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A context-aware concept evaluation approach based on user experiences for smart product-service systems design iteration

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Abstract

With the trend of 'digitalization' and 'servitization' in the manufacturing industry, numerous product-service systems fail to seize a market share and encounter an imbalance between digital investments and expected revenues. This phenomenon is probably caused by the insufficient evaluation on user experience and by the lag between user requirement changes and the offered solutions. Both limitations can be mitigated via automatic Smart PSS evaluation based on broader concerns on user experience information that collected from either product-service bundles or user behavior. In this paper, a context-aware concept evaluation approach is proposed for Smart PSS design iteration, aiming to satisfy users in a more timely and automatic manner. Derived from the conventional information axiom method, the proposed approach introduces a context-aware evaluation indicator identification module and an automatic system range identification procedure based on natural language processing techniques, and eventually return the most robust concepts during the usage phase. With less human intervention in the design process, it relieves the lag between user requirement changes and the solutions, and reduces the prescriptive instructions in the conventional information axiom method. A case study of a 3D printer company's design iteration is conducted, which proves the proposed approach's feasibility. It is hoped that this work provides practical guidance for achieving a more context-aware Smart PSS development.

Keywords: *smart product-service systems; concept evaluation; user experience; information axiom; context-awareness*

Notations and Abbreviations

AI	Artificial Intelligence
ANP	Analytic Network Process
c	Context feature
C_i	Closeness to the best solution (from TOPSIS)
CBOW	Continuous-Bag of Words
CNC	Computerized Numerical Control
CPS	Cyber-physical systems
d_i^+	Distance between the PSB candidate i and the best PSB candidate b (from TOPSIS)
d_i^-	Distance between the PSB candidate i and the worst PSB solution w (from TOPSIS)
dr_{ij}	PSB_i's design range on evaluation indicator j
$evSet$	Event set that identify the patterns of usage scenario s
I_i^j	Information content of PSB_i on evaluation indicator j
I_i	Total information content of PSB_i
ICT	Information and Communication Technologies
IoT	Internet of Things
KPI	Key Performance Indicator
p_{ij}	Ratio of common range and system range of PSB_i on aspect j
$pr_{i,j}(\hat{y} = 1)$	Probability of a PSB_i 's performance belongs to a usage scenario aspect j
pr_{ijt}	Probability of the positive label of PSB_i on aspect j from the PSB_i's t-th comment
pr_{ij}	Probability of total positive user perception pr_{ij} of PSB_i on aspect j
PSB	Product-service Bundle
PSS	Product-service systems
QFD	Qualify Function Deployment
R	Semantic relations between context features
RBF	Radial Basis Function
s	Usage scenario
sr_{ij}	PSB_i's system range on evaluation indicator j
SVM	Support vector machine
TF-IDF	Term Frequency-Inverse Document Frequency
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution

1 Intoduction

With the dramatic transformation of manufacturing servitization, product-service systems (PSS) have been globally accepted by manufacturing companies in recent years [1]. As an inherently dynamic and multi-dimensional system including multiple stakeholders and product-service bundles, PSS delivers user-required functionalities in a way that reduces the impact on the environment [2-4]. Since 2014, a novel business paradigm called Smart PSS [5] appears along with many cutting-edge information and communication technologies (ICT), such as Internet-of-Things (IoT), Cyber-Physical Systems (CPS), and Artificial Intelligence (AI) [6]. Those new techniques enable even more massive accessible data from multiple parties, much more flexible interactive modes, and proper decision supports throughout the product lifecycle [7-10]. From this perspective, the appearance of Smart PSS denotes a further transformation from servitization into digitalization, making the manufacturing business an ever-evolving and much more flexible manner that can be examined and then upgraded even after launching to the market [11, 12].

However, according to an investigation [13], only a small proportion of companies succeeded in their digitalization transformation to obtain the expected economic returns [14]. The imbalance between the digital servitization investments and the expected economic returns, the so-called '*digitalization paradox*', has been discovered in many firms [14, 15]. For example, Michelin has launched a comprehensive tire management solution called Michelin Fleet Solution for the large European transportation companies in 2000, but received far below-expected contracts and profits [16]. Another example is that General Electric has reached $ 3.9 billion in digital revenue in 2018, but it is still nowhere approaching its goal of $15 billion in digital revenue in 2020 [15].

Demonstrating the inherent unsustainability in the economic aspect and some non-linear effects on company performance [17], the traps of digitalization paradox in Smart PSS development are commonly regarded to be caused by (1) the excessive attention on technical possibilities rather than customer experiences [15]; (2) the frequent change of user experience due to the insufficient satisfaction on user requirements and the influence of fashion trend/public media [18]; and (3) the lag between the changes of user experience and the solutions [19].

Facing the above challenges, several strategies are taken to comprehensively and wisely evaluate Smart PSS and pursue a win-win situation for both companies and customers [20]. Firstly, the product-service bundles (PSBs) evaluation should be conducted comprehensively based on user experience indicators, rather than only on technical attributes. Secondly, service providers are expected to offer a quick approach to explore user-concerned indicators to the PSBs. Since the user experience changes can be reflected in both their behavior physically [21] and their attitude cognitively [22], a context-aware concept evaluation approach for Smart PSS design iteration is expected. Thirdly, service providers should select the most robust PSB concepts to relieve the lag effect between the customer experience changes and the solutions [23]. To achieve it, the information axiom in axiomatic design is one of the effective methods for robust concept evaluation [13].

Although the above strategies have been separately discussed in numerous product development studies [13, 24-26], in the big and content-rich world that is encoded by massive user-generated data and sensed-data in Smart PSS design iteration [8, 27], the PSB concept evaluation approach still needs to be further enhanced in automation perspective and rapid reaction capability. Therefore, the primary focus of this paper is on (1) how to identify evaluation indicators automatically and (2) how to rapidly evaluate the current design concepts considering user experience.

The remaining sections are organized as follows. Related studies on concept evaluation and context awareness are reviewed in Section 2. Section 3 expounds on the proposed context-aware Smart PSS evaluation method in detail. Subsequently, in Section 4, an example of a 3D printing company's concept evaluation is demonstrated for the feasibility of the proposed method. Finally, we discuss the primary results and then summarize the main academic contributions in Section 5 and Section 6, respectively.

2 Literature review

To have a whole picture on the concept evaluation in Smart PSS, evolutions towards Smart PSS, current studies on concept evaluation of Smart PSS, and the context-awareness in Smart PSS are summarized and discussed.

2.1 Evolutions towards Smart PSS

PSS, a system that develops and offers integrated product and service bundles, was coined by Goedkoop [28] in 1999. Thereafter, PSS has been examined by both academia and industries in the recent two decades [2, 29-32]. According to the innovations on system architecture of PSS paradigms, the evolutions of PSS can be grouped into three phases, namely conventional PSS, Industrial PSS, and Smart PSS. Table 1 lists their systematic innovations.

Table 1.
Systematic features of PSS paradigms

PSS paradigm	**Systematic innovations**
Conventional PSS [2, 28]	• Servitization of products/productization of services, • Separately developed add-on values • Manufacturer-dominant
Industrial PSS [1, 33]	• Seamless integration between products and service • For industrial applications
Smart PSS [34] (Similar terms: Digitalized PSS [35] and Cyber-physical PSS [36])	• Integration of physical space and cyber space (i.e., a digital-based ecosystem) • Mutual interactions among stakeholders • Value co-creation (i.e., ever-evolving PSB design iterations)

In conventional PSS, the attached products/services perform as add-on values, but they are still separately developed. Besides, conventional PSS is still a manufacturer-dominant system. Although customers have been involved in the value generation process during usage, customers still do not participate in the PSS value proposition stage.

Industrial PSS [1] (also called Technical PSS [33]) arose with seamless integration of Industrial PSS results, associated resources, and stakeholders during each PSS lifecycle stage. For example, Meier, Roy and Seliger [1] underlined the potentials of integrating tangible products and intangible services in industrial production applications. Associated resources, including flexible production scheduling [37], installation planning [32], and IPSS purchasing actions [38, 39] were highlighted by numerous scholars with a more comprehensive insight for IPSS development. Besides, the integration of customers was also studied to promote mutual interaction among stakeholders [40]. All the studies imply that the data/information from downstream scenarios has great values and can facilitate the design of Industrial PSS.

Along with digital servitization, Smart PSS emerged by integrating physical space and cyberspace, making it a digital-based ecosystem [34, 41, 42]. It is widely accepted that Smart PSS is a multipartite system fundamentally consisting of multiple stakeholders, intelligent systems, smart connected products and their generated digital services [11]. At the same time, Smart PSS is also a value-co-creation business paradigm for industry digitalization, where both the customers and the service providers exchange information with each other and further generate values together.

Unlike conventional PSS and industrial PSS, the smartness of Smart PSS is reflected in the *online smartness* and the *offline smartness* [27, 43]. Online smartness refers to the capability of making proper and personalized decisions by intelligent algorithms and analytic tools based on multi-source and heterogeneous data. Meanwhile, achieved by smart connected products, offline smartness refers to the capability of perceiving a specific usage scenario with context-awareness. It can adjust the product itself by leveraging the embedded hardware and the self-learning software [8, 44, 45].

These two types of smartness drive the Smart PSS development up to a much more flexible and ever-evolving manner [34]. Specifically, the design activities in Smart PSS, including requirement identification, solution selection, and reconfiguration, can be agilely conducted with automatic decision supports based on user-generated content. In contrast, conventional PSS design activities are knowledge-intensive and manufacturer-dominant, which is time-consuming and costly [46].

Although the academic community has recognized the unique features of Smart PSS and has attempted to develop design frameworks for Smart PSS, there is still a far long way to a mature and comprehensive Smart PSS development methodology. One typical gap is the excessive emphasis on technical possibilities but insufficient attention on user experience [10], which somehow appears in the non-comprehensive concept evaluation in Smart PSS.

2.2 Concept evaluation in Smart PSS

Concept evaluation, one of the critical tasks in the Smart PSS development process, dominates the success of concepts. Only the concepts comprehensively and periodically evaluated by the users can retain their competitiveness in the fierce market. According to Mourtzis et al.'s study [47], the Smart PSS concept evaluation can be measured via Key Performance Indicators (KPIs) from the perspective of customer perceptions, sustainability, and risks.

Considering that this research emphasizes the concept evaluation based on user experience, only the customer perception-related methods are discussed. The related studies mainly focus on concept evaluation in the early design stage before the market launch and under the PSS paradigm. Kimita, Shimomura, and Arai [48] proposed a non-linear satisfaction-attribute function to estimate customer satisfaction based on the PSS features, wherein the PSS features consist of the customer state changes and function parameters such as cost, physical interference and provider feasibility. Lee et al. [49] concentrated on assessing the probability of new PSS concepts being accepted by users using the analytic network process (ANP) and niche theory.

Although many researchers, such as Lan, Zhang, Zhong and Huang [50], Turkyilmaz, Oztekin, Zaim and Demirel [51] and Wang, Hazen Benjamin and Mollenkopf Diane [52], suggested that this method effectively evaluates customer satisfaction, the limitations can still be found in three folds. Initially, it is engineers/experts rather than customers themselves to decide the evaluation indicators, which cannot straightforwardly reflect the users' perception. Secondly, even if some approaches encourage users to identify the evaluation indicators, the methods to extract the indicators are manually determined instead of automatically extracted. Thirdly, the concept evaluation process is conducted before the market launch once for all without any other reappraisals, which cannot fulfil the requirement of agile reaction in Smart PSS's development manner.

2.3 Context-awareness in Smart PSS

In an effort to automatically detect customer perceptions, a context-aware approach is expected in this article. According to Dey's definition, a system is context-aware if it uses context to provide relevant information and/or services to the user, where relevancy depends on the user's task [53]. Here, the context follows its broad definition that "*any information that can be used to characterize the situation of an entity*" [54], specifically containing the current usage scenarios characterized by sensors and the users' attitude characterized by their satisfaction/sentiments.

To establish context-aware applications, it is critical to ensure the potential context features can be collected and interpreted in a context-aware system. Several context-aware computing techniques are adopted to monitor the end-user's usage contexts [55], which can be divided into three phases, namely *context acquisition*, *context processing*, and *context usage* [56].

As the first phase, *context acquisition* intends to identify and then collect the context information via sensors or user interfaces. Context information collected via sensors is mainly the elementary and physical contexts, such as location information from GPS, time information from the computers' built-in clock, and luminance information from the photosensitive diode. The ones identified from user interfaces will be more advanced, which usually indicates users' current activities or their feedbacks. They can be obtained from computer logs, user schedules, and other artificial intelligence techniques. Then in the *context processing* phase, context processing will systematically transform the context information into useful information for further analysis [57].Finally, during the *context usage* phase, the context-aware system will apply the context information to adjust itself or give relevant responses. The applications of context information vary based on the task purpose. In this study, the usage of contextual information aims to set up the evaluation indicators and collaborate with information axiom to assess the PSBs' performance.

The significance of contexts has been recognized in a Smart PSS survey that context plays a significant role during Smart PSS development [5]. Specifically, end-users expect personalized functionalities rather than generalized ones. Hence, the service providers are expected to give rapid reactions once the end-user's contexts change, in which the context-aware feature should be considered during the usage stage. However, the implementation of using context-aware systems in Smart PSS concept evaluation has yet to be fully explored. To bridge the gap, two prerequisites of the context-aware system in Smart PSS should be implemented. One is the application of multi-sourced and heterogeneous data. The data that is multi-sourced from users and service providers and is heterogeneous with different data formats from user behavior and user perceptions offer a comprehensive analysis towards the Smart PSS's performance. A unified representation format should fuse those data for the ease of machine readability and processing. The other prerequisite is the application of intelligent algorithms that have automatic learning capability from the datasets unless the rapid evaluation and reaction will be hardly realized. In this study, they are the rationales to uniform the heterogeneous user-behavioral data and user perception data and further to collaborate with information axiom and SVM method.

3 Methodology

The information axiom in axiomatic design is a classic and effective method for concept evaluation in PSS, which demonstrates strong effectiveness and extendibility in multiple scenarios [58-60]. Inspired by it, a context-aware concept evaluation framework is proposed for Smart PSS design iteration. This framework takes user experience information into account and integrates natural language processing techniques to fulfil the requirement of comprehensively and automatically evaluating designs in Smart PSS.

As shown in Figure 1, the proposed framework comprises three phases, namely, Phase I: Identify evaluation indicators for Smart PSS concept evaluation (Context acquisition), Phase II: Identify design ranges and system range based on context information (Context processing), and Phase III: Compute information content (Context usage). The uppermost contribution lies in the hybrid evaluation manner that considers both behavior and perceptual perspectives under an environment that user experiences count the final success but hard to perceive rapidly.

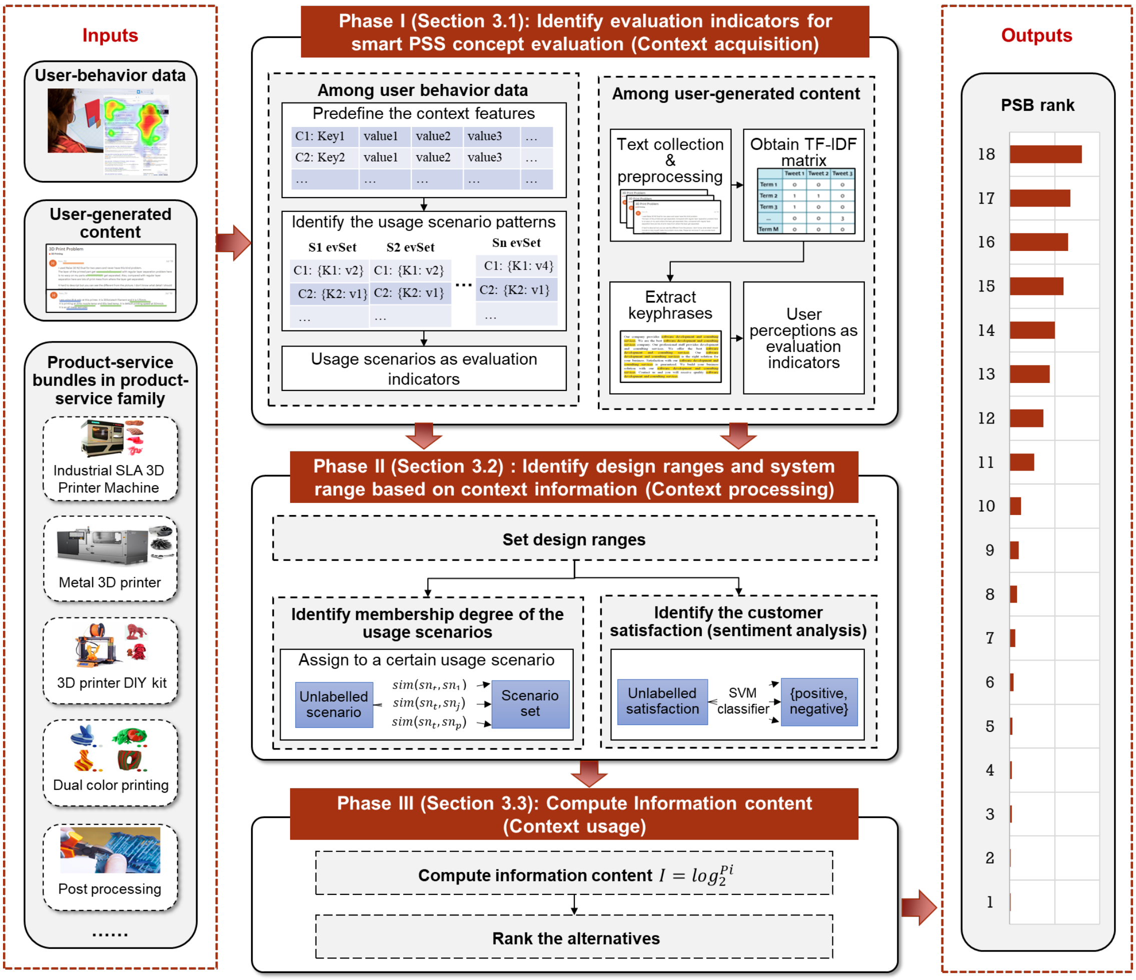

Figure 1. An overview of the proposed context-aware Smart PSS evaluation method

Three inputs are deployed in the proposed Smart PSS concept evaluation framework: PSBs in the product-service family, user behavior data, and user-generated comments. PSBs refer to the customized solutions characterized by different technical parameters, functions, or usage scenarios for user segments/groups in Smart PSS. For instance, industrial SLA 3D printers suit for the manufacturing in the small or medium enterprises; metal 3D printer is valuable for mechanical equipment production; 3D printer DIY kits apply to the novices who want to experience 3D printing with relatively low price; and finally, the dual-colour printers might be required by the creative designers for rapid prototyping. Besides PSBs, user-behavior data denotes the digits/values collected via sensors or IT platforms during the usage process, such as printing speed and layer height set by users. Those values are usually numerical and crisp. Additionally, with the explosive increase of social media, individuals and organizations have widely accepted to express their ideas/perceptions online [61], which is so-called user-generated content. Although the user-generated contents have a broad scope containing text, figure, videos, and other media formats, it refers explicitly to textual customer comments in this study. They are often linguistic and rough.

Phase I aims to identify the user-concerned evaluation indicators based on user-behavior data and user-generated data. On the one hand, the predefined context features, such as selected printing material, and printing speed, will form usage scenarios, reflecting to what extent a user's behavior patterns conform to the typical usage scenarios. Those contextual features establish the behavior-level evaluation model, as addressed in subsection 3.1.1. On the other hand, the user-mentioned features in customer comments, such as quality, delivery, and customer service, will build up the perceptual-level evaluation model, as illustrated in subsection 3.1.2. The extracted indicators will be further applied for the following phases, thus serving as the framework's foundation.

In Phase II, both the design ranges and each PSB alternative's system ranges will be determined for each indicator in Smart PSS. The design ranges mean the user-expected value ranges for the functions/features, which are set by users by default. Nowadays, many methods can be used for design range identification, such as Qualify Function Deployment (QFD), Likert scales, or identifying from explicit descriptions in the initial configuration orders. Considering the different data formats of user-behavior data and user-generated content, two methods for system range identification will also be addressed in this phase, as explained in subsection 3.2. To solve the mentioned problem of time-consuming on perceiving user satisfaction, we extended the information axiom in axiomatic design by automatically identifying the system ranges on user satisfaction.

Finally, each PSB alternative's information content can be calculated and ranked, which is reported in subsection 3.3. The PSB alternatives are ranked in terms of the sum of all criteria' information content. The higher the information content, the more robust the alternatives will be.

3.1 Phase I: Identify evaluation indicators for Smart PSS concept evaluation (Context acquisition)

To make the evaluation process context-aware, we need to clarify the contexts' scope in the initial. Considering the functional basis of designs and the interactions among product, services, and users in Smart PSS, the contexts for PSB design evaluation can be categorized into four groups [62]: (1) physical context (i.e., information about the surrounding environment, such as time and room temperature); (2) social context (i.e., information about the nearby products or services, e.g., a coffee grinder is a nearby product for a coffee machine; additional filament and sandpaper are the nearby products for a 3D printer); (3) user context (i.e., the information about users and user–PSS interactions, such as user demographics, user habit, user preference, user knowledge and so on); and (4) operation context (i.e., information related to the operational status of the Smart PSS, such as power/energy, lifespan and software version). In this study, only PSB-related data (e.g., room temperature or historical purchase log) instead of personal data (e.g., home address or user facial data) is defined to be collected. Contrary to the personal data applied to identify a person [63], the PSB-related data focuses on the interactions with the PSBs. Furthermore, those contextual data can be collected only after the users agree with the data collection regulation offered by the service providers.

As discussed, the user experience will be reflected in their behavior and perceptions. To evaluate the current PSS designs, user-concerned evaluation indicators should be identified from two perspectives: user-behavior data and user-generated data. Figure 2 shows the evaluation identification process.

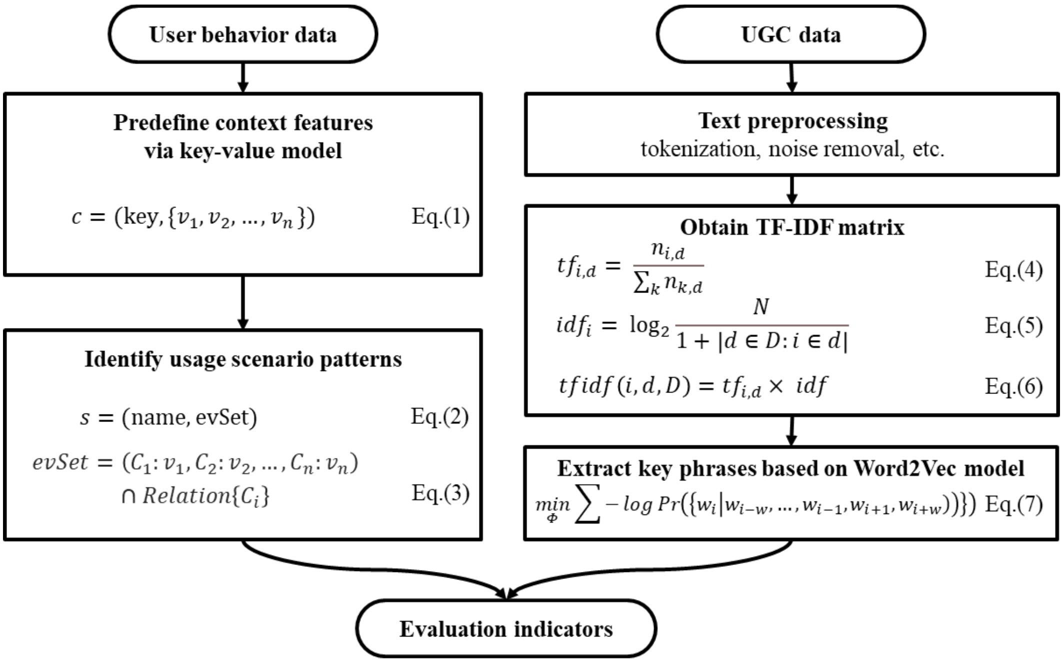

Figure 2. Flowchart of evaluation indicator identification

3.1.1 From user behavior data

(1) Predefine the context features

Key-value modelling [64] is selected in this study due to its simple representation format and fast processing capability. More importantly, to integrate with the information axiom, the PSB evaluation indicators (i.e., the context features related to user experience) should be represented as key attributes with corresponding values. Key-value modelling is applied owing to its strength on solid compatibility with the information axiom as well. Based on key-value modelling, a context feature can be defined as a set that has a key and set of possible values, denoted as follows:

$$c = (key, \{v\}) \tag{1}$$

For example, a 3D printer will have the context feature of *printing speed* and its values set.

However, key-value modelling alone cannot represent the relationships between the context features, so the semantic relations R [65] between context features should also be defined. They are represented as triples $< E_s, P, E_o >$, where E_s is the entity for subjects and E_o is the entity for objects.

(2) Identify the usage scenario patterns

After defining the context models, the scenarios of interest in a Smart PSS can be identified. A scenario refers to the current situation of the product-service bundle and its involved environment, which can be represented as a tuple with its name and a set of events [66]. The mathematical expression of a scenario is given as follows:

$$s = (scenario\ name, evSet) \tag{2}$$

, where $evSet$ refers to the set of predefined contexts with their values, and

$$evSet = (C_1: v_1, C_2: v_2, \dots, C_n: v_n) \cap Relation\{C_i\}. \tag{3}$$

In this way, a set of usage scenarios are determined by the engineers or experts, and are set as the evaluation indicators from the behavioral aspect.

3.1.2 From user-generated content

Another input data for design evaluation is the user-generated content; it is used to extract the perceptual evaluation indicators.

(1) Text pre-processing

After collecting the raw textual user reviews, two pre-processing steps, tokenization and noise removal (e.g. HTML tags, extra whitespaces), are conducted to clean the raw texts. Considering that sentiment analysis will be conducted in the following steps, stopwords are not removed since they could contain users' sentiments.

(2) Obtain TF-IDF matrix

Words in the cleaned sentences will then be transformed into a critical matrix, i.e., Term Frequency-Inverse Document Frequency (TF-IDF) matrix. Term frequency (TF) is the number of a term occurs in a document, denoted as

$$tf_{i,d} = \frac{n_{i,d}}{\sum_k n_{k,d}} \tag{4}$$

, where $n_{i,j}$ refers to the frequency of term i occurring in document d. Inverse document frequency (IDF) is defined as the number of documents containing a specific word, reflecting the importance of a word in a series of documents. IDF is denoted as

$$idf_i = \log_2 \frac{N}{1+|d \in D: i \in d|} \tag{5}$$

, where $N = |D|$ represents the number of documents, $|d \in D: t \in d|$ is the number of documents where the term i appears. Then *tf-idf* is calculated as the multiply of term frequency and inverse document frequency, written as

$$tfidf(i, d, D) = tf_{i,d} \times idf \tag{6}$$

(3) Extract key phrases

To extract the keywords or key phrases as the evaluation indicators, a keyword extraction approach, i.e., TextRank [67], can be applied based on the trained Word2Vec model [68].

Word2Vec model is used to generate word embeddings as the feature presentation. It considers the co-occurrence information of the same contexts in sentences, hence keeping the semantic meanings of words. The Word2Vec generally has two algorithms: Skip-Grams and Continuous-Bag of Words (CBOW). In this article, CBOW is selected because of its better performance on the relatively small data. Its rationale is to learn a function which can predict the word based on the given context words (i.e., the former words and latter words in a window), whose objective function is:

$$\min_{\Phi} \sum - log\, Pr(\{w_i | w_{i-w}, \dots, w_{i-1}, w_{i+1}, w_{i+w})\}) \tag{7}$$

, where w_i is the predicted word and $w_{i-w}, \dots, w_{i-1}, w_{i+1}, w_{i+w}$ are the context words.

TextRank was chosen since it can be extended for phrases and short sentences extraction. Some extracted phrases with the same/similar meanings are integrated to keep the total key phrases concise.

Following these steps, both usage scenario patterns and user-concerned phrases can be extracted for further evaluation.

3.2 Phase II: Identify design ranges and system range based on context information (Context processing)

Based on the extracted evaluation indicators, PSBs' design range dr_{ij} and system range sr_{ij} can be identified, as shown in Figure 3.

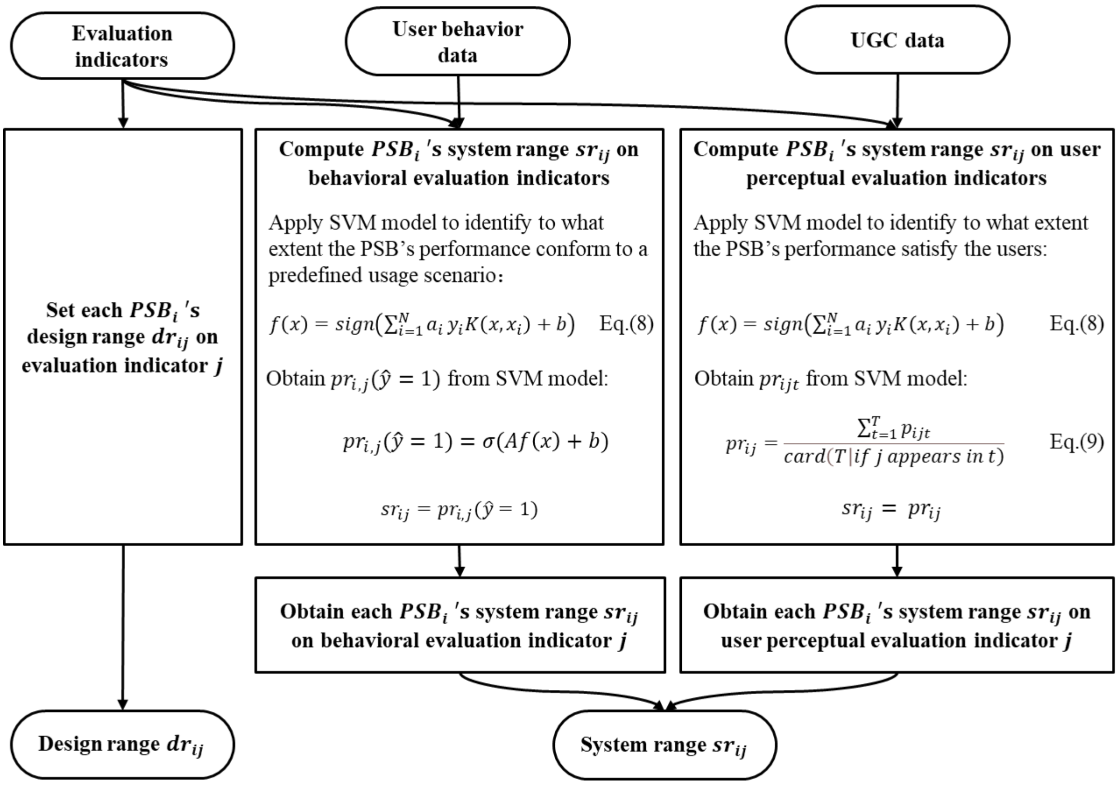

Figure 3. Flowchart of design range and system range identification

(1) Set design ranges

According to axiomatic design theory, the design ranges indicate what the users want. They are all normalized within the range of (0,1), where 1 represents the perfect user experience. Under the situation of design iteration, the design ranges from users can be collected and pre-processed from the recent design iterations. The design range of a PSB candidate PSB_i on an evaluation indicator j can be denoted as dr_{ij}.

(2) Identify the membership degree of the usage scenarios

The membership degree of each usage scenario can be regarded as the system ranges of an alternative. Specifically, we hope to monitor to what extent a usage scenario conforms to the typical ones, which is essentially a classification task. The scenarios in the Smart PSS are domain-specific and can be linearly non-separable in many cases. Support vector machine (SVM) [69] is a well-known classification algorithm to deal with non-linear problems and has already been proved to have better generalization performance than other traditional learning techniques like neural networks [70]. Hence, SVM is adopted in this study to assign the scenarios.

Specifically, given a training dataset S with N scenarios, i.e., $\mathrm{S} = \{(\chi_i, y_i), \mathrm{i} = 1,2, \ldots, \mathrm{N}\}$, $\chi_i \in \mathbb{R}^P$, $y_i \in \{+1, -1\}$ in the binary classification, where χ_i is a feature vector and y_i indicates whether χ_i belongs to a specific scenario group. The non-linear SVM model is

$$f(x) = sign\left(\sum_{i=1}^{N} a_i \, y_i K(x, x_i) + b\right) \tag{8}$$

, where *K(x, x_i)* is the kernel function, which maps the inputs into a high-dimensional feature space to make them linear-separable [70]. Several frequently-used kernel functions can be tested, including linear function, polynomial function, Gaussian radial basis function (RBF), and sigmoid function. The one with the best classification performance will be selected.

(3) Identify customer satisfaction

Besides evaluating usage scenarios, user's satisfaction can be regarded as the system ranges on perceptual indicators, it indicates to what extent a PSB can fulfill the users' expectations. Customer satisfaction is reflected in different aspects among the user comments [71], such as positive in quality, positive on customer service, and negative on price. As illustrated in Figure 4, a sentiment analysis approach based on another SVM classifier [72] is used to predict customers' satisfaction on each perceptual indicator.

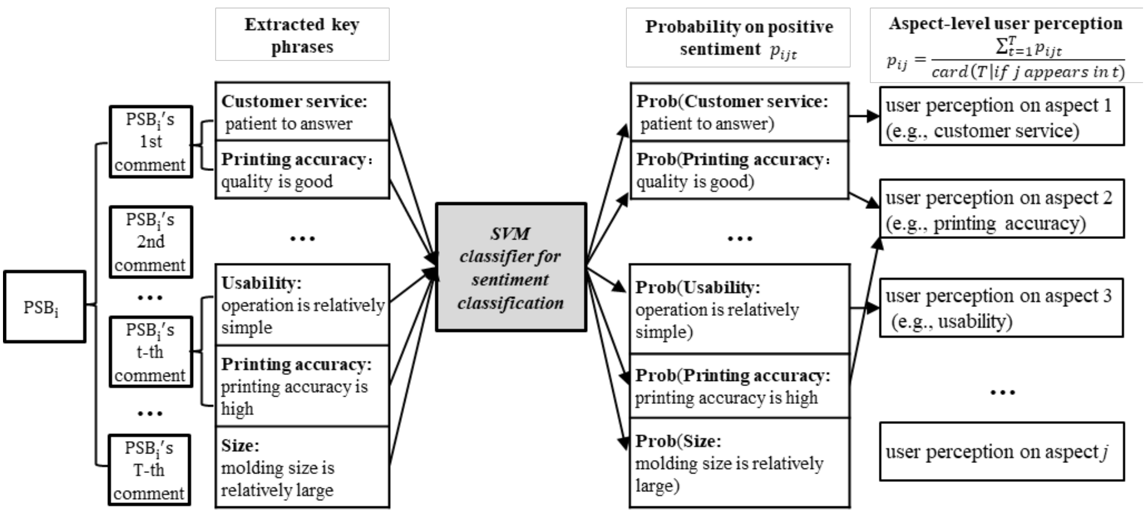

Figure 4. An aspect model of user perception

Initially, a user comment dataset that has been segmented into short phrases with positive or negative labels can be used for the SVM classifier training process. The classifier will learn a function to separate the positive and negative data with the maximum margin. Similar to the membership degree identification for usage scenarios, the kernel function providing the best performance will be selected.

The outputs of the SVM classifier are the short phrases' probabilities of belonging to positive sentiment on different aspects. Let pr_{ijt} be the probability of the positive sentiment of PSB_i on the aspect j from the PSB_i's t-th comment. Consistent with the design ranges of (0,1) where 1 represents the best experience, pr_{ijt} approaching 1 also represents the best experience, and pr_{ijt} approaching 0 denote the worst experience.

To derive the total user perception pr_{ij} of PSB_i on each aspect j, all the pr_{ijt} are averaged, following Equation (9).

$$pr_{ij} = \frac{\sum_{t=1}^{T} pr_{ijt}}{card(T|if\ j\ appears\ in\ t)} \quad (9)$$

, where $card(T|if\ j\ appears\ in\ t)$ is the number of comments in which the aspect j was mentioned. pr_{ij} is the final system range of PSB_i on aspect j, it will be applied for information content calculation in the later step.

3.3 Phase III: Compute information content (Context usage)

In the Phase III, the information content is supposed to be calculated following the information axiom's logic. As shown in Figure 5, the first step in Phase III is to compuate the information content $\boldsymbol{I_i^j}$ for each evaluation indicator, followed by the step of total information content I_i calculation.

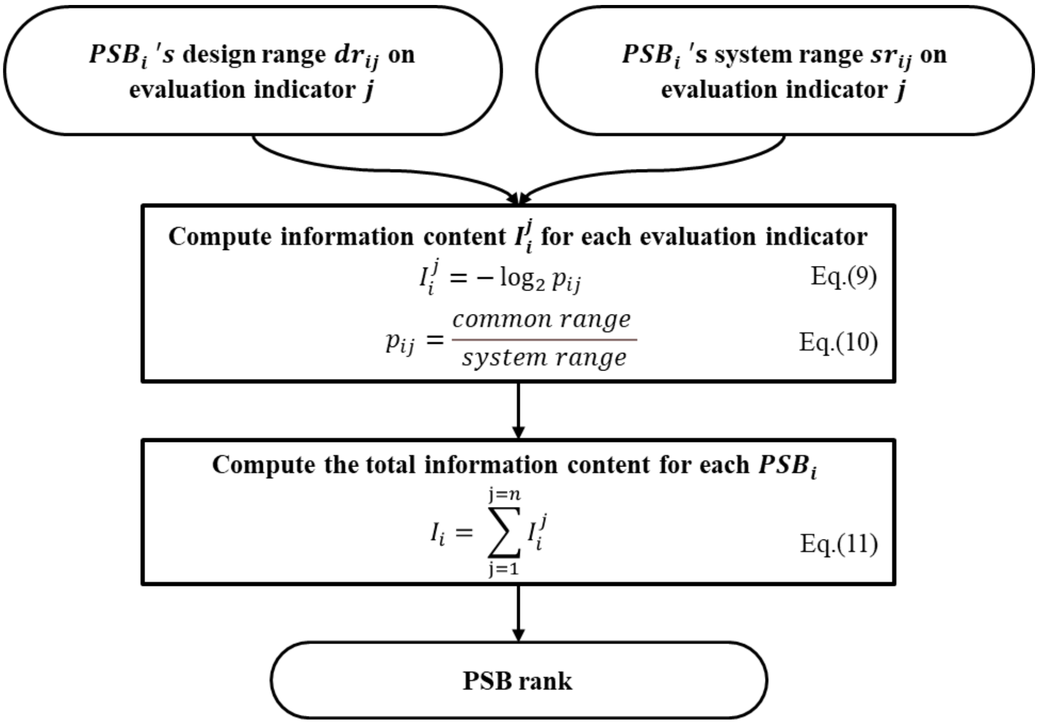

Figure 5. Flowchart of information content calculation

Specifically, the information content I_i^j of each evaluation indicator for each psb_i can be calculated following the equations in axiomatic design [73]:

$$I_i^j = -\log_2 p_{ij} \quad (10)$$

, where p_i is the probability of a design that can fulfill the users' expectations. Meanwhile, p_i is defined as

$$p_{ij} = \frac{common\ range}{system\ range} \quad (11)$$

Particularly, $common\ range$ is the overlapping between the system range and the design range.

To calculate the information content for all PSBs on all evaluation indicators, let $E = \{e_1, e_2, \ldots, e_n\} = S \cup P$ be the set of evaluation indicators, where the subset $S = \{s_1, s_2, \ldots, s_t\}$ is a set of usage scenarios as the evaluation indicators, and $P = \{p_1, p_2, \ldots, p_m\}$ is a set of perceptive features as the evaluation indicators. For each PSB candidate PSB_i, we can set a column vector $PSB_i \in \mathbb{R}^n$ whose elements equal to the system range on each e_j within the range (0,1). The total information content I_k of psb_k is the sum of all the information content on each e_i, expressed as

$$I_i = \sum_{j=1}^{j=n} I_i^j \quad (12)$$

Finally, the PSBs can be ranked in terms of the total information content I_i, the higher the I_i, the more robust the PSB will be.

4 An illustrative example of the design upgrades of a 3D printer company

To address the proposed concept evaluation framework for Smart PSS design, an illustrative example of a 3D printer company was discussed in this section.

3D printing has become widespread among individuals and companies as a new type of manufacturing due to its low cost and ease of customization. This case comes from a 3D printer company that currently sells 3D printers online together with essential services, including install instruction, delivery, and customer service. Now the company attends to expand its market with digital servitization by attracting more novice users. One of the value proposals is to offer 3D printer rents called "try before you buy". However, the company wonders which 3D printers can guarantee success before the design upgrade. During the upgrade, they also hope to quickly check whether the launched solutions can satisfy the user requirements. The situation faced by the 3D printer company is a typical design iteration situation for many manufacturing companies who have the goal of digital servitization.

This example is a typical use-oriented PSS [74] since the users pay for the usage of a 3D printer instead of owning a 3D printer. Meanwhile, this example's "smartness" is reflected in the automation evaluation process, making the design iteration a Smart PSS case in the design field.

4.1 Identify evaluation indicators for Smart PSS concept evaluation

Twenty-six 3D printers are identified as the candidates and 1712 pieces of user reviews on the 3D printers are accordingly collected.

To check the consistency between the user behavior and the assumed usage scenarios, some usage scenarios' patterns were predefined by the experts. Identifying the patterns is based on the accessible data through the daily use of 3D printers provided by the 3D printer company.

Four context features were predefined to constitute the usage scenarios, including *Product speed*, *Model Size, Nozzle number,* and *Print Frequency Monthly*, as listed in Table 2. Each context feature's value boundaries are decided based on the domain knowledge collected online (http://www.3dhubs.com). Those context features are all 3D printing-related data rather than user personal data, which cannot be applied to identify an individual user but only to evaluate the 3D printing service status.

Table 2.
The context features characterizing usage scenarios

Contextual features	**No.**	**Values**
Printing speed	C1	[1-300] (mm/s)
Model size	C2	(0x0x0, 305x305x300](mm^3)
Nozzle number	C3	{1,2}
Printing frequency monthly	C4	$[0, +\infty)$

The scenarios of interest are represented in Table 3, including 'regular printing'(S1), 'frequent printing'(S2), 'precise printing (S3), and 'fast printing'(S4). The change of usage scenarios can be reflected by the change of the patterns which are identified by different value ranges of the predefined context features.

Following the steps in subsection 3.1.2, the task of identifying perceptual evaluation indicators was conducted based on the trained word embeddings from the Word2Vec model, and is programmed under Python environment. Here, to ensure the word embeddings are well-trained with abundant semantic information, a larger pretraining dataset containing electronic products and 3D printers was used. We expanded the dataset by electronic products' comments since the comments on electronic products and 3D printers usually have similar features and sentiments. Totally, 23110 pieces of product comments were applied, containing 12075 pieces of positive comments and 11035 pieces of negative comments. A python package called TextRank [67] was used to extract the key phrases. Some extracted phrases with the same/similar meanings are integrated to keep the evaluation indicators concise.

Table 3.
The usage scenarios as evaluation criterion their approaximate patterns

Scenario No.	**Scenario name**	**Description**	**Approaximate pattern**

S1	regular printing	A new individual user use 3D printing service regularly	{
			(10≤printing speed≤150)
			∩(145x145x145≤model size≤305x305x300)
			∩(nozzle number=1)
			∩(printing frequency monthly)
			}

S2	frequent printing	A user who frequently use 3D printing for production	{
			(10≤printing speed≤150)
			∩(145x145x145≤model size≤305x305x300)
			∩(nozzle number=1)
			∩(printing frequency monthly)
			}

S3	precise printing	A user who use 3D printing for precise printing, e.g., jewelry	{
			(10≤printing speed≤150)
			∩(145x145x145≤model size≤305x305x300)
			∩(nozzle number=1)
			∩(printing frequency monthly)
			}

S4	fast printing	A user who want rapid prototyping	{
			(10≤printing speed≤150)
			∩(145x145x145≤model size≤305x305x300)
			∩(nozzle number=1)
			∩(printing frequency monthly)
			}

Table 4 shows 16 frequently-mentioned perceptions, including printing accuracy, hotbed calibration, accessories, sound and noise, and other features.

Table 4.
Extracted user perceptions as evaluation indicators and their design ranges

General user perception	Detailed user perception	No.	Value range	Design range
Quality	Printing accuracy	PI1	(0,1)	(0.7721,1)
	Hot bed calibration	PI2	(0,1)	(0.8133,1)
	Printing speed	PI3	(0,1)	(0.5214,1)
	Accessory	PI4	(0,1)	(0.7158,1)
	Noise	PI5	(0,1)	(0.4250,1)
	Usability	PI6	(0,1)	(0.8656,1)
	Stability	PI7	(0,1)	(0.6540,1)
	Smell	PI8	(0,1)	(0.3156,1)
Appearance	Beauty	PI9	(0,1)	(0.5231,1)
	Size	PI10	(0,1)	(0.5406,1)
Service	Installation instruction	PI11	(0,1)	(0.8805,1)
	Customer service	PI12	(0,1)	(0.6097,1)
Price	Price	PI13	(0,1)	(0.6587,1)
	Cost-effective	PI14	(0,1)	(0.5172,1)
Delivery	Delivery speed	PI15	(0,1)	(0.7821,1)
	Damage-free package	PI16	(0,1)	(0.8028,1)

4.2 Identify design ranges and system range based on context information

On the one hand, the company sets its target users as the individual product designers who would like to test their product concepts; and identifies their usage scenarios as precise printing (S3) and rapid printing (S4).

The system range identification for the usage scenarios was trained via a SVM classifier under different kernel functions, including Linear function, Polynomial function, RBF, and Sigmoid function. The results using various kernel functions are shown in Table 5, indicating that using RBF leads to the highest F1-score (i.e., 0.974). Thus, the SVM model with RBF should be applied in this example.

Table 5.

Comparison between different SVM models in scenario classification

SVM model with different kernel functions	AUC	F1	Precision	Recall
Linear	0.997	0.971	0.971	0.971
Polynomial	0.997	0.972	0.972	0.972
RBF	0.997	0.974	0.974	0.974
Sigmoid	0.973	0.895	0.895	0.896

On the other hand, all the perceptual evaluation indicators are normalized into a value range of (0,1) that 0 means the worst of the indicators (e.g., expensive, hard, noise, and other features) and 1 indicates the best of the indicators (e.g., cheap, easy, quiet, and other features). The design ranges of the perceptual evaluation indicators determined by the novice users are listed in the last column of Table 4.

To identify the system ranges of the perceptual evaluation indicators, we followed the steps in Section 3.1.2 that first extract the key phrases from user reviews and then determine the user's satisfaction on the user-mentioned aspects. Figure 6 displays some illustrative examples of key phrases extraction. For example, the key phrase "operation is relatively simple" can be extracted and assigned to the perceptual indicator "Usability".

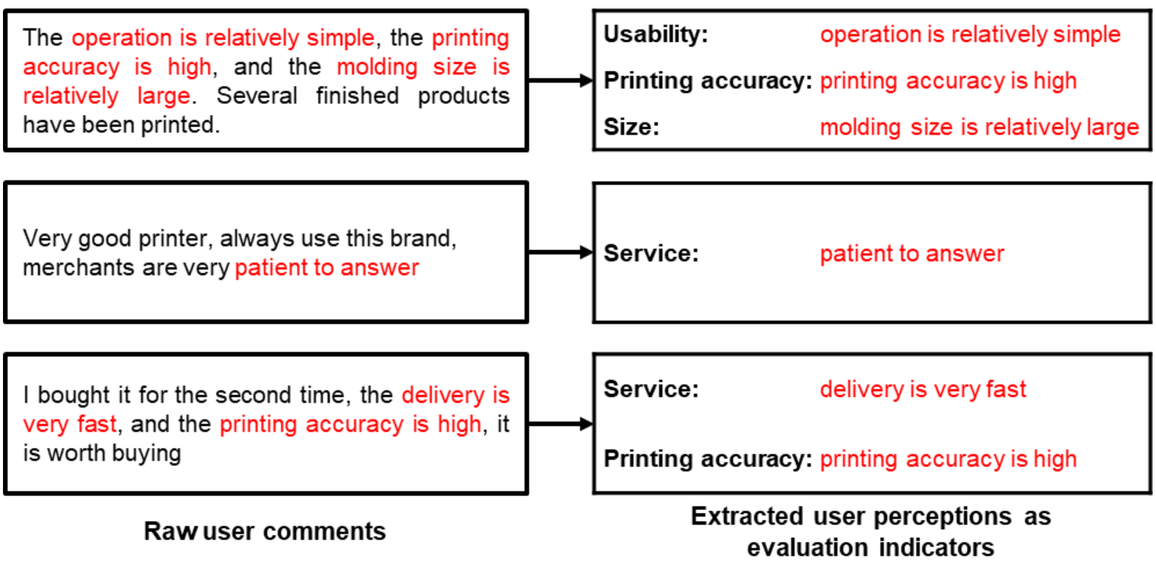

Figure 6. Illustrative examples of extracting user perceptions as evaluation indicators

Based on the pretraining dataset with sentiment labels, an SVM classifier model was trained for sentiment classification. Totally 1176 key phrases were extracted and labelled. Part of them and the predicted sentiment label are listed in Table 6.

Table 6.

Examples of system range identification based on perceptual indicators

User review No.	Psb-id	Extracted user comments	Perceptual indicators	Sentiment label	System range
1	psb1	complete tool accessories	accessory	1	0.9548
2	psb1	intact packing	damage-free package	1	0.9421
3	psb2	printing is very stable	stability	1	0.7697
4	psb4	no smell durign printing	smell	1	0.8022
5	psb11	machine appearance is very beautiful	beauty	1	0.9800
6	psb11	machine is very cost-effective	cost-effective	1	0.9089
7	psb11	customer service attitude is very good	customer service	1	0.8988
8	psb11	logistics shipped quickly	delivery speed	1	0.7617
9	psb11	video solves the problems of new installation	installation instruction	1	0.8218
10	psb11	printing sound is very small	noise	1	0.5972
11	psb11	price is cheaper than the brick-and-mortar store	price	1	0.8719
12	psb11	price is reasonable	price	1	0.6002
13	psb11	printing accuracy is very high	printing accuracy	1	0.7651
14	psb11	machine stability is very good	stability	1	0.9584
15	psb11	easy to operate	usability	1	0.8820
16	psb13	It takes about an hour to assemble	installation instruction	0	0.3581
17	psb21	auto-leveling is great	hot bed calibration	1	0.9627
18	psb26	memory card only has installed software	installation instruction	0	0.1472
19	psb26	if only the sound were smaller	noise	0	0.3293

Table 7 proves the SVM classifier's feasibility that the precision, recall, and f1-score of the sentiment classification are around 0.9. Furthermore, based on the user perception aspect model, the system range on each perceptual indicator for each alternative can be derived by calculating the average user perception in every user review. The results are listed in Table 8. For each PSB, the system ranges on the user-mentioned perceptual indicators are calculated, the blanks in Table 8 indicate that the indicators are not mentioned by users.

Table 7.
Sentiment classification result

Label	**Precision**	**Recall**	**F1-score**
Negative (label =0)	0.90	0.90	0.90
Positive (label =1)	0.91	0.92	0.92

Table 8.

System ranges of each perceptual indicator for each alternative

	PI1	**PI2**	**PI3**	**PI4**	**PI5**	**PI6**	**PI7**	**PI8**	**PI9**	**PI10**	**PI11**	**PI12**	**PI13**	**PI14**	**PI15**	**PI16**
psb1	0.8734	0.4346	0.8277	0.9288	0.2478	0.8354	0.9081	0.9062	0.8746	0.9879	0.9091	0.8411	0.7813	0.9602	0.8972	0.9198
psb2	0.9247		0.6377			0.8697					0.5927	0.6489			0.8997	
psb3	0.9124				0.8740	0.9216	0.8918			0.8312	0.9972	0.7813			0.8683	
psb4	0.9645	0.9600	1.0000				0.6901				0.8588	0.9467		0.9243	0.9620	
psb5	0.9077	0.7763		0.9903	0.9463	0.7893	0.8677	0.7034	0.9623	0.9738	0.6008	0.7879		0.9949	0.7920	
psb6	0.8672				0.5972	0.9144	0.8117		0.9800	0.9820	0.8790	0.9023	0.7817	0.8871	0.8654	
psb7	0.8605					0.8756							0.7974	0.9373	0.6995	0.8597
psb8	0.9079	0.7700				0.7969				0.7775		0.7086			0.7880	
psb9	0.8351		0.7905		0.7255	0.7136					0.9669	0.8025	0.8746			0.9481
psb10	0.8692					0.8918									0.9220	0.9107
psb11	0.7837			0.7934	0.1002	0.8117						0.7254	0.8041		0.7548	0.8657
psb12	0.8811			0.9079	0.7534	0.8887			0.7925	0.2456	0.1794	0.7658	0.8753		0.8810	0.9698
psb13	0.9180			0.7768	0.5972	0.8535			0.9441	0.9794	0.5804	0.8291	0.8965	0.9431	0.8997	
psb14	0.8947	0.9912		0.9584		0.9878				0.8469	0.9960	0.5937	0.8746	0.8461		
psb15	0.9224		0.8283	0.6290	0.4536	0.8295	0.9417		0.9593	0.9799	0.9449	0.6258	0.6222	0.9510	0.9087	0.9030
psb16	0.8675	0.3896		0.7336		0.2991			0.4642	0.0488		0.8626	0.7102			0.9348
psb17	0.8853	0.9555		0.8921		0.9149	0.9832			0.2761	0.7013	0.6557	0.9437			
psb18	0.8624	0.8559	0.8453	0.6741	0.2515	0.8173	0.8405		0.9678	0.9516	0.7789	0.7706	0.8153	0.9231	0.8994	0.9012
psb19	0.9059	0.4531	0.8922				0.7683	0.1146		0.4372	0.4324	0.6982	0.8943	0.9930	0.0857	0.6604
psb20	0.8779		0.9381	0.7633		0.9465	0.7786		0.8347		0.7716	0.7869			0.7987	0.9402
psb21	0.7663			0.8499		0.7506		0.8022		0.2551	0.8991	0.9712	0.7802	0.9639	0.8774	
psb22											0.1086	0.9413				
psb23	0.8153		0.7869	0.8476	0.4039	0.9936	0.9817			0.9617		0.4320	0.9919			
psb24	0.8729		0.9322	0.8764	0.4868	0.8670	0.9518		0.9216	0.5639	0.5024	0.6295	0.8760	0.9358	0.8034	0.9496
psb25	0.8630			0.9548		0.8479			0.9675		0.9805	0.9567	0.7666		0.8650	0.9421
psb26	0.7359	0.9400		0.7453		0.9311					0.9157	0.8160	0.4049	0.8928	0.9760	

4.3 *Compute information content*

The final information contents for each PSB were calculated by averaging the user-mentioned information contents. Then we ordered the PSBs in terms of the final information content from largest to smallest, as shown in Figure 7. Assume that the top 5 PSBs are selected as the most robust PSBs, then $psb_{25} > psb_5 > psb_3 > psb_7 > psb_6$.

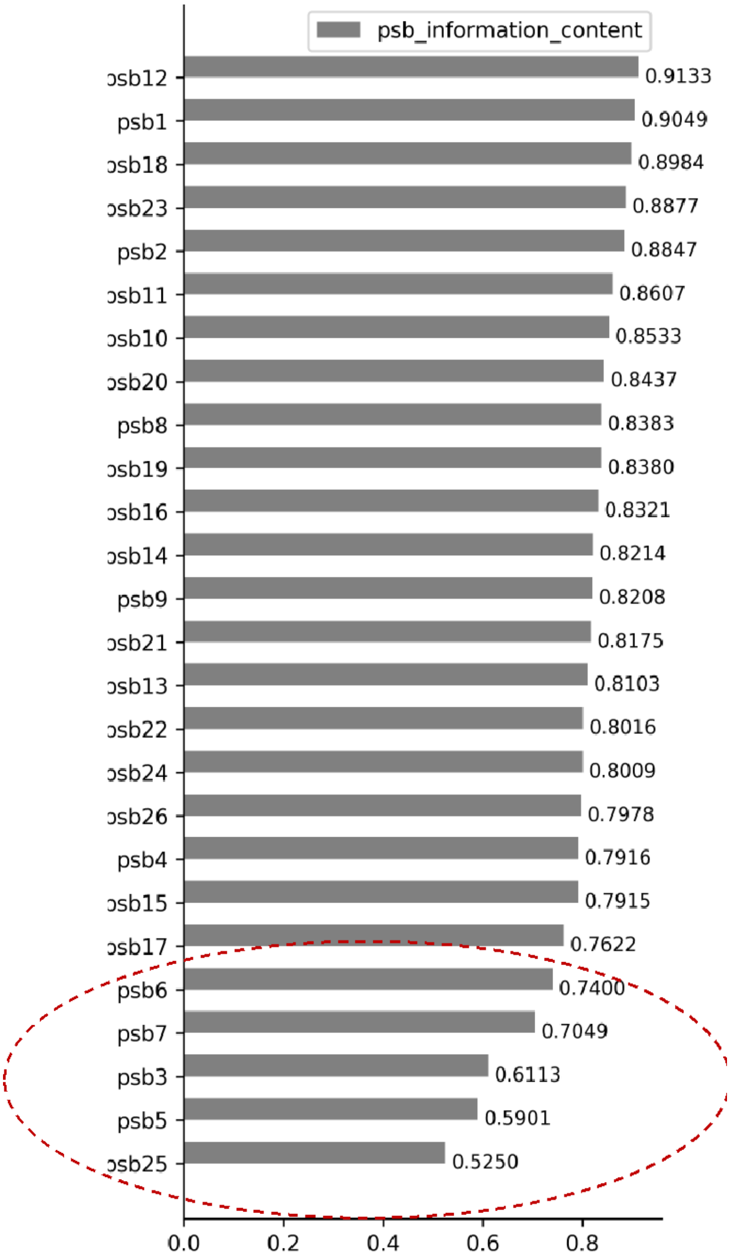

Figure 7. PSB ranking based on the final information content

5 Discussion

5.1 Comparison with TOPSIS

To demonstrate the rationality of the proposed approach, the case was also conducted based on a classic evaluation method, i.e., TOPSIS [75]. TOPSIS method ranks the candidates based on their closeness to the ideal solution; the selected candidate should have the shortest distance to the ideal solution and the longest distance to the worst solution. In this case, we applied the normalized Euclidean distance to measure the distances, following Equation (13), (14), and (15).

$$d_i^+ = \sqrt{\sum_{j=1}^{n}(v_{ij} - v_{bj}^+)^2} \tag{13}$$

$$d_i^- = \sqrt{\sum_{j=1}^{n}(v_{ij} - v_{wj}^-)^2} \tag{14}$$

$$C_i = \frac{d_i^-}{d_i^+ + d_i^-} \tag{15}$$

In the equations, d_i^+ refers to the distance between the PSB candidate i and the best PSB solution b. Similarly, d_i^- indicates the distance between the PSB candidate i and the worst PSB solution w. C_i is the closeness to the best solution that $0 \leq C_i \leq 1$. When the candidate approaches the worst solution, C_i approximately equals 0; in contrast, C_i will approach 1 when the candidate is the best solution. The top 5 results obtained by TOPSIS are ranked as $psb_{25} > psb_5 > psb_3 > psb_{13} > psb_6$, their corresponding measurements are listed in Table 9.

Using TOPSIS as the benchmark, 4 out of 5 candidates have the same sequences, thus proofing the proposed approach's rationality. The variance might be caused by the imputation method on the system ranges of the not-mentioned perceptual aspects. In this showcase, the average values are filled in the blanks.

Table 9.
The top 5 evaluation results based on TOPSIS

	d_i^+	d_i^-	C_i
psb25	0.5518	1.7145	0.756519
psb5	0.55626	1.698	0.75324
psb3	0.551748	1.67317	0.752014
psb13	0.600942	1.662875	0.734545
psb6	0.65812	1.675335	0.717963

5.2 The selection of the evaluation indicators

Compared with the common ways, such as zigzagging and QFD [13, 76], to identify the evaluation indicators in traditional axiomatic design [73], the proposed approach enriches evaluation indicators from user reviews. Its strengths can be seen from the following perspectives.

Firstly, zigzagging and QFD require engineers to predefine the evaluation indicators, heavily relying on the professional understanding of the specific domain; otherwise, it is hard to identify the evaluation indicators. However, in this article, the evaluation indicators were statistically defined from the key phrases, not depending on the skilled domain knowledge.

Simultaneously, the prerequisite of asking engineers to predefine the indicators also leads to zigzagging and QFD's second limitation. The determined evaluation indicators are based on designers/experts' subjective judgment, other than users' real perceptions. Nevertheless, extracting the user-mentioned key phrases directly and explicitly reflects which aspects are the users concerned about, thus reducing the human's prejudices.

Moreover, in a big and dynamic world, zigzagging and QFD will be costly and time-consuming for the system maintenance/update by inviting the experts to update the evaluation indicators. Unlike the traditional ones, the proposed approach used the automatic NLP techniques, enabling the evaluation indicator updates at a relatively low cost.

5.3 The identification of system ranges

The proposed approach can further reduce human interventions by automatically deriving the system ranges for each candidate via SVM classifiers. Considering that many linguistic words, such as "good" and "not bad", are involved in this paper, it is fuzzy and rough to assign them with a certain label. Fuzzy set theory [77] is a conventional method to handle the fuzziness under this situation. It contains the process of fuzziness based on membership functions and de-fuzziness to get the final crisp probability to certain groups [77]. However, the identification of membership functions is still predefined by engineers, leading to a series of system range results based on the engineers' subjective judgment. In contrast, by training the SVM classifiers, no more membership functions are required in our approach; hence fewer human interventions and a more automatic manner are achieved.

5.4 Limitations in the proposed approach

Despite the improvements, some limitations still exist. One limitation is caused by the limited data that only 26 PSBs were tested in this example. The proposed approach is still practicable for some small and medium enterprises that offer just dozens of PSB instead of the e-commerce platforms that sell thousands of PSBs. A scalability concern in the proposed approach will be further investigated, which can be considered from two perspectives. One is to enhance the context-aware concept evaluation approach with a larger number of PSBs, by simulating the concept evaluation situation of an integrated Smart PSS platform with different brands of PSBs. The other scalability concern is that more types of user behavioral data can be tested if accessible.

Another limitation comes from the assumption that system ranges follow the uniform distribution. In practice, users might be prone to give praise. For example, ‘good’ or ‘excellent’ often appear in the user reviews, making the system ranges probably follow other distributions instead of uniform distribution. How the system ranges’ uneven distribution affects the concept evaluation results will be further studied in the future. The pattern recognition techniques such as neural networks can be considered to tackle this limitation.

6 Conclusions

Motivated by digital paradox, and facing the risks of (1) omitting user perceptions during concept evaluation, (2) lacking a rapid evaluation indicator identification approach, and (3) the lag between user requirement changes and solutions, this study proposed a comprehensive user-experience-based concept evaluation framework for Smart PSS under a content-rich, user experience-oriented, and context-aware environment. The main contributions of the proposed approach can be concluded into three points:

(1) *Expand the evaluation scope from functional/technical parameters’ values to a comprehensive scope considering both behavioral and perceptual indicators*. This expansion increases the system’s capability to reflect the real user experience during the usage phase, accordingly reducing the failure possibility of digital servitization caused by insufficient evaluation scope.

(2) *Apply an automatic evaluation indicator identification approach*. It accelerates the evaluation process and relieves the lag between the user requirement changes and the solutions because of less human intervention.

(3) *Use large historical data to identify system range, rather than relying on engineers’ experience*. Hence, the prescriptive instructions in the traditional automation processes, such as manually evaluation indicator identification and fuzzy membership function identification, can be eliminated, therefore, realizing the intelligent automation in the concept evaluation process.

Based on these contributions, future research directions lie in two aspects. On the one hand, a multi-sourced and multi-modal concept evaluation manner can be achieved in Smart PSS by introducing more types of user behavioral data and user perception data, such as human action data or emoji memes. It will enrich the quantity of raw data for the Smart PSS development, making the Smart PSS development a more comprehensive digital-based ecosystem. On the other hand, besides the automatic capability of identifying evaluation indicators and their system ranges, advanced intelligent capabilities such as adaptability should be explored in the future. The adaptability of a concept evaluation approach refers to the capability of adjusting the PSB evaluation indicators or the PSBs' system ranges when the inputs change. These two research directions can further enhance the Smart PSS's capability of perceiving a specific usage scenario with context-awareness (i.e., offline smartness) and its capability of making proper and personalized decisions (i.e., online smartness).

In a competitive market pursuing quick design iteration, it is hoped that this study can offer practical guidance for the design practitioners in Smart PSS development to rapidly evaluate a PSB family and select the most robust PSB for design iteration/upgrade. At the same time, theoretically, it is also an attempt to expand the usability of information axiom into a broader scope with the concern on user experience from both user behavior and user perception.

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