and other criteria over A_W are scored from

1 to 9. $H_B^k = [h_{B1}^k, h_{B2}^k, \cdots, h_{Bj}^k, \cdots h_{Bn}^k]$ is the best-to-other vector, where h_{Bj}^k indicates the degree of preference of the kth expert for the best criterion over criterion j. And m is the total number of experts.

$H_W^k = [h_{1W}^k, h_{2W}^k, \cdots, h_{jW}^k, \cdots, h_{nW}^k]$ is the worst-to-other vector, where h_{jW}^k indicates the degree of preference of the kth expert for the criterion j over the worst criterion, therefore $h_{WW}^k = 1, 1 \le k \le m, 1 \le j \le n$.

Step 3. Construct a rough comparison vector

The comparison vector is roughened to obtain the rough number $RN(h_{Bj})$ and $RN(h_{jW})$.

$$RN(h_{Bj}) = \{[\underline{h_{Bj}^1}, \overline{h_{Bj}^1}], [\underline{h_{Bj}^2}, \overline{h_{Bj}^2}], \cdots, [\underline{h_{Bj}^m}, \overline{h_{Bj}^m}]\}$$

$$RN(h_{jW}) = \{[\underline{h_{jW}^1}, \overline{h_{jW}^1}], [\underline{h_{jW}^2}, \overline{h_{jW}^2}], \cdots, [\underline{h_{jW}^m}, \overline{h_{jW}^m}]\}$$

The average of the rough sequences is expressed as follows:

$\overline{RN(h_{Bj})} = [\underline{h_{Bj}}, \overline{h_{Bj}}] = \frac{1}{m}\sum_{k=1}^{m}[\underline{h_{Bj}^k}, \overline{h_{Bj}^k}]$, where $\underline{h_{Bj}}$ is the lower boundary and $\overline{h_{Bj}}$ is the higher boundary of $RN(h_{Bj})$.

$\overline{RN(h_{jW})} = [\underline{h_{jW}}, \overline{h_{jW}}] = \frac{1}{m}\sum_{k=1}^{m}[\underline{h_{jW}^k}, \overline{h_{jW}^k}]$, where $\underline{h_{jW}}$ is the lower boundary and $\overline{h_{jW}}$ is the higher boundary of the $RN(h_{jW})$.

The two rough comparison vectors can be obtained as follows:

$$RH_B = \{[\underline{h_{B1}}, \overline{h_{B1}}], [\underline{h_{B2}}, \overline{h_{B2}}], \cdots, [\underline{h_{Bn}}, \overline{h_{Bn}}]\}$$

$$RH_W = \{[\underline{h_{1W}}, \overline{h_{1W}}], [\underline{h_{2W}}, \overline{h_{2W}}], \cdots, [\underline{h_{nW}}, \overline{h_{nW}}]\}$$

Step 4. Compute the subjective weight of criteria

To obtain the subjective weight, the multi-objective programming model can be used as follows:

$$\min\max\{\left|\frac{w_{sB}}{w_{sj}}-RN(h_{Bj})\right|,\left|\frac{w_{sj}}{w_{sW}}-RN(h_{jW})\right|\}$$

$$s.t.\begin{cases}\sum_{j=1}^{n} w_{sj}=1\\ \underline{w_{sB}}\le\overline{w_{sB}}\\ \underline{w_{sW}}\le\overline{w_{sW}}\\ w_{sj}\ge 0\end{cases} \tag{1}$$

for all j, where w_{sj} is the subjective weight of criterion j and δ is a statistical value. The above formula can be converted to the following format:

$$\min\delta$$

$$s.t.\begin{cases}\left|\frac{\underline{w_{sB}}}{\overline{w_{sj}}}-\overline{h_{\mathrm{Bj}}}\right|\le\delta;\left|\frac{\overline{w_{sB}}}{w_{sj}}-\underline{h_{Bj}}\right|\le\delta\\ \left|\frac{\underline{w_{sj}}}{\overline{w_{sW}}}-\overline{h_{\mathrm{jW}}}\right|\le\delta;\left|\frac{w_{sj}}{\underline{w_{sW}}}-\underline{h_{jW}}\right|\le\delta\\ \sum_{j=1}^{n} w_{sj}=1\\ \underline{w_{sB}}\le\overline{w_{sB}}\\ \underline{w_{sW}}\le\overline{w_{sW}}\\ w_{sj}\ge 0\end{cases} \tag{2}$$

where w_{sB} and w_{sW} are the weights of the best and worst criteria, respectively. Then $W_S=\left[w_{s1},w_{s2},\cdots,w_{sn}\right]$ is the subjective weight set of the evaluation criteria.

3.1.2 Determine the objective weight by Rough CRITIC

The CRITIC method is a method of obtaining the conflict and difference of the evaluation criteria by calculation using the data, and the method is for calculating the objective weights. The CRITIC is also a more straightforward approach needing less computational effort and considers the correlation and contrast between all criteria (Diakoulaki et al., 1995). CRITIC method directly uses decision matrix while computing criteria weights objectively. The method considers the intensity of the contrast that is contained in the structure of the decision-making problem. It is not necessary for decision-makers to make more pair-wise comparisons like other weighting methods.

Step 1. Convert the programme preference value to a rough mode

There are n evaluation criteria, which can be expressed as $B=\ b_1,b_2,\cdots,b_n$. The experts are required to score the Smart PSS designs 1-9 according to the importance. A score of 1 represents the least important, while a score of 9 means that the criterion is the most important. Then the preference value matrix $P_{s\times n}$ is obtained, where s is the total number of the Smart PSS designs.

Then the preference value matrix $P_{s\times n}$ is roughed and averaged to obtain the rough preference value matrix:

$$RN(B)=\left\{\left[\underline{b_1},\overline{b_1}\right],\left[\underline{b_2},\overline{b_2}\right],\cdots,\left[\underline{b_j},\overline{b_j}\right],\cdots,\left[\underline{b_n},\overline{b_n}\right]\right\}$$

where $\underline{b_j}$ and $\overline{b_j}$ are the lower and higher boundaries of the preference value of the criterion j, respectively, where $1\le j\le n$.

Step 2. Convert the rough preference value matrix to a standard form

There are two kinds of evaluation criteria. One is the set of beneficial criteria, which is better when the preference value is higher. The conversion method is as follows:

$$x_j=\frac{RN(b_j)-\min(RN\left(b_j\right))}{\max(RN\left(b_j\right))-\min(RN\left(b_j\right))}=\frac{\overline{b_j}-\min\left(\underline{b_j}\right)}{\max\left(\overline{b_j}\right)-\min\left(\underline{b_j}\right)} \tag{3}$$

The other is a series of cost criteria. The standard form can be obtained by using the following method:

$$x_j=\frac{\max(RN\left(b_j\right))-RN(b_j)}{\max(RN\left(b_j\right))-\min(RN\left(b_j\right))}=\frac{\max\left(\overline{b_j}\right)-\underline{b_j}}{\max\left(\overline{b_j}\right)-\min\left(\underline{b_j}\right)} \tag{4}$$

where x_j is the standard preference value.

Step 3. Calculate the information measures of each criterion

The information measures of the criteria include the conflict and the difference of criteria, which is calculated as follows:

$$Q_j=\sigma_j\times\sum_{i=1}^{n}\left(1-r_{ij}\right) \tag{5}$$

where Q_j and σ_j are the information measures and the standard deviation of the criterion j. r_{ij} is the correlation coefficient between criterion x_i and criterion x_j, therefore $1\le i,j\le n$.

Step 4. Compute the objective weight of the criteria

$$w_{oj}=\frac{Q_j}{\sum_{j=1}^{n}Q_j} \tag{6}$$

Then $W_o = w_{o1}, w_{o2}, \cdots, w_{on}$ is the objective weight set of the evaluation criteria.

3.1.3 Calculate the comprehensive weight of each evaluation criterion

$$w_j = \frac{w_{sj} \times w_{oj}}{\sum_{j=1}^{n} w_{sj} \times w_{oj}} \tag{7}$$

w_j represents the comprehensive weight of the criterion j.

3.2 Rank the Smart PSS Designs Using Rough TOPSIS

The TOPSIS method is a common method of solving the multi-criteria decision problem. The data are normalized to avoid the influence of different index dimensions and the data information can be fully used to make the result more reliable (Hwang C L, Yoon K 1981).

Step 1. Construct the judgment matrix and transform to a rough number form

Smart PSS designs are scored from 1 to 9 according to the performance. A design score of 1 for the criterion means that the design performs terribly, while 9 means perfect performance. Then the judgment matrix is obtained:

$$P = \left(p_{ij}\right)_{s\times n} = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1n} \\ p_{21} & p_{22} & \cdots & p_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ p_{s1} & p_{s2} & \cdots & p_{sn} \end{bmatrix}$$

where s is the total number of Smart PSS designs and n is the total number of the evaluation criteria, whereby $1 \le i \le s, 1 \le j \le n$.

Then the judgment matrix is roughed and averaged to obtain the rough importance matrix:

$$RN(P) = \begin{bmatrix} \left[\underline{p_{11}}, \overline{p_{11}}\right] & \left[\underline{p_{12}}, \overline{p_{12}}\right] & \cdots & \left[\underline{p_{1n}}, \overline{p_{1n}}\right] \\ \left[\underline{p_{21}}, \overline{p_{21}}\right] & \left[\underline{p_{22}}, \overline{p_{22}}\right] & \cdots & \left[\underline{p_{2n}}, \overline{p_{2n}}\right] \\ \vdots & \vdots & \ddots & \vdots \\ \left[\underline{p_{s1}}, \overline{p_{s1}}\right] & \left[\underline{p_{s2}}, \overline{p_{s2}}\right] & \cdots & \left[\underline{p_{sn}}, \overline{p_{sn}}\right] \end{bmatrix}$$

Step 2. Normalize and weight the matrix

The matrix is transformed to the normalized form according to the following formula:

$$\left[\underline{d_{ij}}, \overline{d_{ij}}\right] = \left[\frac{\underline{p_{ij}}}{\max_{i=1}^{s}\left\{\max\left[\underline{p_{ij}}, \overline{p_{ij}}\right]\right\}}, \frac{\overline{p_{ij}}}{\max_{i=1}^{s}\left\{\max\left[\underline{p_{ij}}, \overline{p_{ij}}\right]\right\}}\right] = \left[\frac{\underline{p_{ij}}}{\max_{i=1}^{s}(\overline{p_{ij}})}, \frac{\overline{p_{ij}}}{\max_{i=1}^{s}(\overline{p_{ij}})}\right] \tag{8}$$

Then the normalized criteria are weighted to obtain the weighted form:

$$\left[\underline{c_{ij}},\overline{c_{ij}}\right]=\left[w_j\times\underline{d_{ij}},w_j\times\overline{d_{ij}}\right] \tag{9}$$

where $\left[\underline{c_{ij}},\overline{c_{ij}}\right]$ is the weighted normalized form of $\left[\underline{p_{ij}},\overline{p_{ij}}\right]$ and $1\le i\le s, 1\le j\le n$.

Step 3. Identify the positive ideal solution H^+ and the negative ideal solution H^-

H^+ is the most satisfactory set of values in the evaluation criteria. In contrast, H^- is the most unsatisfactory set of values in the evaluation criteria. The calculation of H^+ and H^- is as follows:

$$\begin{cases} H^+=\left[h_1^+,h_2^+,\cdots,h_j^+,\cdots,h_n^+\right] \\ H^-=\left[h_1^-,h_2^-,\cdots,h_j^-,\cdots,h_n^-\right] \end{cases} \tag{10}$$

h_j^+ and h_j^- represent the most satisfactory and the most unsatisfactory values of criterion j; therefore, $1\le j\le n$.

When criterion j is a beneficial criterion, v_j^+ and v_j^- can be obtained as follows:

$$\begin{cases} v_j^+=\max(\overline{c_{ij}}) \\ v_j^-=\min(\underline{c_{ij}}) \end{cases} \tag{11}$$

When criterion j is a non-beneficial criterion, v_j^+ and v_j^- can be obtained as follows:

$$\begin{cases} v_j^+=\min(\underline{c_{ij}}) \\ v_j^-=\max(\overline{c_{ij}}) \end{cases} \tag{12}$$

Step 4. Calculate the distance and the closeness coefficient

L^+ and L^- represent the distance from the evaluation criteria to H^+ and H^-, respectively. We can calculate the distance as formula (13):

$$\begin{cases} L_i^+=\sqrt{\sum_{j\in B}\left(\underline{c_{ij}}-h_j^+\right)^2+\sum_{j\in N}\left(\overline{c_{ij}}-h_j^+\right)^2} \\ L_i^-=\sqrt{\sum_{j\in B}\left(\overline{c_{ij}}-h_j^-\right)^2+\sum_{j\in N}\left(\underline{c_{ij}}-h_j^-\right)^2} \end{cases} \tag{13}$$

B and N represent that the criterion is a beneficial criterion and a non-beneficial criterion. L_i^+ and L_i^- represent the Euclidean distance of Smart PSS design i.

The closeness from each solution to the ideal solution is calculated:

$$f_i=\frac{L_i^+}{L_i^++L_i^-} \tag{14}$$

where $1\le i\le s$ and a smaller f_i means a better Smart PSS design i.

4 Case Study

As an essential household appliance, the sale volume of washing machine has exceeded 70 million in recent years. The washing machine market has exhibited a further expanding trend. With the advent of the artificial intelligence era, the intelligent requirements for washing machines have increased. The sale volume of smart washing machines with WIFI function increased by 129% in 2018 compared with 2017. The functions of smart washing machines have also become more diverse, such as with the inclusion of self-cleaning and self-programming design, which offer greater convenience to consumers. With internal inductors and WIFI, the automation level of smart washing machines has dramatically improved. Therefore, it is essential to select the most suitable smart washing machine PSS, and the correct decision will affect the profitability of the enterprise.

Four different smart washing machine PSS designs are provided by the design team in company H: Design Ⅰ, Design Ⅱ, Design Ⅲ and Design Ⅳ. The details of the concept design are shown in Figure 2. In Design I, the company provides maintenance and cleaning services. The product can be controlled by APP and voice. When a fault occurs, there will be a sound reminder. Users can communicate through a group chat. The product is environmentally friendly and recycled after obsolescence. The estimated cost is about 1,500 yuan. In Design II, the machine can be controlled through APP and automatically adjust the washing mode and automatically recover from failures. The company provides back-to-factory maintenance services. Users communicate through forums and will be recycled after obsolescence. The estimated cost is about 2,000 yuan. In Design III, the smart washing machine can push product information through APP and connect to smart grid, which can intelligently save electricity. Companies provide door-to-door maintenance service and users can communicate through APP and forum. The estimated cost is about 1,700 yuan. In Design IV, the product with self-cleaning function and water circulation system is about 2,500 yuan. The machine can automatically contact after-sales after product failure. Users can communicate through product/service forums.

Figure 2. The concept design of smart washing machine PSS

4.1 *Determine the weight of the evaluation criteria of the smart PSS designs*

4.1.1 Determine the Subjective Weight Using Rough BWM

Step 1. Identify the best and worst criteria

Consistent with previous literature (Van de Kaa et al.,2019; Zhang et al.,2019), we invited seven experts to determine the best and worst criteria. The selected experts have comprehensive knowledge in the field of design and development smart washing machine PSS. Specifically, they were three smart washing machine designers, two service engineers, one manufacturing engineer, and one researcher in the field of smart PSS. The work experience of expert team ranged from five to ten years. Delphi method was adopted to determine the best and worst criteria. Experts were required to make independent judgments. In this way, it helps to reduce the impact of influential expert's opinions on other experts' judgments. Finally, C10 and C8 were selected as the best criterion and the worst criterion, respectively.

Step 2. Construct comparison vector

Ten criteria are scored from 1 to 9 respectively by the seven experts based on their preferences. For best-to-other vector, 9 represents the most preferred best criterion, and 1 represents the same preference of these criteria. For other-to-worst vector, 9 represents the most preferred criterion, and 1 represents the same preference of the two criteria.

Step 3. Construct a rough comparison vector

To avoid the influence of uncertain factors on the solution of objective weights, the best-to-other set and the other-to-worst set are converted into rough form. Taking the result of the best criterion C10 to C1 as an example, the result is [4,3,2,2,4,4,2].

$$\overline{Lim}(2) = (4+3+2+2+4+4+2) \div 7 = 3.5$$
$$\underline{Lim}(2) = 2$$
$$\overline{Lim}(3) = (4+3+4+4) \div 4 = 3.75$$
$$\underline{Lim}(3) = (3+2+2+2) \div 4 = 2.25$$
$$\overline{Lim}(4) = (4+4+4) \div 3 = 4$$
$$\underline{Lim}(4) = (4+3+2+4+4+4+2) \div 7 = 3$$

The rough preference set of the best criterion to criterion C1 is $RN(h_{B1}) = \{[3,4],[2.25,3.75],[2,3],[2,3],[3,4],[3,4],[2,3]\}$ The average rough set is $\overline{RN(h_{B1})} = [\underline{h_{B1}}, \overline{h_{B1}}] = \frac{1}{7}\sum_{k=1}^{7}[\underline{h_{B1}^k}, \overline{h_{B1}^k}] = [2.3571, 3.5]$.

The rough comparison vectors are provided in Table 2.

Step 4. Calculate the subjective weight of the criteria

According to formula (1), the subjective weights of the ten criteria are calculated and shown in Table 2.

Table 2. The results of $RN(h_{Bj})$, $RN(h_{jW})$ and subjective weight W_S for evaluation criteria

4.1.2 Determine the Objective Weight Using Rough CRITIC

Step 1. Convert the programme preference value to a rough mode

Seven experts are asked to score the performance of the four smart washing machine PSS designs from 1 to 9 respectively according to the ten criteria, where a score of 9 represents that the design performed very well with respect to the criterion and score of 1 represents that the design performed worse.

The preference value matrix is roughed and averaged to obtain the rough preference value matrix. The results are shown in table 3.

Table 3. The results of rough preference value

Step 2. Convert the rough preference value matrix to a standard form

These criteria are the set of beneficial criteria, and therefore, the rough preference value matrix is converted to a standard form by using formula (3).

Step 3. Calculate the information measures of each criterion

The information measures Q_j of criterion j are calculated by using formula (5), and the result is shown in Table 4.

Step 4. Compute the objective weights of the criteria

The objective weights can be computed by formula (6). The results are shown in Table 4.

4.1.3 Calculate the Comprehensives Weight of the Criteria

Calculate the comprehensive weights according to formula (7). The results are listed in Table 4.

Table 4. The results of information measures, objective weight W_O and comprehensive weight W

The criteria could be ranked based on comprehensive weight. The most important criterion is the influence on the Safety and health (C10) with a weight of 0.1832. Total cost (C1) with a weight of 0.1664 ranking second and Reliability (C2) with a weight of 0.1389 ranking the third, respectively. Thus, an inexpensive, safe, healthy and reliable system is the features that users pay most attention to when evaluating Smart PSS.

4.2 Rank the Smart PSS Designs Using Rough TOPSIS

Step 1. Construct the judgment matrix and convert to a rough number form

The scores of each design are scored by seven experts, which constructs the importance matrix. Then the importance matrix should be roughened and averaged to obtain the rough number form.

Step 2. Normalize the matrix and calculate the weighted normalized rough matrix

The rough judgment matrix is transformed into a standard form by using the formula (7). Then the normalized criteria are weighted to obtain the weighted form by using formula (8), which is shown in Table 5.

Table 5. The weighted normalized rough importance matrix

Step 3. Identify the positive ideal solution and negative ideal solution

These criteria are all the set of beneficial criteria, and thus, the ideal solutions can be obtained by formula (10).

Step 4. Calculate the distance and the closeness coefficient

Compute the distance from the criteria to L^+ and L^- by using formula (13). Then the closeness from each solution to the ideal solution can be obtained by using formula (14). The outcomes are shown in Table 6 and Figure 3.

Table 6. The Euclidean distance and the closeness coefficient

The lower the value of the closeness coefficient, the better the Smart PSS design. The ranking results of the Smart PSS designs are shown in Table 6. The optimal design is Design Ⅲ, in which the value of the closeness from each solution to the ideal solution is 0.2754. values in C6 and C1 are high, and the weights of C1 and C6 are also better than those of the others. Design Ⅱ, Design Ⅳ and Design Ⅰ rank the second, third and fourth place respectively.

Figure 3. The closeness coefficient of designs

4.3 Comparative Analysis

In this section, a comparison analysis was conducted using Rough BWM-CRITIC-TOPSIS and four other methods to demonstrate accuracy and effectiveness. The five methods are AHP-TOPSIS (A-T), BWM-TOPSIS (B-T), CRITIC-TOPSIS (C-T), BWM-CRITIC-TOPSIS (B-C-T), and Rough BWM-CRITIC-TOPSIS (R-B-C-T). Table 7 shows the weights of criteria. Table 8 and Figure 4 show the rank of four designs using five methods above.

Table 7. Comparison of different methods of criterion weights

The weight of evaluation criteria is important for concept evaluation. Therefore, the weights of five methods are compared first. The subjective weights are obtained by experts based on experience, which reflects the importance of the evaluation criteria. Generally, the results are stable. However, the objective weights are obtained based on the distinction of the evaluation criteria. The results are affected by the value of the evaluation criteria. The comprehensive weights consider the importance and distinction of the evaluation criteria, which reduces the subjectivity and instability of the criterion weights. Table 7 shows the criteria weights of five methods. For subjective weight, the results calculated by AHP are not much different from those calculated by rough BWM. For example, the fifth most important criterion is C6 in AHP method while C8 in BWM method. However, the BWM used in this research only requires fewer comparisons (2n-3) compared to the other matrix-based methods such as AHP (n (n-1)/2) (Rezaei, 2015). BWM is obviously superior to AHP in terms of the magnitude of calculation. For the objective weight, C5, C2 and C10 rank in the top three, while C3 is ignored. For comprehensive weight, the rank of weight is $C10 > C2 > C4 > C3 > C8 > C5 > C9 > C4 > C7 > C6$ in BWM-CRITIC method, while the rank is $C10 > C1 > C2 > C6 > C3 > C5 > C4 > C9 > C8 > C7$ in rough BWM-CRITIC method.

Rough number is introduced to deal with vague evaluation information. In the stage of weight calculation, the individual judgments can be converted into rough numbers considering the overall distribution. For example, the judgements provided by the seven experts is [4,3,2,2,4,4,2] in the weighting process, and then, they are converted and aggregated into a rough number form [2.357,3.500]. The rough interval indicates the vagueness involved in expert judgments. The use of rough numbers can fully consider the vague information and avoid overestimation or underestimation of criteria weights.

Table 8. Comparison results of the different methods

Figure 4. Ranking of the smart washing machine PSS design with different methods

The first comparison is about A-T and B-T. Although the weight order calculated by AHP and BWM is almost the same, the evaluation results are different. Design Ⅰ ranks 4th, and Design Ⅱ ranks 2ed, and Design Ⅲ ranks 1st, and Design Ⅳ ranks 3rd in A-T method while Design Ⅰ ranks 4th, and Design Ⅱ ranks 1st, and Design Ⅲ ranks 2nd, and Design Ⅳ ranks 3rd in B-T method. AHP is a commonly used method of calculating subjective weights, but it wastes much time. AHP is based on $n(n-1)/2$ pairwise comparisons. Moreover, it is not easy for decision-makers to obtain a pairwise comparison matrix with satisfied consistency. In contrast, BWM only requires $2n-3$ pairwise comparisons.

The second comparison is about B-T, C-T and B-C-T. Different weighting methods provide different ranking results when evaluating the designs with TOPSIS method. When using B-T and C-T for design decision-making, the optimal design is Design Ⅱ and the worst design is Design Ⅰ. Design Ⅲ and Design Ⅳ rank the second and the third respectively. However, when using B-C-T for design evaluation, the optimal design is Design Ⅳ and the worst design is Design Ⅰ. The different weights make the Euclidean distance change in the TOPSIS method, and thus change the rank of the designs. The subjective weight calculated by the BWM method reflects the subjective preference of the evaluators, while the objective weight calculated by the CRITIC method based on the correlation and contrast between all criteria. However, the B-C-T method considers both the correlation between the evaluation criteria and the preference for the criteria, which is more comprehensive than others.

The third comparison is conducted between B-C-T and R-B-C-T. The rank in B-C-T is Design Ⅳ>Design Ⅱ>Design Ⅲ> Design Ⅰ, while the rank in R-B-C-T is Design Ⅲ>Design Ⅱ>Design Ⅳ>Design Ⅰ. Rough set theory is used to reduce the inconsistency and uncertainty of evaluation information. Taking [4,3,2,2,4,4,2] as an example, the mean of these values is 3. Actually, the mean value is easily affected by extreme values and the inconsistency between evaluations is ignored. Rough set theory is used to obtain the rough interval as [2.357,3.500]. The form of interval numbers can flexibly reflect the evaluation situation. The accuracy of the results is improved by using rough set theory.

To show the effectiveness of the proposed method, we used total deviation degree R^g to reveal the discrimination ability of different methods (Fang et al., 2020).

$$R_i^g = \frac{f_i^g - f_{\min}^g}{f_{\min}^g} * 100\%, \qquad R^g = \sum_{i=1}^{s} R_i^g$$

R_i^g is the deviation of the design i calculated with the gth method, and f_i^g is the coefficient of the design i calculated with the g^th method, and $f_{\min}^{g}$ is the minimum value of design calculated with the g^th method.

A larger deviation degree means that the method is more efficient in discriminating concept designs. The comparison results are shown in Figure 5 and Table 9. Obviously, it can be seen from the Figure 5 that the proposed method has the highest offset line. Moreover, as shown in Table 9, the proposed method has the largest total deviation degree, which indicates that the proposed method is more efficient in discriminating concept designs than other approaches.

Figure 5. Design deviation in different methods

Table 9. The total deviation degree of different methods

5 Conclusion

It is necessary to evaluate Smart PSS designs during the design stage. Based on the characteristics of the Smart PSS and the triple bottom line, an evaluation framework including ten criteria in economic, environmental and social categories is developed. Aiming at the characteristics of Smart PSS designs and the conventional MCDM method, this paper proposes a Rough BWM-CRITIC-TOPSIS method and applies it to a case study of smart washing machine PSS design to verify its effectiveness and efficiency. In summary, Rough BWM-CRITIC-TOPSIS has advantages as follows:

A combined weighting approach developed in this research has the advantage of integrating the benefits from both subjective and objective weighting methods. Specifically, compared to the other matrix-based methods such as AHP, the proposed method only requires fewer pair-wise comparisons when determining the subjective criteria weights, which reduces the decision-making burden of experts. In addition to considering the preference of decision-makers, the proposed method also considers the correlation and contrast between all criteria that are contained in the structure of the decision-making problem when determining the objective weights. Moreover, Rough Set Theory is integrated into the method to flexibly deal with the decision-making vagueness without much prior information (e.g., pre-set membership function).

Despite its advantages, the proposed method still has some limitations to be improved. For instance, some criteria cannot be described accurately and objectively, which may cause the objective weights to be affected by subjective factors. In addition, the sustainability of Smart PSS was not considered in the evaluation. In future research, the interrelationships between different criteria can be considered to achieve more accurate ranking results of the design solutions of Smart PSS. Moreover, the information of user feedback will be used in the preliminary design of the Smart PSS. To further reduce the computation burden of design decision-making team and improve the method implementation efficiency, a computerized and automatic tool based on the proposed method will be developed.

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Tables List

Table 1. Description of the evaluation criteria

Category	Label	Criterion	Description
Economic	C1	Total cost for Smart PSS (Dreyer et al., 2006, Watanabe, 2016)	Including design/manufacturing cost and resource utilization, among which energy saving and emission reduction standards can refer to GB12021.4-2013
	C2	Reliability (Kim et al., 2013)	The ability to improve the durability of product systems by using ICT and the ability to prevent and correct errors
	C3	Digital controlling and smartness (Valencia et al., 2015)	The intelligent level of product-service systems, including self-adaption, and self- perception ,etc
	C4	The ability to provide services (Zhang et al. 2012)	Whether the product-service systems use ICT to improve the ability to provide services, which includes the speed of services, and the speed of maintenance, etc
	C5	Interactive customization (Valencia et al. 2015)	It provides customized design to products and services
Environmental	C6	Influence on the environment (Kim et al. 2013)	Impacts of product-service systems on the environment including disposal of scrapped products, and product recycling, etc
	C7	Working conditions (Kim et al. 2013)	The conditions for the product operating
Social	C8	Community feeling (Valencia et al. 2015)	It is used to establish an online contact platform between users and Smart PSS providers, and collect users' demand to the company
	C9	Ease to use (Kim et al. 2013)	Whether users use the systems quickly and easily
	C10	Safety and health (Kim et al. 2013)	Whether the PSS considers the safety of the manufacturer, the user, and the environment when it is designed

Table 2. The results of RN(h_{Bj}), RN(h_{jW}) and subjective weight W_S for evaluation criteria

Criterion	RN(hBj)	RN(hjW)	W_s
C1	[2.3571,3.5000]	[6.3163,7.1276]	0.1216
C2	[2.2327,3.2177]	[6.4643,7.5357]	0.1290
C3	[2.6122,3.9769]	[6.2020,7.4605]	0.1273
C4	[6.1769,6.9932]	[3.0068,3.8231]	0.0656
C5	[4.3592,5.3673]	[4.5429,5.4571]	0.0872
C6	[3.5034,4.2163]	[5.6122,6.9769]	0.1190
C7	[6.3592,5.3673]	[2.6327,3.5837]	0.0513
C8	[8.5102,8.9184]	[1,1]	0.0398
C9	[4.6122,5.9769]	[4.0231,5.3878]	0.0793
C10	[1,1]	[8.5102,8.9184]	0.1799

Table 3. The results of rough preference value

Criterion	Design Ⅰ	Design Ⅱ	Design Ⅲ	Design Ⅳ
C1	1500	2000	1700	2500
C2	[3.9133, 5.2483]	[5.6327, 6.6408]	[7.1769, 7.9932]	[8.3265, 8.8163]
C3	[6.0952, 7.7571]	[8.5102, 8.9184]	[5.9864, 7.1412]	[3.2585, 4.9871]
C4	[8.1939, 8.9150]	[6.2020, 7.4605]	[4.1456, 6.1514]	[4.1748, 5.4605]
C5	[7.0068, 7.8231]	[3.8895, 5.5112]	[8.5102, 8.9184]	[5.5429, 6.4571]
C6	[3.3592, 4.3673]	[5.4575, 7.2058]	[7.2020, 8.4605]	[4.5939, 6.2279]
C7	[3.0952, 4.9048]	[5.2327, 6.2177]	[3.0422, 5.6755]	[4.1218, 6.5170]
C8	[4.7517, 6.0867]	[8.1837, 8.6735]	[5.9864, 7.1412]	[7.3163, 8.1276]
C9	[7.4388, 8.7776]	[6.6871, 7.8027]	[4.5306, 6.5316]	[5.8435, 7.1959]
C10	[6.2585, 7.9871]	[5.6245, 6.9959]	[4.5395, 5.8551]	[8.3265, 8.8163]

Table 4. The results of information measures, objective weight W_O and comprehensive weight W

Criterion	Q_j	W_O	W
C1	3.6723	0.1423	0.1664
C2	2.8891	0.1119	0.1389
C3	2.2730	0.0881	0.1078
C4	2.6550	0.1029	0.0649
C5	2.7148	0.1052	0.0882
C6	2.8268	0.1095	0.1253
C7	1.7465	0.0677	0.0334
C8	2.3912	0.0926	0.0355
C9	1.9108	0.0740	0.0565
C10	2.7329	0.1059	0.1832

Table 5. The weighted normalized rough importance matrix

Criterion	Design Ⅰ	Design Ⅱ	Design Ⅲ	Design Ⅳ
C1	[7.5429, 8.4571]	[5.3592, 6.9133]	[6.9133, 8.2483]	[3.6122, 4.9769]
C2	[3.9133, 5.2483]	[5.6327, 6.6408]	[7.1769, 7.9932]	[8.3265, 8.8163]
C3	[6.0952, 7.7571]	[8.5102, 8.9184]	[5.9864, 7.1412]	[3.2585, 4.9871]
C4	[8.1939, 8.9150]	[6.2020, 7.4605]	[4.1456, 6.1514]	[4.1748, 5.4605]
C5	[7.0068, 7.8231]	[3.8895, 5.5112]	[8.5102, 8.9184]	[5.5429, 6.4571]
C6	[3.3592, 4.3673]	[5.4575, 7.2058]	[7.2020, 8.4605]	[4.5939, 6.2279]
C7	[3.0952, 4.9048]	[5.2327, 6.2177]	[3.0422, 5.6755]	[4.1218, 6.5170]
C8	[4.7517, 6.0867]	[8.1837, 8.6735]	[5.9864, 7.1412]	[7.3163, 8.1276]
C9	[7.4388, 8.7776]	[6.6871, 7.8027]	[4.5306, 6.5316]	[5.8435, 7.1959]
C10	[6.2585, 7.9871]	[5.6245, 6.9959]	[4.5395, 5.8551]	[8.3265, 8.8163]

Table 6. The Euclidean distance and the closeness coefficient

Design	L^+	L^-	F	Rank
Design Ⅰ	0.1304	0.1464	0.4712	4
Design Ⅱ	0.1254	0.2855	0.3052	2
Design Ⅲ	0.1162	0.3056	0.2754	1
Design Ⅳ	0.1416	0.2909	0.3275	3

Table 7. Comparison of different methods of criterion weights

Criterion	A-T	B-T	C-T	B-C-T	R-B-C-T
C1	0.1319	0.1419	0.1015	0.1435	0.1664
C2	0.1456	0.1473	0.1082	0.1588	0.1389
C3	0.1223	0.1328	0.0850	0.1125	0.1078
C4	0.0756	0.0569	0.1040	0.0590	0.0649
C5	0.0822	0.0811	0.1123	0.0907	0.0882
C6	0.1062	0.0343	0.0962	0.0329	0.1253
C7	0.0313	0.0499	0.0982	0.0488	0.0334
C8	0.0435	0.1029	0.0947	0.0971	0.0355
C9	0.0857	0.0733	0.0956	0.0698	0.0565
C10	0.1757	0.1796	0.1044	0.1869	0.1832

Table 8. Comparison results of the different methods

Design	A-T		B-T		C-T		B-C- T		R-B-C-T	
	f	Rank	f	Rank	f	Rank	f	Rank	f	Rank
Design Ⅰ	0.4676	4	0.4626	4	0.4845	4	0.4697	4	0.4712	4
Design Ⅱ	0.2934	2	0.2800	1	0.2870	1	0.2928	2	0.3052	2
Design Ⅲ	0.2919	1	0.2963	2	0.2962	2	0.2943	3	0.2754	1
Design Ⅳ	0.3178	3	0.3075	3	0.3249	3	0.2919	1	0.3275	3

Table 9. The total deviation degree of different methods

method	A-T	B-T	C-T	B-C-T	R-B-C-T
R	0.7227	0.8077	0.8514	0.6208	1.0076

Figures List

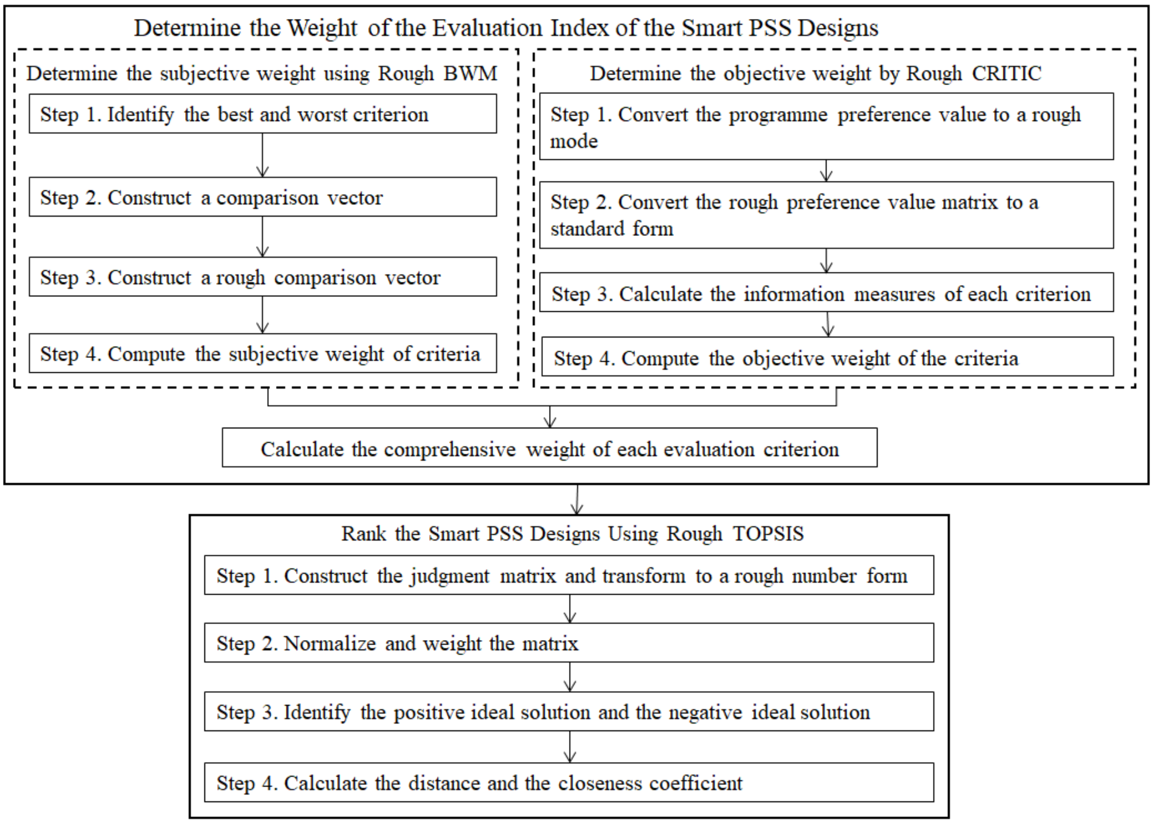

Figure 1. The proposed evaluation framework using Rough BWM-CRITIC-TOPSIS

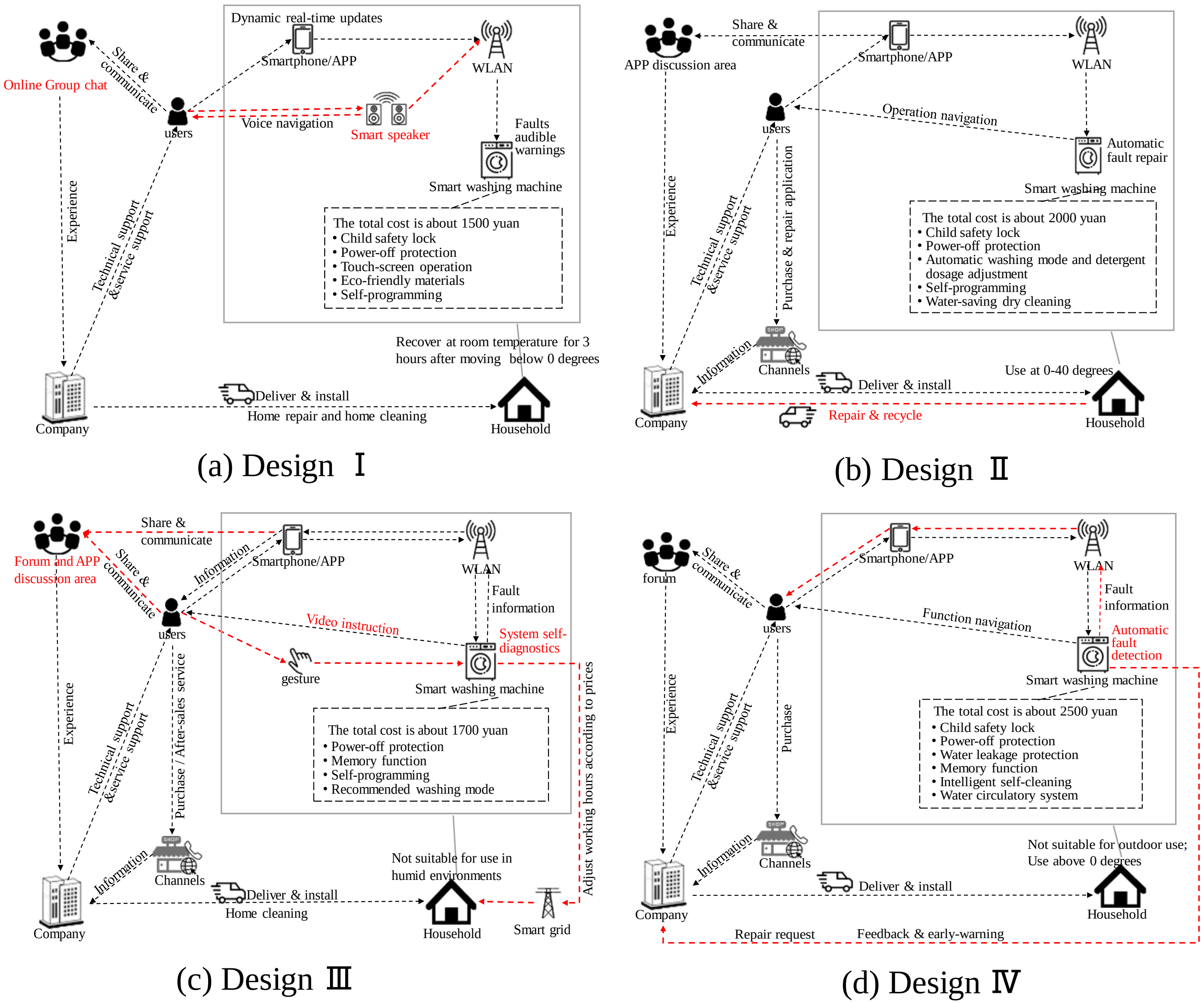

Figure 2. The concept design of smart washing machine PSS

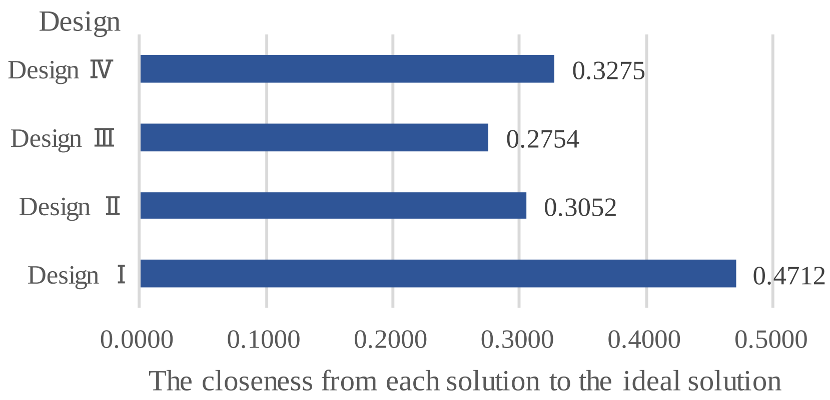

Figure 3. The closeness coefficient of designs

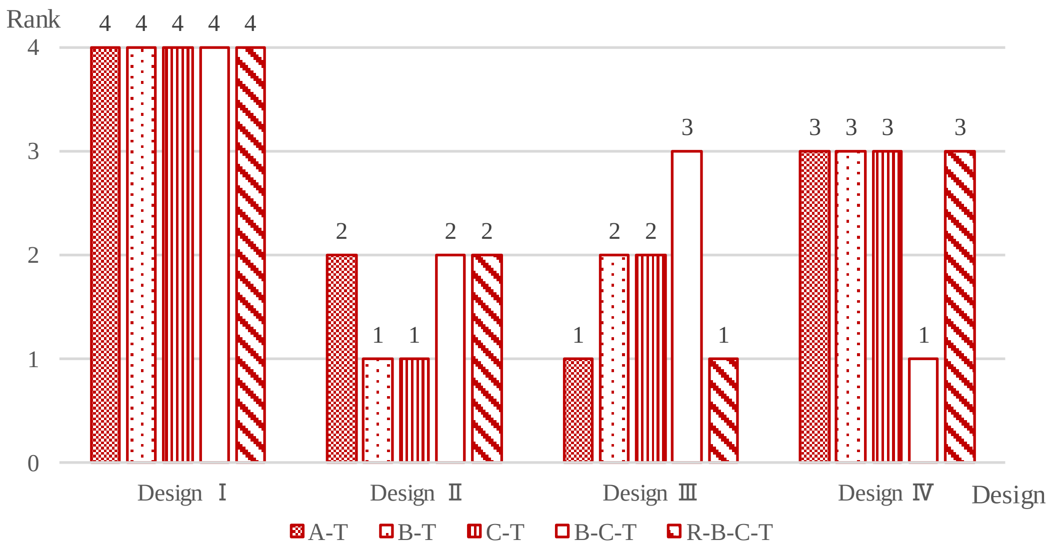

Figure 4. Ranking of the smart washing machine PSS design with different methods

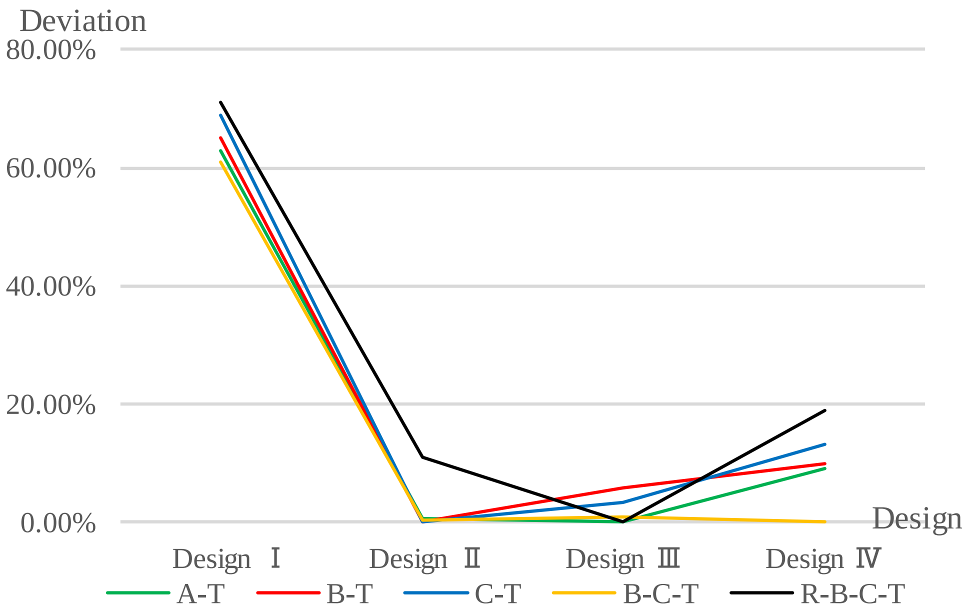

Figure 5. Design deviation in different methods

CRediT author statement

Wenyan Song: conceptualization, the methodology, writing the original draft and project administration.
Zixuan Niu: data acquisition and investigation, validation and writing the original draft.
Pai Zheng : formal analysis and methodology.
All the authors work together on the revision and editing of the manuscript draft.

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