UX- for Smart-PSS: Towards a Context-Aware Framework

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Abstract: Smart-product service systems are a business strategy that combines product and service into one value proposition. The user experience of digital services and the smart product can be a clear differentiator among competitors to achieve economically sustainable solutions. Hence, offering a more personalized experience is an important aspect of S-PSS. This paper aims to provide a theoretical framework for a context-aware user experience in S-PSS by providing adaptive and personalized services to the users according to their needs in a given context, by exploiting the digital capabilities of smart products and referring to the use of recommendation systems. The paper presents an application scenario using a smart-wearable as an example of a product-oriented PSS to better describe the framework and each component while stating the future challenges.

1 INTRODUCTION

Smart-Product Service Systems (S-PSS) is an ecosystem that proposes the combination of both product and service into one value proposition. The design of S-PSS has received increased attention in recent years (Carrera-Rivera et al., 2022; Cong et al., 2020; Dou and Qin, 2017) and implies several challenges. From the service perspective, S-PSS offers digital services that can be product independent or product dependent, powered by the integrated sensors in smart connected products or by technologies like digital twin or augmented reality (AR) (Zheng et al., 2019b). Zheng et al. (2019b) defined S-PSS as *"an IT-driven value co-creation business strategy consisting of various stakeholders as the players, intelligent systems as the infrastructure, smart, connected products as the media and tools, and their generated e-services as the key values delivered that continuously strives to meet individual customer needs in a sustainable manner"*. However, the design of S-PSS in multiple studies is only limited to the early phases of the product development and they do not address the evolution and adaptability that S-PSS should have. S-PSS follows the Service-Dominant (S-D) logic, a fundamental pillar of Service Design, that characterizes for a "value co-creation" view that uses experiences, context and multi-stakeholder participation to create innovative business value propositions(Wetter-Edman et al., 2014). Users may have different roles as co-creators in the different phases of S-PSS lifecycle: co-ideators, co-innovators, co-evaluators, co-testers or experience creators (Pezzotta et al., 2017). Users as *experience creators* can be involved in the solution conceptualization supporting better customization. Pezzotta et al. (2017) stated that providers can generate richer experiences for customers by understanding their preferences. A deep understanding of the customer experiences could help companies in defining and re-defining better value propositions. User Experience(UX) can be a clear differentiator among competitors to achieve economically sustainable PSS. Cong et al. (2020) highlighted that "user preferences should be associated with different design elements of Smart PSS in specific usage contexts". Previous studies have focused their attention on the connection between some user preferences and design elements. Misaka and Aoyama (2018) use Knowledge Engineering and machine learning for correlating users based on KANSEI engineering, a methodology to transform customer feelings into design as-

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pects of a new product. However, the studies in this research area are still limited to user-specific preferences in the usage stage of Smart PSS. A current challenge is a way to collect and process user behavior data in real time and define how it will be used. Existing research focused primarily on customer data from surveys or data from online reviews on social media. Further work on adaptation of the means of interaction with S-PSS needs to be done in order to improve the user experience to meet individual user needs. This paper proposes a framework to provide an adaptive UX according to user context, considering the interactions and data from devices and user profiles. The structure of this work is as follows: Section 2 starts with the fundamental background related to UX and Context-Awareness. Section 3 presents the framework and provides a detailed explanation of each phase. Section 4 provides a proof of concept of the framework using a wearable S-PSS. Finally, Section 5 presents the description of challenges, future work and conclusion of this work.

2 Background

UX is a result of the internal state of the user, the characteristics of the designed entity and the **context features** where the interaction occurs (Hassenzahl and Tractinsky, 2006). According to Valencia et al. (2015), in S-PSS, the UX is characterized by feelings of *customer empowerment*, *the individualization of services*, *the sense of ownership*, and an *individual and shared experience*. Non-engineering approaches and qualitative tools (i.e., observation, interviews, experience maps, etc.) are broadly used by UX designers at the very early stage of design for user research, to understand the context of use and users involved. Chang et al. (2019) presented a case study for a smart pillbox directed at the elderly; using behavioural analysis and interviews they perform a user analysis not only to capture their specific requirements but also to understand the physiological and cognitive dimensions. Similarly, Jia et al. (2021) used behavioural analysis and experience maps for the development of a smart rehabilitation assisting device. In both cases, current users' problems, popularly denominated 'pain points' usually highlight service opportunities.

However, there is a need to exploit the digital capabilities of S-PSS to generate an adaptive UX with the collected data available. A data-driven UX is a particular characteristic of S-PSS where data from smart products and digital services is easily accessible (Carrera-Rivera et al., 2022). Furthermore, the ability to capture user-generated data in real-time should be an important part of the design process, and it is a way of identifying and evaluating users' needs. For instance, methods to collect and process real-time user behaviour data and define in what ways it will be used. Existing research mainly focuses on online reviews data on social media or customer data from surveys. Wang et al. (2019) used user ratings and comments related to smart bicycles service from a website, and with the use of Natural Language Processing (NLP) techniques were able to capture implicit requirements that users had. Similarly, Mourtzis et al. (2018) presented a framework to evaluate the PSS services using the feedback received from shop floor experts and business customers through social media platforms. They also considered the information from machines and manufacturing execution systems to obtain KPI values. Therefore, user behaviour data from devices and interactions with service applications are typically not discussed.

In S-PSS, the delivery of personalized services can have a great impact on UX to affect the level of user satisfaction. Multiple approaches beyond PSS have used adaptive user interfaces as a way to offer personalization. Reguera-Bakhache et al. (2021) captured the interaction sequences, consisting of a series of click events from the interface of a mixing machine to understand the patterns of interaction from operators through a clustering analysis, and in this way reduce the time and interaction sequences of operators to perform a task. Todi et al. (2021) presented a system for adaptive menus using the data from user clicks on menu items and reinforcement learning to approximate menus to the user's expertise and interest. However, the use of context can further improve the personalization and adaptation by capturing the real needs of the user at a given time.

2.1 Context-Awareness

Context is defined by Abowd et al. (1999) as "any information that can be used to characterize the situation of an entity. An entity is a person, place, or object that is considered relevant to the interaction between a user and an application, including the user and applications themselves". In UX, the context of use represents the users, tasks, equipment (i.e. hardware, software), and the physical and social environments in which S-PSS is used (Iso, 2010).

The term "context-aware" was defined by Schilit and Theimer (1994) as the "ability to discover and react to changes in the environment". In general, a context-aware system uses context to deliver information and/or services relevant to a user's task (Abowd et al., 1999). Thus, a context-aware system does not necessarily imply automatization or real-time processing, instead, it refers to the ability to respond to context. For instance, context can be used to resolve what services or information need to be presented to the user. Therefore, context-awareness capability can be used to personalize the UX by providing services for a specific user situation.

In the design of S-PSS, multiple context-aware approaches have been proposed for the requirement-elicitation phase. For instance, Wang et al. (2019, 2021) proposed a graph-based context-aware framework for the requirement elicitation process in a data-driven manner. The framework includes a knowledge management layer that uses domain ontologies to model the product's components, services, and context; and a requirement elicitation layer, which uses graph algorithms to discover implicit requirements that user's had by analyzing reviews and comments from social media. For UX, context-awareness has been used to create realistic prototypes. For instance, Seo et al. (2016) proposed a hybrid evaluation method for smart home services based on VR and AR prototypes using a UX ontology for smart home services and semantic reasoning using the open source framework Jena. On the other hand, Dou and Qin (2017) obtained physiological data from several sensors including electrocardiography (ECG) and facial electromyography (fEMG) from elderly people combined with environmental information, to build a user mental model to better understand the experience of a smart TV S-PSS. The authors used clustering analysis as a way to identify patterns and build user profiles according to the context. Such approaches, however, do not address the need of adaptation in the means of interaction with the smart products in the usage stage of S-PSS.

Users' short term memory is limited to a few items of information. Cognitive load refers to the total amount of mental activity on working memory at an instance in time. If the user interface requires the user to hold more than it can retain, it will produce a cognitive overload (Tracy and Albers, 2006). Therefore, providing customized services recommendations address this problem in applications designed to fully manage or interact with smart products. Context-awareness recommendation systems have been proved to provide better customization since context information is very important in improving recommendation accuracy (Yang, 2018). Tarus et al. (2018) proposed a context-aware recommender system for e-learning, using collaborative filtering (CF) algorithms and learner´s goals and study patterns as sources of context in addition to a traditional rating of courses. Yang (2018) presented a recommender system model, implemented as a website for movie recommendation. Users are allocated to the corresponding set of similar users using the Top-N algorithm. In the user behaviour analysis step, popular movies are recommended. Then, a matrix of user scores is established by analyzing the results of user-registered movies and using time as context of each score (i.e. season of the year, weekday or weekend).

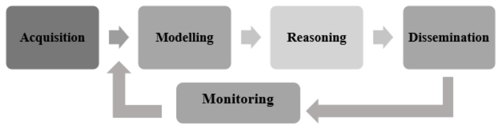

Figure 1: Context-aware life cycle

This section has attempted to provide a brief summary of the literature. As discussed above, the proposed approaches to UX focus their attention only on the design stage, before the use phase. As S-PSS represent a way of continuously striving to meet customer needs, adaptation needs to be reflected also in the interaction with smart products. The section below describes the framework proposed in this paper.

3 Framework

Perera et al. (2013) defined four general steps in context life cycle as a way to describe the process of developing context-aware applications (Figure 1). The first step is *Context Acquisition*, which refers to data that needs to be acquired from different sources (i.e. sensors, cyber-physical systems (CPS), databases, etc). In Context Modelling, the collected data needs to be represented in a meaningful way. Then, in Context Reasoning, data is processed to provide useful information and insights (context). Context Dissemination phase distributes context to consumers, which can be end-users or other applications. Lastly, Context Monitoring represents the evolution of the design of S-PSS. It is a stage not broadly represented and should be considered after Dissemination because context may change at some point. Systems or applications have to be able to identify changes and update the models accordingly. Following the context-aware life cycle, this paper proposes a theoretical framework to provide a personalized UX where services are recommended and shown according to context when the interaction occurs. Figure 2 presents the overall graphic representation of the framework. The following subsections will describe each layer of the framework in detail.

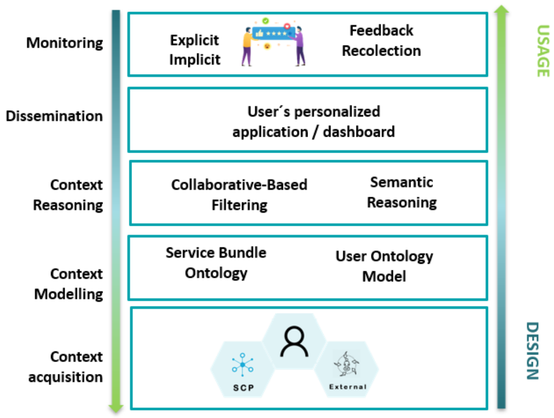

Figure 2: Context-aware framework for UX

3.1 Context Acquisition

The process of context acquisition will require capturing the data from multiple sources. This process can be classified by the source of context and the nature of the data. Figure 3 presents three main data sources, *Smart Connected Product* (SCP), *user*, and *external*. The nature of the data can be dynamic or static. User context refers to any information related to the user. User static data might include user personal information or user preferences (Liu et al., 2011). The dynamic information might include: the user's current and historical location, user's current and historical activity, user's current emotion, relationships, etc. For instance, capturing the data from users while they interact directly with products or e-services usually delivered by mobile apps or web applications. SCP data is acquired from the device through sensors in smart products that can proportionate relevant information of the user when the smart products are used to monitor the user routine, for instance, wearable devices. Finally, external sources contain dynamic environment physical information(i.e lighting , noise, temperature, and humidity level, traffic conditions)

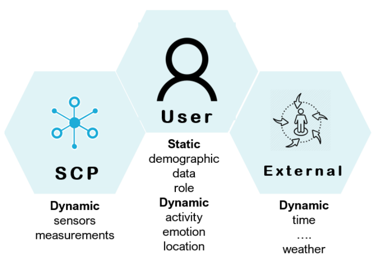

Figure 3: Context data sources

3.2 Context Modelling

Context modelling allows the representation of the data acquired in terms of attributes, characteristics, and relationships with previously specified context (Liu et al., 2011). Thus, a static model is necessary to represent the services of smart devices where each of them groups low-level services or sub-services related. A sub-service will represent a very specific function of the e-service platform or smart device. According to (Maleki et al., 2018) in an S-PSS architecture, the domain knowledge models function in an intermediary role to integrate the S-PSS services with the cyber-physical components. One approach is the use of domain ontologies. Ontologies are a means to formally model concepts from a particular domain into a detailed specification of entities with properties and relations. Domain ontologies define the vocabulary related to a particular domain (Guarino et al., 2009). In this case, each service is modelled into a pattern that relates the product, service and required information (Maleki et al., 2018) and integrates it with context-specific classes and relationships (see Figure 4). In this way, the interactions with the service can be labelled into multiple categories (i.e. click, like, close) and then linked to the services to understand user behaviour for each of the sub-services.

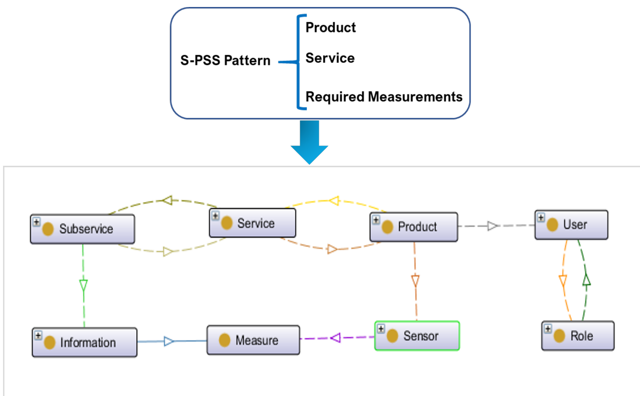

Figure 4: S-PSS Pattern and derived ontology

3.3 Context Reasoning

Context reasoning is the process of deducting new information that is useful for a task or user, from multiple context-data sources. The relevance of a recommendable service solution not only depends on the users' general preferences but also on their current situation and their short-term interaction and interests (Quadrana et al., 2018). Furthermore, the data from the product itself is a source of context. Collaborative Filtering (CF) is a recommendation tech-

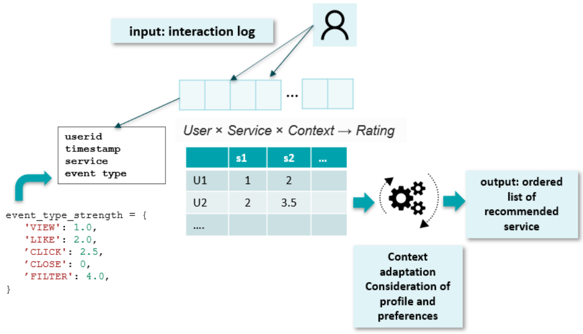

Figure 5: Reasoning process context-aware recommendation systems

nique largely used in e-commerce to provide personalized recommendations on items (i.e. books, movies, clothes, etc). It uses similarities between users and items simultaneously to provide recommendations. CF exploits the ratings provided to products explicitly (i.e. starts ratings) to measure the similarity and provide adequately recommendations (Elahi et al., 2016). However, is also possible to get implicitly forms of ratings by obtaining and evaluating the interactions that the user had (i.e. page views, clicks, purchases, etc), which is the more adequate method in the case of S-PSS. Each type of interaction could represent a higher level of engagement with a specific service. For example, monitoring events such as *filter changes* and *clicks* would represent a higher rating in comparison with a page view event (Chen, 2005; Núñez-Valdez et al., 2018) as seen in Figure 5. In a context-aware scenario, ratings are modeled as a function of: users, service as well as context. Hence, the rating function can be defined in three dimensions (Tarus et al., 2018): *User x Service x Context →Rating*, the process will produce as output an ordered list of recommended services based on the generated ratings of other users with similar preferences in the same context (Figure 5). Although collaborative filtering is the most popular recommendation technique, its major disadvantage is the new user and new item problems (Barjasteh et al., 2016), referred commonly as the cold-start problem, which occurs in scenarios where it is not possible to make reliable recommendations due to an initial lack of ratings (Adomavicius and Tuzhilin, 2005). Semantic reasoning can be used to explicitly infer the preference of implicit users, reducing the sparsity of user information, and alleviating the problems of cold start (Yang, 2018). Considering the use of ontologies in the modelling stage, semantic reasoning could take advantage of this to infer new knowledge based on established relationships.

3.4 Context Dissemination and Monitoring

Context Dissemination is related to the methods to deliver context to clients or users. The purpose of this stage is to provide the individualization of the experience by providing services adequately for each user situation. Digital services should be adaptive to user context and easily accessible through digital platforms provided by the service in the form of apps or websites or the product means of interaction by itself. Furthermore, the process of context monitoring represents the evolution of the design of S-PSS. It is important to monitor user feedback regarding the services delivered by the application. Feedback from users can come through integrated surveys, but also from user behaviour. For instance, if a user is not happy with the service that the application is offering, it is likely they will return to an old state of the application, or do not interact with the information. This can be taken as negative feedback and a negative rating for the service provided. Having discussed each layer, the following section of this paper addresses an application scenario to understand the implementation process.

4 Application Scenario

In order to demonstrate the proposed framework, an activity monitoring scenario is used for a product-oriented PSS. Tukker (2004) classified PSS into three main categories from the business aspect : *Product-oriented*, *Result-oriented*, and *Use-oriented*. Product-oriented is related to services that facilitate the sales of products or add functionality or personalize existing products. In Result-oriented and Use-oriented, the ownership usually remains with the provider. Fitbit is one of the most popular multi-purpose activity wearable trackers and smart-watch and represents a clear example of *Product-oriented* PSS for endconsumers (B2C). An important part of the product is the e-services platform since it represents a means of interaction with the device and also a source of information to the user which is accessible through the mobile app or web application.

In the framework, the context acquisition layer collects the information from the device, which in this case represents data about the user's behaviour, for instance, the number of steps taken by the user in a day. This translates into information such as the distance, the duration as well as the intensity of activity. User interaction with the e-service platform will be captured using Matomo[1], which is an open-source platform capable to capture user interaction (i.e clicks, page views) from a web application into a Mysql database. Figure 6 represents the context modelling layer. Using an ontology, according to section 3.2, each high-level service provided by the S-PSS (i.e activity monitoring) has associations with low-level services that represent specific options on the e-service platform. Each interaction that is recorded can be related to a specific service and further enriched with contextual information, for instance, weather, time and device status. Another significant aspect is that the use of an ontology could mitigate the 'cold start' problem when there is a lack of historical interactions. In this scenario, profiles were defined using a dataset from 30 anonymous users (Furberg et al., 2016) by means of a non-supervised machine learning technique, using the clusterization algorithm, *K*-Means (Figure 7).

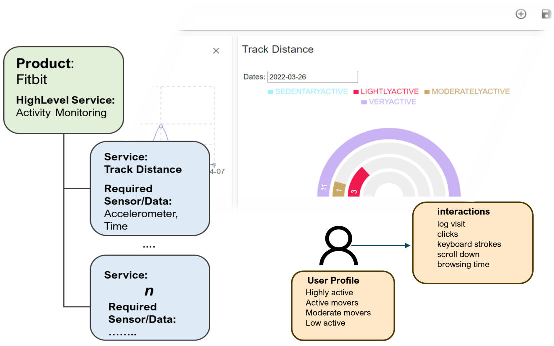

Figure 6: Fitbit application scenario

Four profiles were identified, in base of their behavioural information, and further used to model an ontology using GraphDB. The ontology can define the relationships among users, profiles and high-level and low-level services as shown in Figure 8, *User1* has an *Active* profile and uses *trackExercise* low-level service. Using semantic reasoning, it can be inferred that users with *Active* profile use the *trackExercise* service. In future work, the reasoning layer will use collaborative filtering algorithms to produce an ordered list of recommended services. These services will be delivered through the e-service platform application in the form of widgets or personalized notifications in a web application using React framework. One of the challenges will be to achieve a way to deliver the adaptive services in several S-PSS interfaces; software frameworks for application creation are very diverse. *Javascript* is the ultimate web standard with multiple frameworks available (i.e. React, Vue, AngularJS), which have extended to mobile apps. But, forms of interactions might vary in industrial (i.e. manufacturing) settings. This highlights the importance to understand the type of market where the S-PSS is directed. It is key to validate the framework in both, B2C scenario and also in a Business to Business scenario (B2B), where the UX can be perceived differently by users, and the means of interaction and feedback recollection can also change.

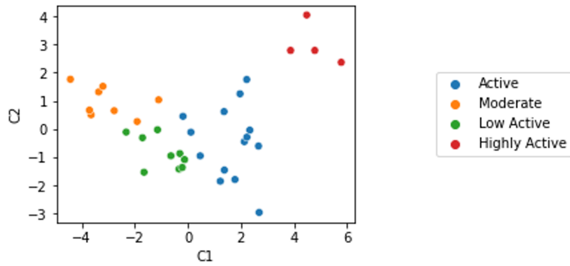

Figure 7: K-means clustering

Another challenge of a data-driven UX is the need for users' personal and behavioural information, which could vary depending on S-PSS' application domains (i.e health & welfare, manufacturing, smart home, etc.). The services created must help users make informed decisions about their privacy. Similarly, users must have control over their personal information (van Ooijen and Vrabec, 2019). Privacy regulations should be followed (i.e. General Data Privacy Regulation GDPR) and ensure users' consent and awareness of the data collected (Zheng et al., 2019a).

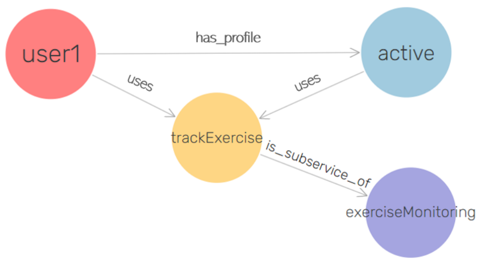

Figure 8: Ontology query in GraphDB

[1] https://matomo.org/

5 Conclusions

S-PSS emerges as a way to provide a market offer combining both product and service while maintaining a lasting relationship between provider and customer. It is important to comprehend the role of UX to understand the use and expectations of users with smart products and e-service platforms. Continuously delivering personalized experiences for users is challenging. The creation of value with user interactions can allow maintaining the system relevant to the changing needs. This can be accomplished, by implementing technology in a way that it results in a simple and intuitive experience. This work described a theoretical context-aware framework for the UX of S-PSS, following the life cycle of context-aware application and considering the use of context in recommendation systems and the users interactions. The goal is to provide a personalized and adaptive e-service S-PSS platform for each user. An application scenario of a wearable activity tracker device was presented as a product-oriented S-PSS that allows to better showcase the general overview of the framework. The work also presented a description of the challenges that brings S-PSS, such as a multi-business perspective to understand users in different scenarios and industries, and the management of behavioural data and how to handle privacy aspects within the applications. Future work will provide an implementation of the framework and further analyze each of the stages described in this paper.

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