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A Proactive Interaction Design Method for Personalized User Context Prediction in Smart-Product Service System

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Abstract

Smart product-service system (Smart PSS), as an emerging digital servitization paradigm, has attracted strong interest from both industry and academia worldwide. Compared with traditional PSS, Smart PSS has three unique characteristics, namely context awareness, closed-loop design, and IT-driven value co-creation, which put forward higher requirements for its solution design. Specifically, it aims for proactive interaction with users, which emphasizes context-aware prediction in the targeted service scenarios other than passive responses to the users. Meanwhile, smart connected products can be empowered to become agents to recommend personalized services accordingly. Nevertheless, few studies have considered a proactive interaction design approach in the Smart PSS context. Aiming to fill the gap, this study presents a systematic method that mainly includes three parts: context awareness, interaction decision-making graph, and interaction solution recommendation. By utilizing the proposed method, Smart PSS can actively interact with users and further provide optimal solutions according to personalized context data. At last, an illustrative case study of a smart reading solution is demonstrated to show its feasibility and effectiveness.

Keywords: Smart Product-Service System; Proactive Interaction Design; Smart Connected Products; User Experience; Context Awareness;

Nomenclature

Smart PSS	Smart Product-Service System
ICT	Information and Communication Technology
IoT	Internet-of-things
CPS	Cyber-Physical Systems
AI	Artificial Intelligence
PSS	Product-Service System
SCP	Smart, Connected Product
UXI	User Experience Indicator
HCI	Human-Computer Interaction
HMI	Human-Machine Interaction
HRC	Human-Robot Collaboration
CSet	Context Set
LightGBM	Light Gradient Boosting Machine
GBDT	Gradient Boosting Decision Tree
SVM	Support Vector Machine
RMSE	Root Mean Squared Error
MAE	Mean Absolute Error
Corr.	The correlation coefficient
IDMG	Interaction Decision-Making Graph
SSSQ	Short Stress State Questionnaire

1. Introduction

Nowadays, to maintain competitive advantages, many manufacturing enterprises are paying ever-increasing attention to digitalization and servitization with the advent of Industry 4.0 [1]. Rapid advances in ICT, such as IoT, CPS, and AI, have driven conventional PSS to shift into a new paradigm known as Smart PSS, first coined by Valenci et al. [2].

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With the gradually increasing interest in research works on Smart PSS, many descriptions and definitions have been given in the literature [3-4]. Among these studies, a widely accepted definition is given as "*An IT-driven value co-creation business strategy consisting of various stakeholders as the players, intelligent systems as the infrastructure, SCPs as the media and tools, and their generated services as the key values delivered that continuously strives to meet individual customer needs in a sustainable manner*" [4]. Owing to the advanced computation and communication capabilities of SCPs, it seems by nature that Smart PSS can serve as an assistive system. Meanwhile, the road map of AI has experienced several phases, from perceptual intelligence to today's cognitive intelligence and foreseeable action intelligence, where proactive interaction design of Smart PSS has become more feasible. More importantly, to achieve this goal, Smart PSS must be capable of initiating interaction proactively and further improving user satisfaction degree [5], instead of just reacting passively to user's instruction.

Nevertheless, based on the authors' best knowledge, most of the existing research concentrates on user satisfaction degree prediction based on product-sensed data and user-generated data. There are few studies concerning how to provide an improved design solution according to context information after obtaining the prediction result in a Smart PSS environment, let alone a proactive interaction mechanism to assist users in interacting with SCPs in different contexts. Aiming to fill this gap, this study presents a proactive interaction design approach based on AI technology, including machine learning, knowledge graph, and context recommendation system, to provide personalized interaction solutions in the contexts.

The rest of this paper is organized as follows. Section 2 reviews relevant research works. In Section 3, a proactive interaction design method is proposed. Section 4 presents a case study of the smart reading service system to validate the feasibility of the proposed framework. The conclusions and limitations are summarized in Section 5.

2. Related works

To provide a better view of background knowledge, relevant notions, comprehensive development of Smart PSS, and recent advances in proactive interaction design are introduced in this section.

2.1. Smart PSS design development

Smart PSS, a bundle of tangible products and intangible services to satisfy users' requirements, has attracted abundant attention from manufacturing enterprises and scholars. Whereas the wide conception of Smart PSS, numerous studies have been done on its definitions [4], characteristics, design methodologies, and applications [6].

Based on the previous research, three unique features of Smart PSS are primarily described, i.e., design with context awareness, closed-loop design/re-design iteration, and IT-driven value co-creation in the context [7]. What's more, diverse design frameworks have been proposed to achieve additional value based on the three distinctive characteristics. The context-awareness could be achieved by functional sensors, to assist in the adaption of Smart PSS to changing contexts [8]. Product-sensed data and user-generated data could be collected to determine the current context and understand user behaviors [9]. More importantly, it is advised that massive data should be captured to alter/upgrade products/services predictably in line with the perceptual context. The closed-loop design cycle includes requirement elicitation, innovation design, design evaluation, and re-design iteration[8]which highlights that relevant information in the context should be collected and processed throughout the whole design cycle from the development phase to the usage phase. Specifically, Wang et al. [10] proposed a graph-based context-aware requirement elicitation approach, where implicit demands of different stakeholders can be derived from user-generated information and product-sensed data. Meanwhile, Wu et al. [11] presented a function-oriented optimizing approach at the conceptual design stage. Also, a novel design entropy theory and a machine learning-based iterative design approach were proposed by Cong et al. [12] to determine the best design/re-design solution and conduct design iteration respectively. Moreover, IT-driven value co-creation emphasizes the participation and cooperation of relevant stakeholders, such as users, manufacturing companies, and service providers, to empower Smart PSS innovation and development [5]. Liu et al. formulated a framework integrating an interval-valued hesitant fuzzy-DEMATEL method to capture co-creative value propositions [13].

It can be found that existing studies always focus on requirement elicitation and re-design iteration with context awareness. However, from the users' perspective, Smart PSS solutions must respond to users' requirements in real-time and proactively, to achieve better user satisfaction.

2.2. Proactive interaction design method

Based on the view of technical systems and organizational psychology and management, proactivity means that actions should be taken to foresee problematic conditions and avoid negative experiences [14-15]. For example, when the infrared sensors perceive that a user is feeling cold by measuring body temperature, the smart system improves the indoor temperature proactively, which is considered as proactive behavior. The proactive systems, driven by machine learning, recommendation system, and other technologies, could empower SCPs to accomplish context-specific abilities, such as proactive interaction and instant feedback [15], and provide more efficient interaction utilizing relevant predictions [16].

Tan et al. [17] explored the relationship between five levels of proactive behaviors about social robots and the users' anthropomorphic factors. It was concluded that Level 4 (i.e., proactively initiating interactions with users and recommending service solutions) was the most thoughtful and polite, making users feel concerned. Relevant studies have proved the positive influence of proactive behaviors [17-18] and HCI has been prevailing over the last decade[14, 18]. Consequently, transferring the concept of proactivity to HCI is adopted to assist users in initiating actions to avoid possible problems in advance. Kang et al. [19] built a speech-based experience sampling device to concentrate on understanding opportune moments for proactive conversational interactions, which also emphasized that temporal and spatial patterns in domestic contexts should be considered. Matthias et al. [20] presented a novel user study for trust prediction during the proactive interaction phase in the HCI process. Another stream of research on proactive interaction is in the field of HMI. Peng et al. [18] evaluated the effect of three levels (high, medium, and low) proactivity of service robots on user perceptions and interaction behaviors. Li et al. [21] introduced a foreseeable manufacturing paradigm known as proactive HRC and proposed a multimodal transfer-learning-enabled prediction method to conduct proactive HRC assembly [22].

Following the studies above, most of the previous research mainly focuses on the effect of proactive behaviors on user perceptions, preliminarily proactive HCI, and HMI. However, few studied systematically proactive interaction behaviors. Aiming to fill the gap, this work proposes a proactive method to provide personalized interaction solutions in the context of Smart PSS.

3. The proposed proactive interaction design method

Based on the analysis above, the framework of a novel proactive interaction design approach is depicted in Fig.1. Three key parts can be clarified with 1) context awareness, 2) IDMG, and 3) interaction solution recommendation.

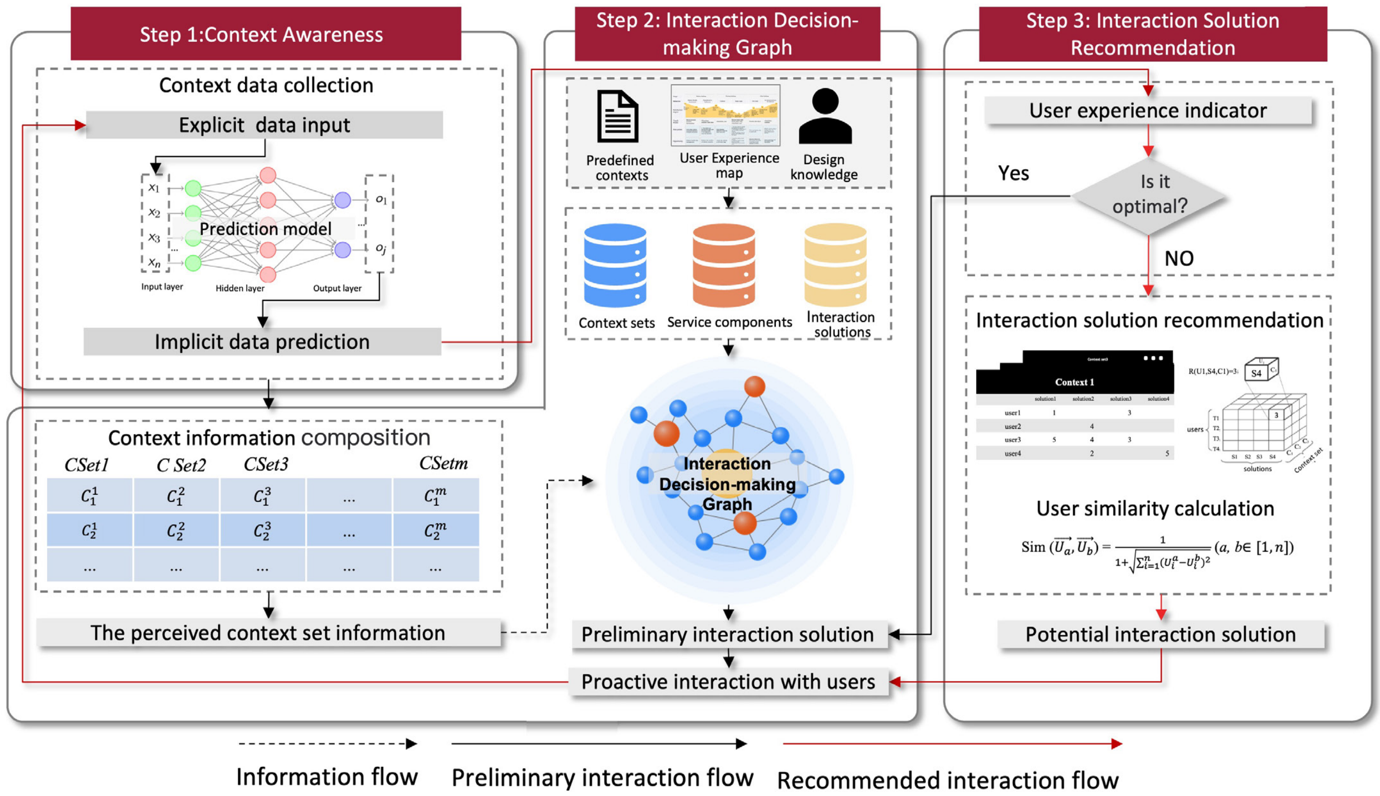

Fig. 1. Framework of the proposed method for proactive interaction design.

3.1. Context Awareness

Context awareness is a touch point of proactive interaction, which means that when the value of UXI is judged as low level, proactive interaction should be initiated to improve the present situation.

For one thing, the context involved in this study can be considered to include the following three types [23]: 1) physical context (i.e., information about the surrounding environment, such as light intensity and location), 2) user context (i.e., information about the psychological and physiological status of users), and 3) task context (i.e., information about the operational task and its interaction status with PSS, such as the content of the smart reader).

For another thing, context data can be reflected by both the collected explicit data (e.g., the environmental temperature) and the predicted implicit data (e.g., user attention degree). The single explicit context data is derived directly from different functional sensors and user historical operation logs. The implicit context data is the value of UXI, the selection of which depends on the specific application scenario. Meanwhile, with the rapid advances of AI, collected explicit context data can be transferred to implicit context data (i.e., UXI values) through a prediction model (e.g., the user attention prediction model established via eye tracking movement data and user subjective attention level). In this paper, explicit user physical data (various types of eye movement data) and subjective UXI data (five levels of stress state) are collected and inputted. Then the UXI prediction model is established via LightGBM, which implements the GBDT algorithm and supports high-efficiency parallel training. Afterward, 10-fold cross-validation is utilized to examine the performance of LightGBM and compare it with other machine learning regression models, including Linear Regression, SVM, and so on. These performance metrics to quantify the quality of prediction results are described as follows.

- RMSE is to measure the deviation between the predicted value and the true value, denoted as follows:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{N}} \quad (1)$$

- MAE is the mean value of the absolute error to better reflect the actual situation of the forecast error, denoted as follows:

$$MAE = \frac{\sum_{i=1}^{N}|y_i - \hat{y}_i|}{N} \quad (2)$$

- Corr. is a parameter measuring the degree of correlation between the true value and the predicted value, denoted as follows:

$$Corr. = \frac{\sum_{i=1}^{N}(\hat{y}_i - \bar{\hat{y}}_i)(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{N}(\hat{y}_i - \bar{\hat{y}}_i)^2 \sum_{i=1}^{N}(y_i - \bar{y})^2}} \quad (3)$$

where N is the number of instances in the dataset, y_i is the *i-th* value of true stress score, $\hat{y}_i$ is the *i-th* predicted stress score, $\bar{y}$ is the mean value of all stress scores in samples, $\bar{\hat{y}}_i$ is the mean value of all predicted stress scores. More importantly, the smaller the value of RMSE and MAE performs, the more accurate the prediction model is.

3.2. IDMG

The purpose of building IDMG is to map the context information to the relevant service components and their interaction solutions. In the IDMG, knowledge can be represented as "under what context, system service component(s) shall/should/will do process" [24]. Moreover, interaction solutions should be provided to users considering the complex impact of multi-context factors instead of a single context. Therefore, the recognized various context data can be defined as the CSet, denoted as follows:

$$CSet_m = (C_1^m, C_2^m, C_3^m, \ldots, C_n^m) \quad (4)$$

In this way, CSet information consisting of explicit and implicit context data is perceived and then the context-awareness interaction solution is provided to the user by querying the predefined IDMG. The IDMG consists of three parts: 1) the CSets defined by designers through the various predefined contexts, 2) service components derived from the user experience map, which includes stage, behavior, touch point, emotional curve, and pain point (e.g., the voice assistant reminding the rest time), and 3) interaction solution developed by the interaction designer. In addition, the relationship among the three parts is defined by the prior constraint knowledge from in-field experts and out-field professionals (e.g., the system should provide a brighter light when the user is in a low-light environment). Based on the above content, the schema of IDMG is established as shown in Fig.2.

There are three main types of nodes in this graph, which can be connected with their interrelationships defined by designers and experts. The extracted process of interaction solution takes the CSets obtained at the context-awareness stage as the input and queries them in the IDMG to map the corresponding service component and provide the initial interaction solution to the user. For instance, when a user is perceived under slight fatigue while reading a book with the smart reader in his home, the system will decrease the contrast ratio of the current interface proactively (the low contrast ratio of interfaces can alleviate users' vision fatigue). More importantly, designers and experts should update the IDMG when the UXI value has been at a low level.

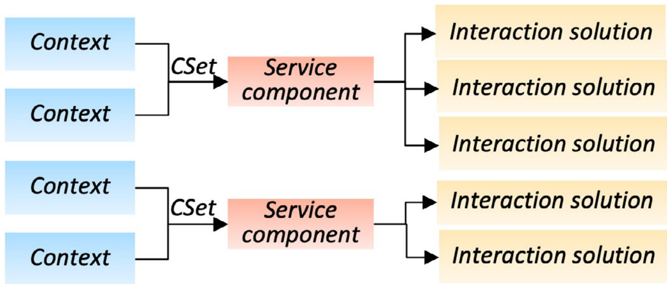

Fig.2. Schema of IDMG.

3.3. Interaction Solution Recommendation

The reason to establish the interaction solution recommendation system is that the interaction alternatives are various even if the context information and its corresponding service component are determined. To reduce the interaction turns and achieve the optimal interaction solution, the interaction solution with a better UXI value should be recommended to similar users.

First, the UXI value should be predicted and judged whether it is optimal. Then, the UXI value of each user during the usage phase should be recorded in a database including three dimensions: CSet, service component, and interaction solution. When the preliminary interaction is situated at a lower UXI level, the interaction solution with a high user similarity degree should be proactively recommended to the user. And user similarity degree can be calculated by the Euclidean similarity, denoted as follows:

$$\text{Sim}\,(\overrightarrow{U_a}, \overrightarrow{U_b}) = \frac{1}{1+\sqrt{\sum_{i=1}^{n}(U_i^a - U_i^b)^2}} \; (a, b \in [1, n]) \quad (5)$$

When the UXI value is always at a lower level and not able to be improved, the current CSet should be labeled and informed to designers and professional experts to update the IDMG.

4. A design case study

A smart reading service system consisting of smart readers and value-added services is demonstrated along with the proposed proactive interaction method. In this case, when the user is perceived under stress condition by the smart reader while reading, the proactive interaction solution in the reader interfaces will be provided through the reader interfaces to improve user pressure status.

4.1. Context Awareness

The starting point of proactive interaction is context awareness, which is achieved by functional sensors to collect explicit data. Specifically speaking, the smart reader is equipped with an eye tracker to obtain eye movement data, which was used to establish a stress prediction model and some functional sensors (e.g., position sensor, light sensor, etc.) to acquire other context data.

Forty-three students, aged 20-30 years old (M = 24.2, SD = 2.4), were invited to attend the stress-free and stress-induced reading experiments respectively. The stimuli were two short passages, each with three corresponding choice questions, which were selected from GRE Verbal Reasoning Practice. Eye movement data and subjective stress data were collected via the Tobii X3-120 eye tracker and SSSQ [25] respectively during the experiment. The experimental process is as follows, also shown in Fig.3.

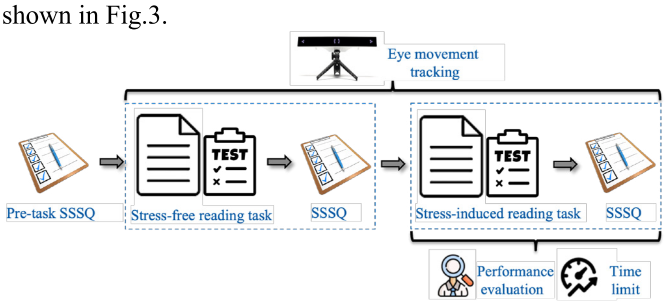

Fig.3. The experimental process.

- Firstly, participants were asked to finish the SSSQ before the experiment.
- Then, participants attended the stress-free reading task, where there is no time limit and performance evaluation. After completing the task, the SSSQ was asked to finish.
- Next, participants also took part in the stress-induced ergonomic experiment with 15-min time limit and performance evaluation, regarding both the accuracy of their answers and the reaction time they took, compared with peer participants. Finally, the SSSQ also were filled by participants again after finishing the stress-induced experiment.

Table 1. The performance of different regression models.

Regression Model	RMSE	MAE	Corr.
Linear Regression	0.159	0.124	0.733
Linear SVM	0.160	0.123	0.731
Random Forest	0.150	0.119	0.776
XGBoost	0.148	0.115	0.784
Gradient Boosting	0.145	0.112	0.793
LightGBM	**0.138**	**0.107**	**0.816**

The eye movement data, including four fixation features (i.e., fixation count, mean fixation duration, mean fixation velocity, and mean fixation stability) and seven saccadic-related characteristics (i.e., saccade count, mean saccade duration, mean saccade velocity, saccade peak velocity, mean saccade amplitude, mean absolute saccadic direction, and mean relative saccadic direction), and subjective stress data (1 represents none stress and 5 means extremely strong stress) were utilized to establish a stress prediction model by Python 3.6.5 with an environment established in Jupyter Notebook 6.0.1. The performance of the prediction models has been acquired using the selected regression models. As shown in Table 1., it is found that LightGBM was the most precise regression model with the smallest RMSE and MAE values.

4.2. The IDMG of a smart reader

The IDMG of the smart reading service system should be established to support proactive interaction while reading. The contexts predefined by designers, the service components elicited by the user experience map, and the corresponding interaction solution are linked by the interaction designers considering the ergonomic knowledge.

When the system predicts the user's stress level (e.g., existing strong stress situated between levels 3 and 4) based on the user's eye movement data, the physical context data (e.g., the period (evening)and the light-sensitive intensity belongs to ([0,200])), and the task context (e.g., reading the English journal) are collected. And the acquired data is taken as the input to query in IDMG, to map the service component (e.g., the screen lightness) and its preliminary interaction solution (e.g., the value of the screen lightness is 25) to interact with the user. After that, the value of UXI (stress level) is observed and judged whether there is any improvement. Meanwhile, the UXI value is recorded in the database which can support the interaction solution recommendation system when the predicted UXI is not ideal.

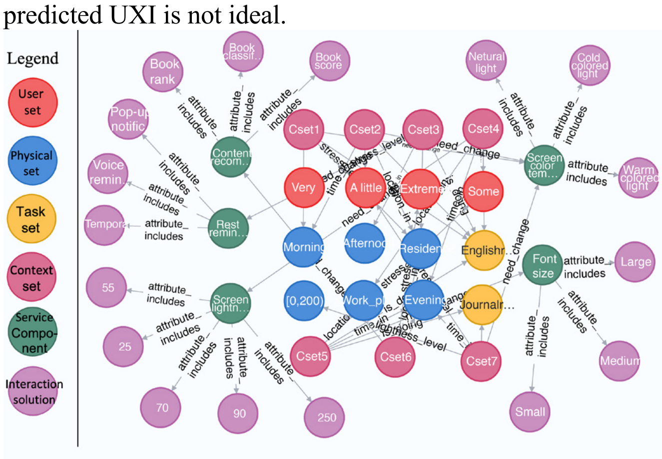

Fig.4. The IDMG of the smart reading service system.

4.3. The Optimal Interaction Solution Recommendation

The interaction solution recommendation system established is to provide each user with the optimal interaction solution based on similar CSet information and UXI value. According to the obtained value of UXI, the user similarity degree can be calculated. Following the example in Section 4.2, if the interaction solution (i.e., the value of the screen lightness is 25) cannot change the UXI level, another interaction solution (e.g., pop-up notification of rest) with a higher user similarity degree should be recommended to the user.

5. Conclusion

Smart PSS design characteristics emphasize offering real-time interaction solutions to meet users' personalized and dynamic demands. However, few studies proposed a systematic approach for the proactive interaction design work of Smart PSS. To fill the gap, this paper introduced a proactive interaction method by utilizing personalized context information in Smart PSS development, which can be used in the process of perceiving and predicting the possible context and providing personalized interaction solutions. The main contribution of this paper can be summarized as follow:

1) An interaction decision-making graph was established to achieve value co-creation in the Smart PSS environment, which emphasized the professional knowledge utilization and the cooperation between users and designers.

2) A proactive interaction design approach was proposed, which can provide users with a real-time and personalized interaction solution based on explicit and implicit context data to achieve better UXI.

Nevertheless, there are still some limitations in this work. The information overload brought by proactive interaction will make users feel unsafe about personal data privacy. Meanwhile, abundant context information has to be effectively collected and stored during proactive interactions, which may become costly and hard to process instantly. More work can be done to further address them, but as explorative research, it is expected that this study can provide insightful guidance to Smart PSS on proactive interaction.

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