

A Data-driven Reversible Framework for Achieving Sustainable Smart Product-Service Systems

Xinyu Li

Cash.li@ntu.edu.sg (Corresponding author)

Delta-NTU Corporate Laboratory for Cyber-Physical Systems, School of Electrical and Engineering, Nanyang Technological University, Singapore, 639798

School of Mechanical and Aerospace Engineering, Nanyang Technological University, Singapore, 639798

Zuoxu Wang

Zuoxu001@e.ntu.edu.sg

School of Mechanical and Aerospace Engineering, Nanyang Technological University, Singapore, 639798

Chun-Hsien Chen

Mchchen@ntu.edu.sg

School of Mechanical and Aerospace Engineering, Nanyang Technological University, Singapore, 639798

Pai Zheng

Pai.zheng@polyu.edu.hk (Co-corresponding author)

Department of Industrial and Systems Engineering, The Hong Kong Polytechnic University, Hung Hom, Hong Kong, China, 999077

A Data-driven Reversible Framework for Achieving Sustainable Smart Product-Service Systems

Abstract: Higher sustainability with extended product lifecycle is a tireless pursuit in companies' product design/development endeavours. In this regard, two prevailing concepts, namely the smart circular system and smart product-service system (Smart PSS), have been introduced, respectively. However, most existing studies only focus on the sustainability of physical materials and components, without considering the cyber-physical resources as a whole, let alone an integrated strategy towards the so-called Sustainable Smart PSS. To fill the gap, this paper discusses the key features in Sustainable Smart PSS development from a broadened scope of cyber-physical resources management. A data-driven reversible framework is hereby proposed to sustainably exploit high-value and context-dependent information/knowledge in the development of Sustainable Smart PSS. A four-step context-aware process in the framework, including requirement elicitation, solution recommendation, solution evaluation, and knowledge evolution, is further introduced to support the decision-making and optimization along the extended or circular lifecycle. An illustrative example is depicted in the sustainable development of a smart 3D printer, which validates the feasibility and advantages of the proposed framework. As an explorative study, it is hoped that this work provides useful insights for Smart PSS development with sustainability concerns in a cyber-physical environment.

Keywords: smart product-service system; sustainability; knowledge management; reversible design; context-awareness

Nomenclature

Smart PSS	Smart Product-Service System	CE	Circular Economy
ICT	Information and Communication Technology	IoT	Internet-of-Things
CPS	Cyber-Physical System	DT	Digital Twin
AR/VR	Augmented Reality/Virtual Reality	KG	Knowledge Graph
ML/DL	Machine Learning/Deep Learning	PLM	Product Lifecycle Management
4V Data	High Volume, Variety, Veracity, and Velocity Data	SCP	Smart, Connected Product
4R	Re-design, Remanufacturing, Reuse, and Recycle	RUL	Remaining Useful Life
DIKW	Data-Information-Knowledge-Wisdom	C-K Model	Concept-Knowledge Model

1 Introduction

Sustainable development is the main theme of today's production systems, and has gained increasing attention among academia, practitioners, and policymakers (Gianmarco Bressanelli, 2018). Responding to a call for "*doing more with less material*" (Westkämper et al., 2000) in CE, one prevailing concept for promoting sustainability, i.e. circular system, was introduced by transforming the linear system of production (produce, sale, and dispose after

use) to a circular one with reversible strategies (e.g. re-design, remanufacturing, reuse and recycle). Hence, it can effectively reduce un-renewable resource consumptions and mitigating environmental impact (Murray et al., 2017). Another concept, termed product-service system (PSS), proposed a paradigm that tightly couples products and add-on services to fulfil customized requirements. Extending the lifespan with product reconfiguration and service innovation, PSS also promotes sustainability by “doing more” (Tukker, 2015; Tukker and Tischner, 2006).

Owing to the recent rapid development of advanced ICT infrastructure, digitalization technology and AI techniques, these two concepts individually evolve to be smarter, as the so-called Smart Circular System and Smart PSS, respectively. For the former, the increasing usage of IoT allows a higher level of traceability of materials and products in the circulation (Whitmore et al., 2014), and the leveraging of big data analytics techniques provides ever sufficient product lifecycle information (e.g. degradation status, remaining useful life) for decision-making (Bressanelli et al., 2018; Li et al., 2015; Zhang et al., 2017). For Smart PSS, the novel techniques provide capabilities to collect and transmit sensed-data and user-generated data among various SCPs and multi-stakeholders (Zheng et al., 2018a; Zheng et al., 2018b; Zheng et al., 2020), and also enable a rapid (even real-time) reconfiguration solution of hardware and software with requirement-orientation and context-awareness (Wang et al., 2019b; Zheng et al., 2019a).

Note that Smart Circular System provides competitive advantages for Smart PSS with cost reductions and new revenue potentials in commercialization (Michelini et al., 2017), and Smart PSS revealed great built-in-flexibility and self-adaptability to implement the lifecycle management of Smart Circular System (Zheng et al., 2018b). A meeting-point of the two prevailing concepts, so-called Sustainable Smart PSS (or Smart Circular PSS), is about to emerge. By collecting and analysing the meaningful product-sensed and user-generated data, Sustainable Smart PSS can better perform its sustainable use/reuse, maintenance, reconfigure, and recycle processes throughout the whole lifecycle. This provides a promising manner to enable sustainable development in the production system.

However, to the authors’ knowledge, only a few qualitative studies have proposed the potential of Sustainable Smart PSS (Alcayaga et al., 2019; Li and Found, 2017), while little research has further discussed its development process or realized it. More importantly, most existing studies still restrain themselves in a conventional perspective of product lifecycle management, which only considers the sustainability of tangible materials and components along the 4R process (Zheng et al., 2019b). Since the value-creation of products/services relies on massive operation datasets and effective data analytics manners, the discussion of sustainability is required to be extended to the cyber space and consider the cyber-physical resources as a whole. Rather than the well-known reversible strategies for material circularity, a novel perspective of sustainable information/knowledge management needs to be emphasized via the digital servitization business model (Kuhlenkötter et al., 2017). It will maximize the value of exploiting and reallocating cyber-physical resources in the development of Sustainable Smart PSS.

Aiming to fill the abovementioned gaps, this paper will first discuss the key features of Sustainable Smart PSS in a cyber-physical environment, and then propose a data-driven reversible development framework, and finally

validate the proposed framework with an illustrative example. The remainder of this paper is organized as follows. Section 2 briefly introduces the key terms and approaches for sustainability strategies and Smart PSS development. Section 3 discusses the key features in Sustainable Smart PSS development. The overall framework for its development process is presented in Section 4, with each module illustrated in detail. Section 5 provides an illustrative example of a smart 3D printer development to further validate the proposed framework towards smart sustainability. At last, the conclusion and future work are highlighted in Section 6.

2 Terms and approaches for sustainability and Smart PSS development

2.1 Reversible strategies for achieving higher sustainability

In order to balance economic development with environment and resource protection, the report of UN Environment Programme (UNEP) in 2006 initially outlined *sustainability* in the production system as “*restorative or regenerative by intention and design*”, and generically proposed the criterion of *low consumption of energy, low emission of pollutants, and high efficiency* (Murray et al., 2017). It was then derived and clarified for product development and product lifecycle management (PLM) into three aspects, namely, *environmental sustainability* (less material/fuel consumption, carbon emission, air/water pollution), *economical sustainability* (allowing an upgrade of components, reducing transportations) and *social sustainability* (shared value, customer loyalty, human well-beings improvement) (Li and Found, 2017; Liu et al., 2020a).

Originated from PLM, typical reversible strategies for achieving higher sustainability in product development includes *Re-design, Remanufacturing, Reuse, and Recycle* (4R), which reform the linear system of product lifecycle stages (design, manufacturing, distribution, usage, and disposal) to a circular system (Alcayaga et al., 2019; Zheng et al., 2019b). As shown in Figure 1, *Re-design* bridges customer experience in the usage stage and the end-product with an inverse-design principle and ‘configure-to-order’ manner (Jiao and Helander, 2006). Rather than start from scratch, it selects the appropriate components/modules from the existing product family to rapidly offer an upgraded design solution, thus providing higher flexibility and fewer un-renewable resource consumptions (Miranda et al., 2017). *Remanufacturing* is a series of manufacturing steps on a used product, to return or restore it to at least equivalent or better performance than that of the newly manufactured product (Diallo et al., 2016). Several techniques are leveraged under this generic definition, like remaining useful life (RUL) assessment (Hu et al., 2015), predictive maintenance (Kerin and Pham, 2019), refurbishing or reassembly (Niu and Xie, 2020). *Reuse* is regarded as a non-destructive process that allows additional lifecycle cycles of the whole or partial of product in an alternative scenario, without changing their original state. It is widely adopted in the industrial sectors of construction, packaging, and textiles (Cooper and Gutowski, 2017; Damirchi Loo and Mahdavinejad, 2018). *Recycle* aims at extracting raw materials or useful components from end-of-life products, and typically consists of three main phases: collection, sorting and recycling processing (Thoroe et al., 2011). Since the recycled materials and components are

usually leveraged in the strategies of *Re-design*, *Remanufacturing*, and *Reuse* and start another loop of the product lifecycle, *Recycle* is often considered as an ultimate closing-step in the circular system.

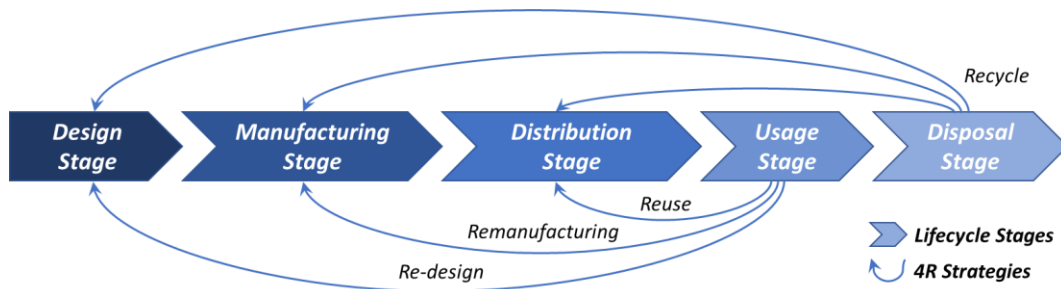


Figure 1. 4R strategies in product lifecycle stages

With the advanced ICT infrastructures (e.g. IoT, smart sensors, cloud computing), digitalization technologies (e.g. CPS, DT, AR/VR) and AI techniques (e.g. machine/deep learning, 4V Data mining and large-scale KG), the reversible strategies have become smarter. Typical studies are listed in Table 1. Generally, the smartness of the strategies is usually achieved by IoT-enabled product lifecycle data collection, Big data-supported decision making, and CPS-based simulation and operation, and it hence outperforms its predecessor in increasing resource efficiency, extending lifespan and closing the circulation (Alcayaga et al., 2019; Bressanelli et al., 2018). However, due to an inheritance from PLM, only tangible materials and components are considered in the majority of reversible strategies. Data itself, as well as the high-value information/knowledge mined from it, is often dismissed in the sustainability considerations due to intangibility and context-dependency, which sometimes contributes to the high cost and unexpected failures in adopting these smart strategies (Kerin and Pham, 2019).

Table 1 Typical smart strategies for achieving higher sustainability via reverse engineering

Strategies	Representative Studies	Specifications / Applications	Smart Techniques
Smart Re-design	(Savarino et al., 2018)	Adaptable product with context-aware modules	IoT, Smart sensors
	(Bressanelli et al., 2018)	Remote product upgrade to postpone replacement	Big data mining
Smart	(Chang et al., 2017)	Virtual disassembly platform for remanufacturing (and recycle)	AR/VR, CPS
Remanufacturing	(Zhang et al., 2017)	Lifecycle-data-driven decision-making for remanufacturing	Big data mining, ML
	(Alcayaga et al., 2019)	IoT-enabled remanufacturing planning and real-time monitoring	IoT, Smart sensors
Smart Reuse	(Zhang et al., 2017)	Lifecycle-data-driven decision-making for reuse	Big data mining, ML
	(Iacovidou et al., 2018)	Reusable materials/components evaluating, tracking and tracing	IoT, CPS
	(Bressanelli et al., 2018)	Usage data supported decision-making for reuse	IoT, Big data mining
Smart Recycle	(Zhang et al., 2017)	Lifecycle-data-driven decision-making for recycle	Big data mining, ML
	(Luscuere and Mulhall, 2018)	IoT-enabled mechanism to collect, process and report lifecycle data	IoT, Big data mining

2.2 Smart PSS and its development

It is widely accepted that Smart PSS fundamentally composed of Smart, connected product (SCP) and its generated digital services (Kuhlenkötter et al., 2017; Valencia et al., 2015; Zheng et al., 2018a). Compared to conventional PSS, the smartness is reflected in two aspects, namely, *online smartness* and *offline smartness*. *Online smartness* is implemented by intelligent algorithms and customized analytic tools, which leverage a huge amount of multi-source, heterogonous data generated from the communications of SCPs to deliver valuable insights for design, manufacturing, distribution, usage and disposal (Rymaszewska et al., 2017; Zheng et al., 2018b). On the other hand, *Offline smartness* is that Smart PSS can perceive a specific user scenario with context-awareness, and then adjust itself with built-in-flexibility hardware and self-learning software (Zheng et al., 2019a; Zheng et al., 2020). Based on these two aspects of smartness, Smart PSS is capable of following the sustainable business model with an ever-evolving manner (Sousa-Zomer and Cauchick Miguel, 2018). Specifically, novel digital services can be innovated to continuously meet customers' requirements, while the physical components can be adaptively reconfigured with changeable modules or open architectures to extend their lifespan.

To develop an evolving Smart PSS and continuously deliver value in its lifetime, several manners are proposed and tentatively implemented. Systematically, the development processes fall into two categories: (1) data-driven platform-based approach and (2) multi-stakeholder value-cocreation approach. The first approach follows a hierarchical flow of data-information-knowledge-wisdom (DIKW). It firstly collects massive user-generated data and product-sensed data through SCPs, and then analyses them in a service platform, and finally provides requirement-oriented solutions for product upgrade and service innovation (Wang et al., 2019a, b; Zheng et al., 2019a). The second approach investigates Smart PSS development from a value-driven perspective and depicts a co-evolvment process with the engagement of multiple stakeholders (end-user/designer/manufacture/service provider). Four phases, namely, requirement co-generation, function co-design, process co-implementation, and performance co-monitor, composes the co-development process of Smart PSS (Liu et al., 2020b; Liu et al., 2019c).

Although several studies attempt to develop an evolving Smart PSS, there is still a rather long way to go before a true Sustainable Smart PSS that coordinates the principles of CE can be realized. Two factors need to be further considered in development. Firstly, the objectives of Sustainable Smart PSS development should be promoted to 'develop for circularity', instead of 'develop for fail' (Tietze and Hansen, 2013). Extending the product-service portfolio may lengthen the lifetime, but it does not lead to the reduction of resource consumption. A reversible development method, which places emphasis on the organization of materials/information flows and reuses them as possible, is the fundamental solution to increase resource efficiency in CE (Michelini et al., 2017). Secondly, implementing Sustainable Smart PSS development requires moving the business model towards service and retaining long-lasting customer relationships (Alcayaga et al., 2019). In this ever-evolving value proposition process, stakeholder requirements vary frequently due to the changing contexts/scenarios, which directly affect the

performance of the product-service bundles (Wang et al., 2019a). Therefore, improving customer experience with context-awareness will be an indispensable consideration in Sustainable Smart PSS development.

2.3 Knowledge gaps addressed by this paper

As reviewed in section 2.1 and 2.2, most existing studies have been dispersed in two separate directions, namely, enabling reversible strategies with smartness via the advanced ICT and AI techniques, and improving the sustainability of Smart PSS by ever-evolving product development and service innovation. As the first gap, few studies have attempted to merge the two directions together via an integrated concept of Sustainable Smart PSS, not to mention a comprehensive summarization of the key features and systematic methodical support for its development process.

Moreover, inherited from product lifecycle management, many previous studies mainly concentrated on the sustainability of tangible components and resources in the product lifecycle, and thus emphasized more on the aspects of *environmental sustainability* and *economical sustainability* in sustainability evaluation and optimization (Liu et al., 2020a). Actually, with growing concerns on digital servitization to further improve *social sustainability*, increasing amounts of personalized data/information/knowledge leveraged and generated in Smart PSS development. However, due to the innate characteristic of context-dependency in these heterogeneous datasets collected from historical Smart PSS design, usage and disposal (Zheng et al., 2019b), there is still a lack of comprehensive sustainable/circularity strategies to ‘reuse’ or ‘recycle’ these intangible but equally-important resources in the cyber space, serving as the second gap.

To fill these two gaps in this paper, key features in Sustainable Smart PSS are firstly synthesized and analyzed (Section 3), and a data-driven reversible framework for Sustainable Smart PSS development is then established based on the context-awareness (Section 4).

3 Key features in Sustainable Smart PSS development

After reviewing the related literature on sustainable/circularity strategies and Smart PSS in section 2.1 and 2.2, and identifying the knowledge gaps in section 2.3, this section discusses the fundamental of Sustainable Smart PSS and then accordingly propose the key features in its development process.

3.1 The fundamental of Sustainable Smart PSS

Inspired by Alcayaga et al. (2019), the concept of Sustainable Smart PSS can be regarded as the trinary intersection of sustainable strategy, smart technology, and PSS, as illustrated in Figure 2. It can be further elaborated in three perspectives:

- From the perspective of sustainable strategy, Sustainable Smart PSS achieves extended product lifespan by better reallocating tangible and intangible resources in a cost-efficient manner (*economical sustainability*) with less environmental impact (*environmental sustainability*), and it moves forward to maintaining long-lasting customer relationships with ever-evolving manners (*social sustainability*).
- From the perspective of smart technology, Sustainable Smart PSS is enabled with *ubiquitous connectivity* to collect and transmit lifecycle big data via IoT infrastructure. Supported by massive internal information retrieved from these product-sensed and user-generated data, and explained with transdisciplinary external domain-specific and common knowledge, Sustainable Smart PSS is capable to self-learn the surrounding environment and self-configure itself under various contexts for better performance (*autonomous*).
- From the perspective of PSS, Sustainable Smart PSS still follows the business paradigm of value co-creation, while further enhances the openness of its hardware and software via open-architecture and open-source, and improves the involvement of its massive users via service-based incentive mechanism, thus achieving user-oriented *open-innovation* and continuously deliver value in its extended or circular lifecycle.

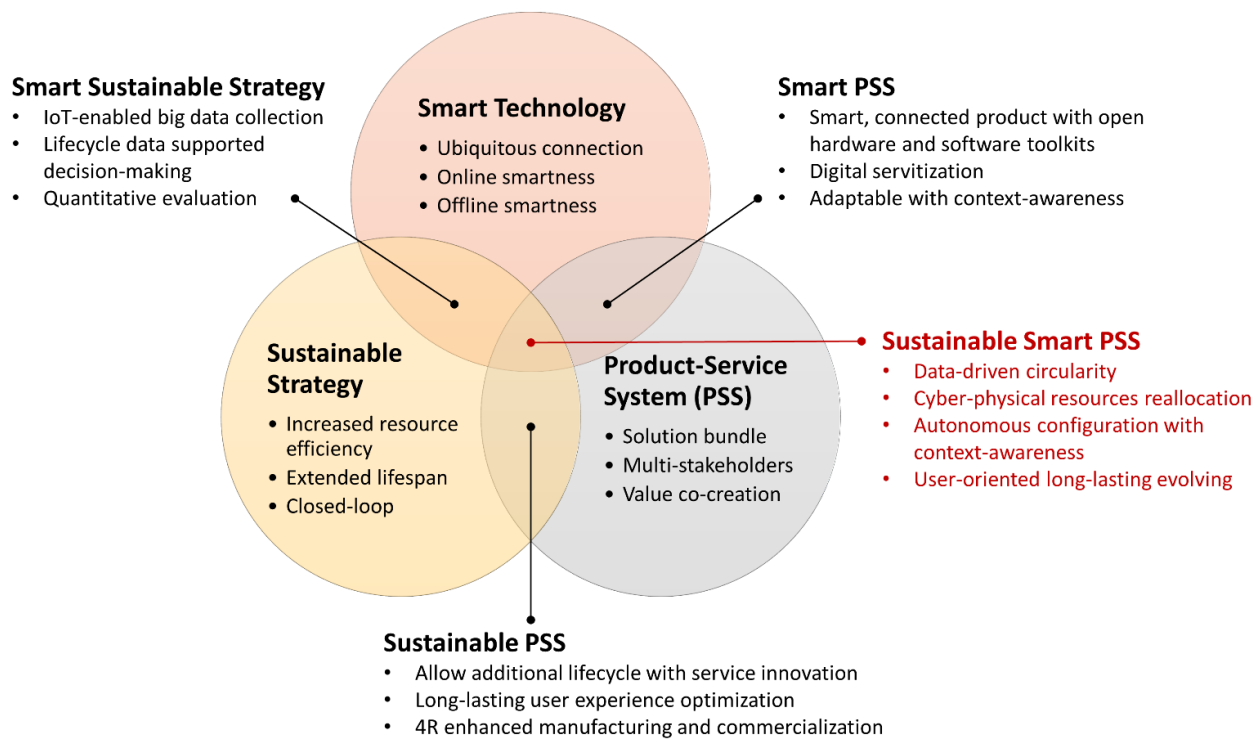


Figure 2. Sustainable Smart PSS: the trinary intersection of sustainable strategy, smart technology, and PSS

3.2 Key features in the development process

A systematic development process is determinant to the final success of implementing Sustainable Smart PSS, of which the key features can be summarized into four aspects, namely, *data-driven circularity* as its essence, *cyber-*

physical resource reallocation as its methodology, *autonomous configuration with context-awareness* as its manifestation, and *user-oriented long-lasting evolving* as its motivation.

Data-driven circularity follows the hierarchical flow of *DIKW*, where massive product-sensed and user-generated data in all lifecycle stages are incrementally acquired via IoT-enabled sensing devices (e.g. smart sensors, smart meters) and social sensors (e.g. web crawler, event-listener) (Zheng et al., 2019a). With universal models (e.g. regression, classification, clustering) and/or domain-specific models (e.g. ontology, UML diagram), the status information of the Sustainable Smart PSS itself (e.g. reusability, reconfigurability) and the dependent enablers/ecosystems (e.g. third-party service availability, logistics capability) is dynamically mined, integrated and traced (Alcayaga et al., 2019). This further contributes to extracting more precise lifecycle management rules and empirical knowledge, thus supporting the circularity decision-makings in the development process (e.g. remanufacturing process optimization, service capability upgrade) with a more solid basis but shorten latency (Liu et al., 2019b; Zhang et al., 2017).

Cyber-physical resource reallocation aims to achieve the goal of sustainability in both physical and cyber spaces in the development process. In the physical space, tangible resources of materials and components in Sustainable Smart PSS are reallocated in the circular production systems via 4R strategies, as referred in the previous studies (Alcayaga et al., 2019; Zheng et al., 2019b). More critically, in the cyber space, the intangible resources of collected dataset, annotated information, and mined knowledge are also reallocated in the process of product upgrade and service innovation via an information/knowledge management mechanism, where the previous concepts and propositions are reused or re-organized to offer a novel but cost-effective solution (i.e. knowledge transfer (Li et al., 2019)).

Autonomous configuration with context-awareness reflects the highest level of smartness and connectedness in the 5C level architecture (Lee et al., 2015). Relying on the PSS-related knowledge as well as other common knowledge, the contexts in the development process are perceived and the informed circularity decisions are self-made. According to these decisions, it is capable to self-configure the product/service components under different physical/social/user/operational contexts in real-time for better performance and higher sustainability.

User-oriented long-lasting evolving is critical to fulfilling the ever-changing user's requirements in the development process to continuously meet their satisfaction and maintain a long-lasting relationship (Liu et al., 2020b). With a higher degree of innovation flexibility enabled by open-architecture hardware and open-source software, massive users can originate the development process in its extended or circular lifecycle. Therefore, the achieved functionality and the delivered value may far beyond the originally designed propose (Zheng et al., 2018b), and reverse processes that start from the usage/disposal stages and end at the design/manufacturing/distribution stages (e.g. 4R) will be the mainstream in the long-lasting development process.

4 Data-driven reversible framework for Sustainable Smart PSS development

4.1 Overall framework

Based on the features summarized in section 3.2, this paper proposes a conceptual framework for Sustainable Smart PSS development, as shown in Figure 3. Considering the cyber-physical resources as a whole, two closed-loops separately describe the reversible development process in physical space and cyber space.

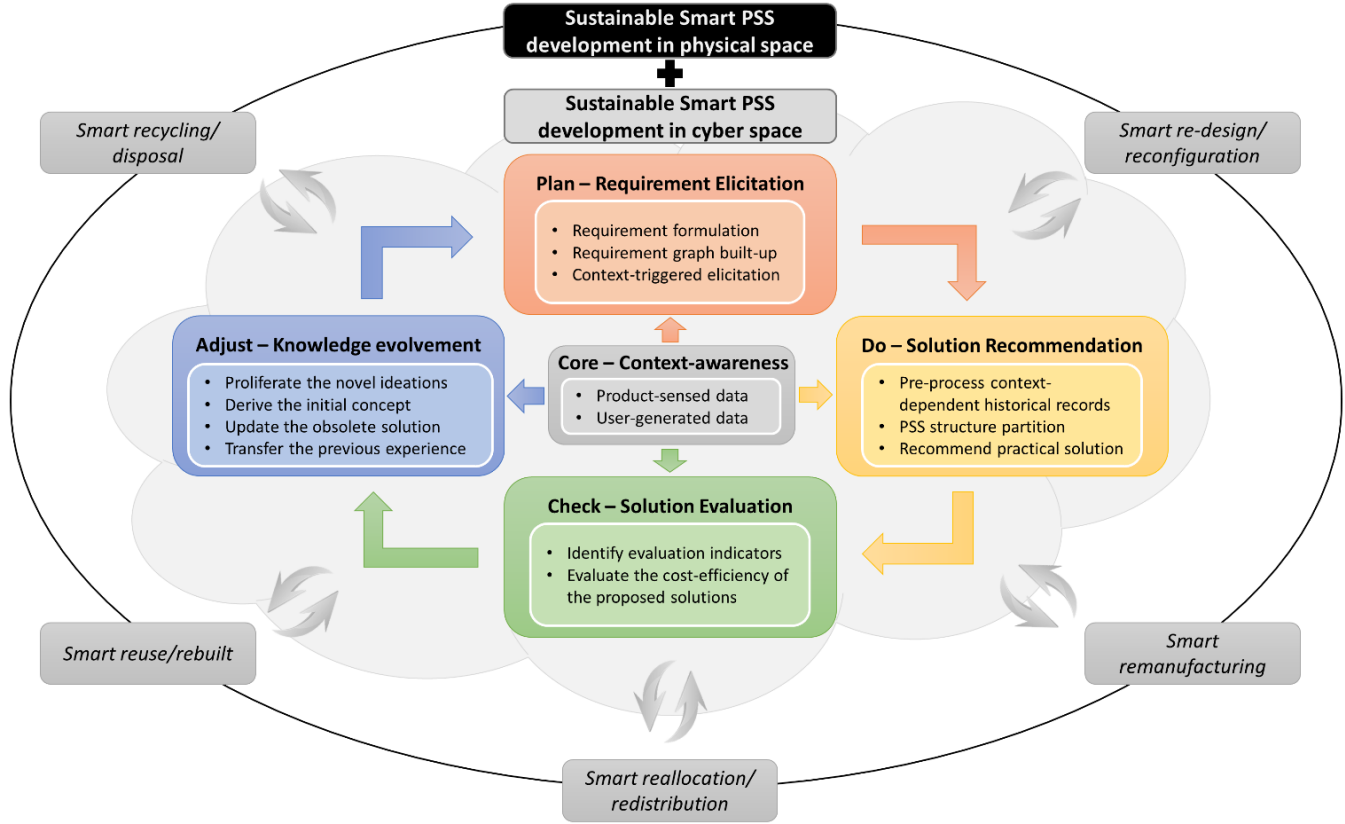


Figure 3. Data-driven reversible framework for Sustainable Smart PSS development

4.1.1 The outer loop: smart reversible strategies for product/service lifecycle management

Referring to previous studies regarding the reversible strategies (i.e. 4R) and Smart PSS lifecycle management (Alcayaga et al., 2019; Zheng et al., 2019b), the outer loop in the framework comprises five lifecycle-data-driven sustainability strategies, i.e., smart re-design/reconfiguration (e.g. automated engineering change management), smart remanufacturing (e.g. predictive maintenance), smart reallocation/redistribution (e.g. smart logistics and packaging), smart reuse/rebuilt (e.g. smart rental/second-hand system), and smart recycling/disposal (e.g. smart sorting and disassembly). Applying these strategies, the reallocation of the physical resource can be achieved in the development process.

Note that each smart sustainability strategy in the outer loop possesses individual characteristics regarding the frequency in the lifecycle stage and the type of lifecycle data analytics, as briefly summarized in Table 2. To handle these multi-source, heterogeneous datasets generated, collected, stored, and leveraged in conducting these strategies with higher cost-efficiency and running fluency, a generic process is further prescribed, namely, the inner closed-loop designed for the reallocation of the cyber resources.

Table 2. Smart sustainability strategies for Sustainable Smart PSS

Strategies	Specifications and functionalities	Frequency in the lifecycle stages	Type of lifecycle data analytics	References
Smart re-design/reconfiguration	Engineering change management; Product-service reconfiguration	Constantly in both design stage and usage stage	Online and all the time; Requires data about product/service design parameters, product/service operational status	(Zheng et al., 2019a)
Smart remanufacturing	Predictive and proactive maintenance; Production process plan and control	Regularly in both manufacturing stage and usage stage	Online and many times; Requires data about maintenance history, product/service operational status, disassembly and reassembly	(Maleki et al., 2018)
Smart reallocation/redistribution	Smart logistics; Smart packaging	Rarely in the logistic stage	On request and few times; Requires data about location of product, and availability of service	(Vazquez-Martinez et al., 2018)
Smart reuse/rebuilt	Smart rental; Smart second-hand system; Real-time performance assessment	Regularly in the usage stage	On request and many times; Requires product/service operational status, location of product, and availability of service	(Alcayaga et al., 2019)
Smart recycling/disposal	Smart sorting; Smart disassembly	Rarely in the disposal stage, design stage and manufacturing stage	On request and one time; Requires data about product/service operational status, dismantling process, and material parameters	(Alcayaga et al., 2019)

4.1.2 The inner loop: four-step context-aware process

Aiming to achieve the reallocation of the high context-dependent cyber resource in the development of Sustainable Smart PSS, a four-step context-aware process is proposed as the inner closed-loop in the conceptual framework. The core of the inner loop is context-awareness, which perceives the scenarios from product-sensed data and user-generated data collected in different lifecycle stages and encodes them with multiple context features. Then, inspired by an iterative four-step management method leveraged for continuous improvement, PDCA (plan-do-check-adjust) cycle, the inner loop is composed of four steps, namely, requirement elicitation, solution recommendation, solution evaluation, and knowledge evolvment. Based on these four context-aware steps, data-driven solutions for the development of Sustainable Smart PSS are generated. Details of the core and four steps in the inner loop will be further described in Section 4.2.

4.1.3 The interrelationship between the inner loop and the outer loop

Regarding the interaction between the inner loop and the outer loop, the four-step context-aware process in the inner loop can be universally leveraged to support each smart sustainability strategy in the outer loop, as listed in the interaction matrix of Table 3.

Table 3. Interaction matrix between the four-step context-aware process and five smart sustainability strategies

Interactions	Requirement Elicitation	Solution Recommendation	Solution Evaluation	Knowledge Evolvement
Smart re-design/ reconfiguration (Zheng et al., 2019a)	Functional requirement capture	Engineering change management	Feasibility analysis	Design concepts and principles
Smart remanufacturing (Maleki et al., 2018)	Re-production planning and maintenance planning	Work-in-progress and maintenance schedules	Re-production/ maintenance capacity assessment	Knowledge of re-processing/maintenance techniques
Smart reallocation/ redistribution (Vazquez-Martinez et al., 2018)	Logistic demand and supply forecasting	Warehouse and transportation management	Time/cost analysis	Information about supply chain
Smart reuse/rebuilt (Alcayaga et al., 2019)	Potential requirement extraction	Rental/second-hand market orders	Performance assessment	Usage records and Kansei knowledge
Smart recycling/disposal (Alcayaga et al., 2019)	Recycling demand estimation	Sorting features and disassembly sequences	Recycling capability and environmental impact assessment	Information on structure, dismantling, and materials

Taking smart re-design (Zheng et al., 2019a) as an example, the user's latent requirements for the current product/service functionalities under a specific context are elicited from the recent usage data as the start-up. Considering the historical engineering change records (e.g. update log), reconfiguration solutions on the design parameters and/or modularity correlations are recommended. After evaluating the feasibility of the solutions under the target context, product/service modules are reconfigured with all the corresponding design concepts and principles updated in the knowledge base.

Seen from Tables 2 and 3, one can find that the inner loop will drive and advise the outer loop in the whole lifecycle stages, by offering multiple data-driven and context-aware solutions. Specifically, relying on the use/reuse of valuable but context-dependent cyber resources, it recommends a decision-making solution of what and how product/service components need to be reconfigured, remanufactured, reallocated, reused, or recycled under a specific scenario. With this informatics-based guidance, the material/components circularity processes in the sustainable strategies of the outer loop can be conducted more smoothly and cost-efficiently.

Since this paper aims to highlight the sustainability in the cyber space, rather than its well-known connotations in the physical space, detailed sustainable processes of material circularity in each lattice in Table 3 will not be

further specialized. Only a general flow of the four-step context-aware process in the inner loop will be elaborated in the following subsections.

4.2 The process of the inner loop

Concentrating on the flow of the four-step context-aware process in the inner loop, this subsection elaborates on the data analytics manners and information/knowledge management processes. As shown in Figure 4, data analytics manners for mapping the requirement sets and solution sets are proposed based on the product-sensed and user-generated data, and an evolvement mechanism with four management strategies is also established to update the supportive information and knowledge in Sustainable Smart PSS development.

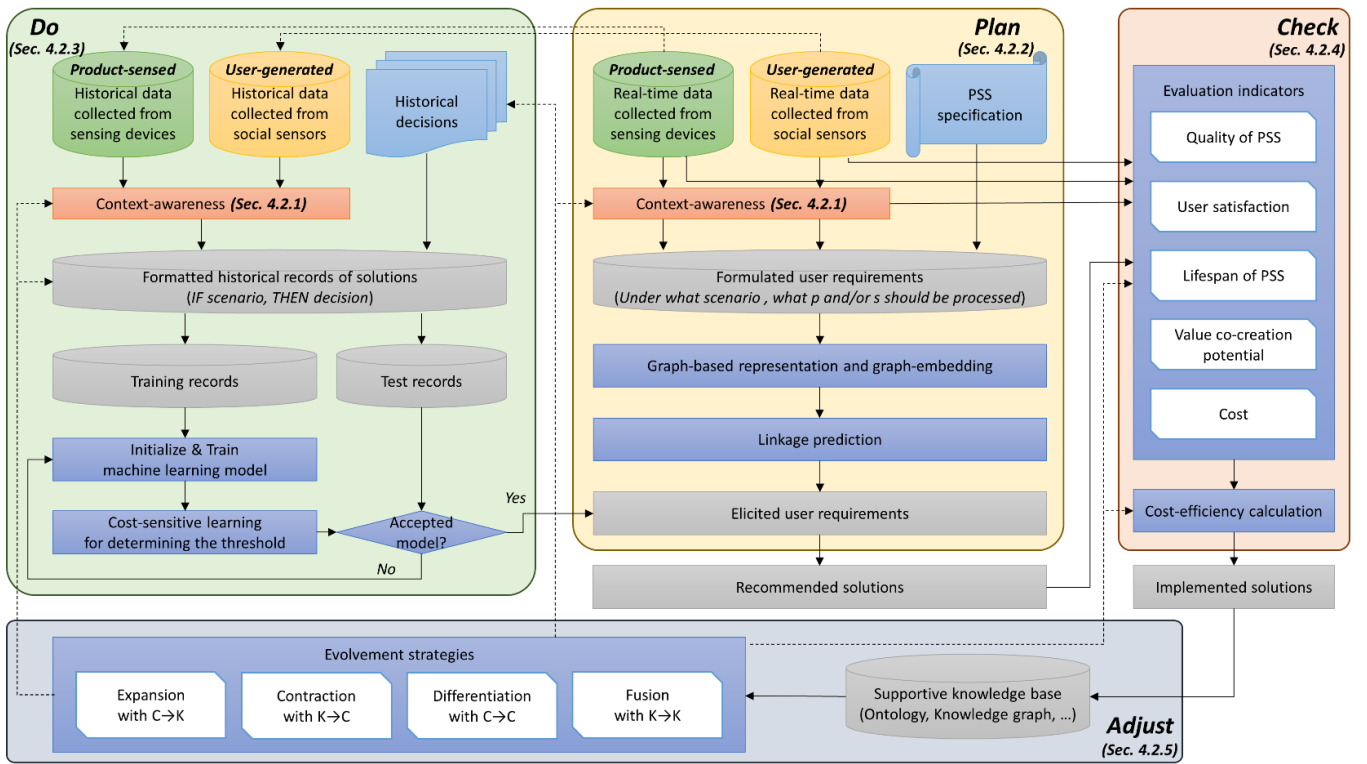


Figure 4. The flowchart of the four-step context-aware process in the inner closed-loop

4.2.1 Core of the inner loop: Context-awareness

As the core of the loop, context-awareness aims to model the multifarious scenarios in massive user-generated data and product-sensed data. Considering the sorts and contents that can be cost-effectively perceived via IoT-enabled sensing devices and social sensors, context features in Sustainable Smart PSS development are firstly categorized into four domain-independent classes (Liu et al., 2019a): (1) *Physical context* (information about the surrounding environment), (2) *Social context* (information about the nearby products and services), (3) *User context* (information about the users and user-PSS interactions), and (4) *Operational context* (information about the

operational status of PSS). Table 4 lists some examples of context features in each class for the development of Sustainable Smart PSS, and more features can be added if necessary and available. Based on these context features, a specific scenario in the dataset can be encoded with key-value modeling. Specifically, for each context feature c_i in k -elements set $C = \{c_i\}_k$, a corresponding value v_i is determined, and then forms a k -dimensional vector for the scenario, namely, $sn = [v_1, v_2, \dots, v_k] \in \mathbb{R}^k$, as illustrated in Figure 5. Note that the datasets generated and collected in the development process are heterogeneous, Table 5 also lists out the frequently used data analysis manners for typical data sources and types in context value determination.

Table 4. Perceived context features in the development of Sustainable Smart PSS

Context classes	Example context features
Physical Context	Date; Time; Location; Direction; Temperature; Humidity; Odor; Air/Water quality; Weather.....
Social Context	Peer products; Third-party service provider; Available recycler; Resource supply; Second-hand market orders.....
User Context	User demographics; User mood/health; User knowledge/profession; User preference/habit; Usage type
Operational Context	Power/energy; Software version; Maintenance history; Portability/Wearability; Computing power.....

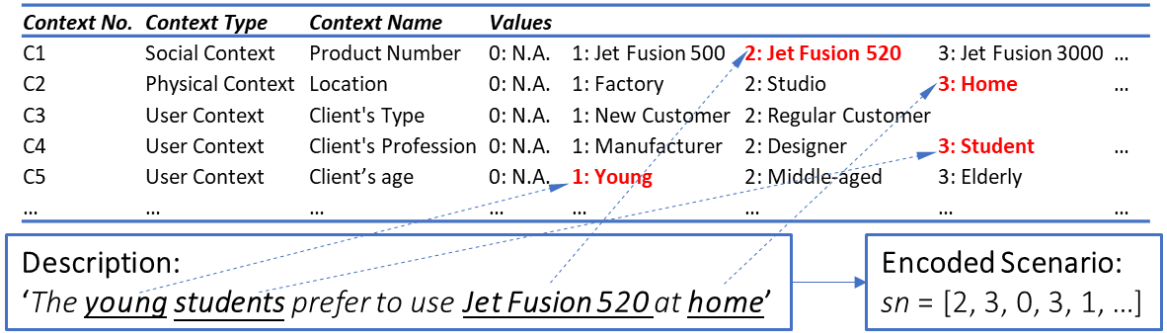


Figure 5. Encoding the scenarios based on context features

Table 5. Data analysis manners in context value determination

Data sources & types	User-generated data			Product-sensed data
	Structural text	Natural language	Numerical value	Numerical value
Frequently used data analysis manners	Table headers & elements	Keyword extraction	Use domain knowledge	Pattern recognition
	Formal concept analysis	Named-entity recognition	Use common knowledge	Use domain knowledge
	Schema-based annotation	Syntax analysis	Fuzzy rules	Fuzzy rules
	Predefined template	Sentiment analysis	Rough sets	Rough sets

4.2.2 Plan step in the inner loop: Requirement elicitation

As the *plan* step in the loop, requirement elicitation aims to detect and model requirements of end-user in a distributed IoT-enabled environment (e.g. a cloud-based on-demand sharing platform). Under this context, implicit

user requirements are extracted in a data-driven manner, and then serve as the guidance for the following product-service solution innovation.

Datasets used for requirement elicitation mainly come from two resources, user-contributed feedbacks from mobile/ social networking (e.g. ratings, comments, Q&A threads) and signal data collected by embedded sensor devices (e.g. position, acceleration, angular velocity, temperature). To consider the context-dependency in these datasets, a formulation template is proposed for Sustainable Smart PSS development, namely, “*given a certain scenario, what product structures and/or service modules should be changed/updated/reused/recycled*” (Wang et al., 2019a, b). A piece of requirement is hence denoted as a tuple $req = \langle \{p\}, \{s\}, sn \rangle$, where $p \in P$ and $s \in S$ are decomposed components in the system (i.e. $PSS = P \cup S, P \cap S = \emptyset$), and $sn \in SN$ is encoded by the k -dimensional vector in context-awareness. In this data-driven situation, requirement elicitation is transformed into exploring the co-occurrence relationship among product, service and scenario information, and a graph-based approach is suitable for solving this issue when tackling massive data. Specifically, a requirement graph, $RG = \langle V, E \rangle$, is built, where the vertex set $V = P \cup S \cup SN$ and the edge set E refers to the co-occurrence relations mined from the dataset (e.g. two entities appear simultaneously in a piece of comment). Moreover, RG can be incrementally expanded with new product, service and scenario information, if more data are generated and collected in the development of Sustainable Smart PSS.

Based on the representation of RG , the elicitation of novel user requirements in the development process follows the model of linkage prediction. When a particular scenario is perceived, top K p - sn / s - sn edges which have the highest appearance probabilities predicted by graph-embedding algorithms (e.g. SkipGram, DeepWalk) can be selected to form an explicit user requirement. It is then leveraged as the user-oriented guidance for the subsequent PSS provision upgrade.

4.2.3 Do step in the inner loop: Solution recommendation

Since requirement elicitation is conducted from the user’s perspective, instead of a designer/manufacturer/supplier/operator/recycler’s perspective, it is regardless of some practical constraints in the development process. Therefore, solution recommendation, as the *do* step in the loop, is conducted to offer a more feasible solution from massive historical records accumulated in Sustainable Smart PSS development.

Similar to the data-driven situation, the historical records can be regarded as an empirical knowledge base storing the cases about “*IF a scenario occurs, THEN change/update/reuse/recycle the selected product/service components*”. Here, the scenario concerns the constraints in the sustainable processes, which are encoded by the context features shown in Table 4 and Figure 5. A typical format of a historical record can hence be partitioned into two parts, namely, $rec = \langle sn, d \rangle$, where sn also indicates a specific scenario with a k -dimensional vector, and $d = \langle \{p\}, \{s\} \rangle$ is the historical decision of selecting product and service components. Obviously, if a particular

scenario re-occurs in the elicited user requirement, stored empirical knowledge can be directly reused to rapidly offer a practical solution by changing/updating/reusing/recycling the previously mentioned components in the corresponding cases. However, when a novel scenario with an unknown combination of context feature values is perceived, the previous solutions need to be automatically revised before recommendation, and hence a machine learning manner can be adopted (e.g. Random Forest, Naïve Bayes, SVM). Specifically, a prediction model is trained with a large volume of historical records, which is partitioned into a matrix of context feature values (scenario set) and a corresponding matrix of the selected product/service components (decision set). After the training process, the occurrence probability of each product/service component in the recommended solution is separately predicted for the scenario in the test set, thus evaluating the performance of machine learning manner with the classification error. Besides, in order to determine the possibility threshold for selecting the product/service component in the recommended solution, a teaching cost for the classification of boundary region is also considered in a cost-sensitive training (Zheng et al., 2019a).

For a complex PSS possessing increasing numbers of product/service components and exponentially growing combinations of decisions, the precision of prediction may be deteriorated if only a relatively small training dataset is available. To handle this, clustering methods can be leveraged to effectively reduce the dimensions in the learning process. A co-occurrence matrix can be generated with the historical records, where each lattice in the matrix depicts the co-occurrence frequency of two components in the total records. Communities in PSS can be detected and partitioned with the calculation of modularity via community-partitioning algorithms (Blondel et al., 2008). The decision set in the historical records can be updated to the component-cluster level, before conducting the abovementioned machine-learning-based prediction, thus further improve the practicableness of this data-driven solution recommendation step in the loop.

4.2.4 Check step in the inner loop: Solution evaluation

To retain the competitiveness in the fierce market, only cost-effective solutions will be adopted in the development of Sustainable Smart PSS, rather than blindly pursuing better performance, longer lifespan or higher user satisfaction. Therefore, as the *check* step in the loop, solution evaluation aims to balance the cost and benefits by measuring and optimizing the cost-efficiency of the proposed solutions.

Based on the previous studies (Liu et al., 2020a; Shen et al., 2017), 5 criteria are firstly proposed for solution evaluation, considering value-proposition capability via product/service innovation, the long-lasting customer relationship, and the cost in the development process, namely, (1) maximize the quality of PSS (Q); (2) maximize the user satisfaction (US); (3) maximize the lifespan of PSS (LS); (3) maximize value co-creation potential (VC); and (5) minimize the cost for evolvement (C). They can be measured with Eq. 1-5.

$$Q = 1 - \alpha_1 \sum_{PSB} k (performance - goal)^2 \quad (\text{Eq. 1})$$

$$US = \frac{\alpha_2}{|PSB|} \sum_{PSB} (\overline{rate} - \overline{rate}_0) \quad (\text{Eq. 2})$$

$$LS = \alpha_3 \frac{\overline{lifespan}_{PSB} - \overline{lifespan}_0}{\overline{lifespan}_0} \quad (\text{Eq. 3})$$

$$VC = \frac{\alpha_4}{|PSB|} \sum_{PSB} Score_{potential} \quad (\text{Eq. 4})$$

$$C = \alpha_5 \sum_{PSB} (C_P + C_S + C_H + C_I) \quad (\text{Eq. 5})$$

Q in Eq. 1 is calculated as a remaining quality after subtracting Taguchi's quality loss (Taguchi, 1995), and the loss is accumulated with the normalized deviations for the goals caused by each product-service bundle (PSB). US in Eq. 2 indicates the average improvement of user satisfaction on each product-service bundle in the recommended solution, which can be quantified by conducting sentiment analysis and time-series analysis on the user-generated online ratings and/or sentiment-rich feedbacks. LS in Eq. 3 measures the extendibility of lifespan when a specific solution is implemented, which is estimated with the lifecycle data. VC in Eq. 4 represents a series of capabilities of product-service bundles (like smartness, connectedness and openness) that can be provided to the users in value-co-creation, which can be scored with predefined rules and models (e.g. 5C model (Lee et al., 2015)). As for C in Eq. 5, it includes the cost of physical resources C_P , service-related processing C_S , involved human resources C_H , and intellectual resources C_I , which can be collected from the multi-stakeholders. α_1 - α_5 in Eqs. 1-5 are five constant normalization coefficients that align the order of magnitude of Q , US , LS , VC , and C .

After the evaluation on each criterion, the cost-efficiency of the proposed solution can be calculated by Eq. 6, where w_1 - w_4 are four dynamic and personalized weights that can be valued and adjusted by the user preference in the extended or circular lifecycle. Obviously, for a group of recommended solutions, the feasible ones with higher CE will be further implemented for a particular scenario in the development of Sustainable Smart PSS.

$$CE = \frac{w_1 * Q + w_2 * US + w_3 * LS + w_4 * VC}{C} \quad (\text{Eq. 6})$$

4.2.5 Adjust step in the inner loop: Knowledge evolvement

When a novel product-service solution is verified and implemented, the product/service components have been partially or wholly changed/updated/reused/recycled. Correspondingly, the related knowledge accumulated in the whole lifecycle stages, like design principles, manufacturing methodology, logistic constraints, usage manners, and dismantling information, also needs evolvement. Hence, as the *adjust* step in the loop, knowledge evolvement aims to manage these modifications and close the loop in the cyber space. It guarantees the consistency in the knowledge base of the Sustainable Smart PSS during the long-lasting development process.

Inspired by the four patterns recognized in the long-term knowledge evolvement (Li et al., 2018; Li et al., 2017) and the four operators proposed in Concept-Knowledge theory (Hatchuel and Weil, 2009), four heuristic strategies

are proposed to trigger the knowledge evolvement, and an information/knowledge management mechanism is hence established with these strategies to periodically modify the nodes and relations in the knowledge base (e.g. ontology, knowledge graph).

➤ *Expansion Strategy with $C \rightarrow K$ operator: Proliferate the novel ideations.*

$C \rightarrow K$ operator indicates a process of linking and re-organizing the concepts to form a novel knowledge. Based on this operator, an expansion strategy can be proposed to establish a ‘knowledge family’ based on the implemented innovative solutions. Namely, by linking the concepts leveraged in these solutions via default inference, a group of proliferated propositions can be generated, if no logical conflict to other existing knowledge is observed.

➤ *Contraction Strategy with $K \rightarrow C$ operator: Update the obsolete solution.*

As a symmetrical process for $C \rightarrow K$ operator, $K \rightarrow C$ operator introduces new properties and imported the specialized concepts from the existing knowledge, which guarantees the logical consistency in the evolvement. In this situation, obsolete solutions that leverage original concepts need to be accordingly updated, and the chances for adopting these solutions in the subsequent development process is hence reduced with a contraction strategy.

➤ *Differentiation Strategy with $C \rightarrow C$ operator: Derive the initial concept.*

$C \rightarrow C$ operator also discovers novel attributes to propose a new concept, but it aims to differentiate the definition and scope of for an existing generic concept in the new scenarios. Inheriting this idea, the differentiation strategy will seek for a derived concept in PSS-related entities with the considerations of unusual context features, thus providing the alternative options for self-adaptation in different scenarios.

➤ *Fusion Strategy with $K \rightarrow K$ operator: Transfer the previous experience.*

$K \rightarrow K$ operator establishes the logical relationship between newly generated knowledge and the existing one with all classic types of reasoning (classification, deduction, abduction, inference). Based on the logical chain established in this fusion process, reusing of previous experience generated in other scenarios is enabled, thus generating a wholly or partially transferred solution under the new scenarios.

5 An illustrative example

5.1 Background and pre-processing

In order to demonstrate the performance of the proposed framework, an illustrative example of a 3D printer is presented in this section. 3D printer is widely recognized as an eco-friendly product with high sustainability in the physical space, which is able to rapidly reconfigure and remanufacture itself with reusable/recyclable materials and components. Coupling with a digital twin in the cyber space, 3D printer can be bundled with multiple customized services, like remote printing monitoring, maintenance scheduling, and inventory management. In this regard, 3D printer possesses a *Cyber level* of smartness and connectedness in the 5C architecture (Lee et al., 2015), i.e.,

possessing the capabilities of gathering, storing, transmitting, and analyzing massive data to provide preliminary insights for production.

Although these features indicate great potentials for the 3D printer as a Sustainable Smart PSS, due to the poor exploitation of high context-dependent information/knowledge mined during its lifecycle, current 3D printer doesn't contribute much to improving sustainability in cyber space. Hence, an illustrative example of the application of the proposed data-driven reversible framework is presented for this situation, and this example was conducted on a cyber-physical smart 3D printer prototype, as shown in Figure 6.

Due to the complexity of realizing every aspect along its whole lifecycle, this example only showcased the implementation of the inner loop on the reconfiguration, which is an outer loop's sustainable strategy constantly-used in the design and usage stage. The structure of the 3D printer was also accordingly simplified to 20 product components and 6 service components, as listed in Table 6. To enable context-awareness with high feasibility and reliability, 7 context features were selected in this example according to the recommendation from the experts in 3D printing, as listed in Table 7. These experts were also invited to evaluate the reasonability of the reconfiguration solutions, and hence validate the proposed framework.

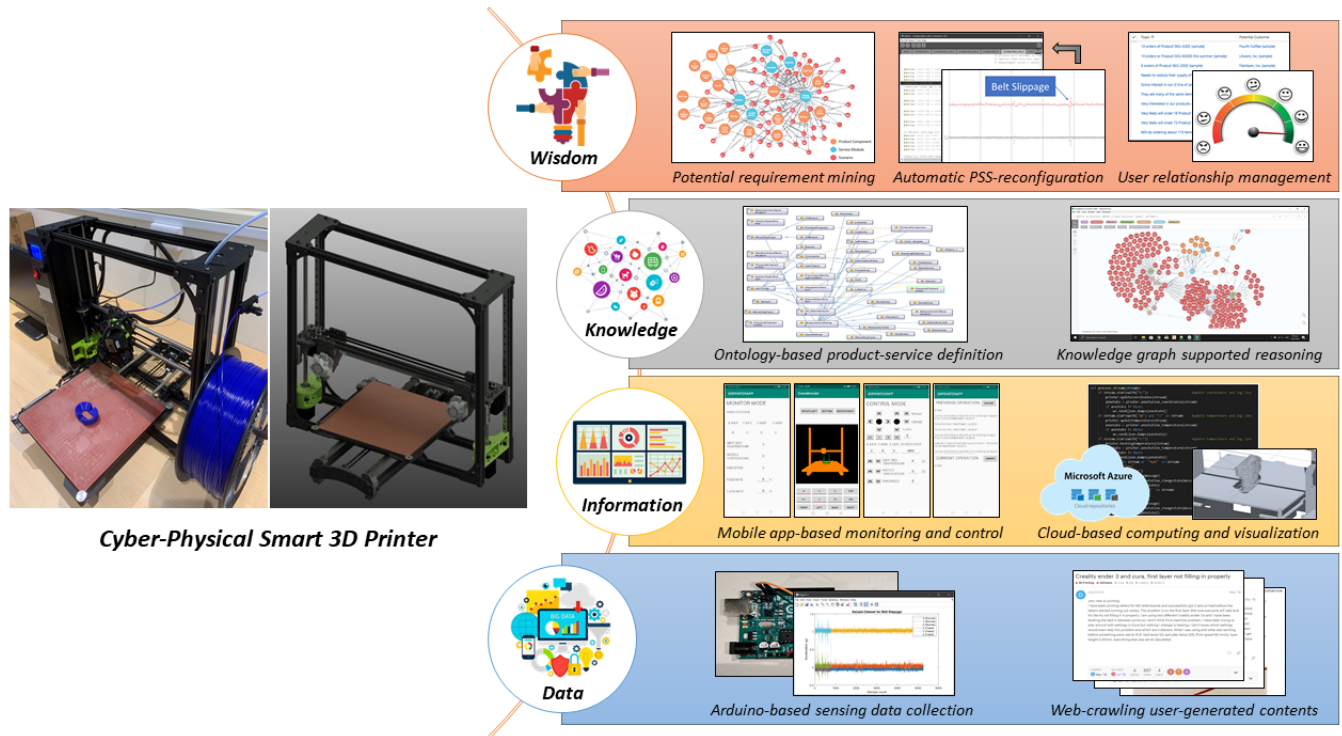


Figure 6. Cyber-physical smart 3D printer prototype

Table 6. Product components and service components of the smart 3D printer

Product Components		
<i>p1</i> : Nozzle	<i>p8</i> : Extruder Gear	<i>p15</i> : Thermistor
<i>p2</i> : LCD Screen	<i>p9</i> : Z-Axis Lead Screw	<i>p16</i> : Heat Break
<i>p3</i> : X Tension Belt	<i>p10</i> : X Stepper Motor	<i>p17</i> : Heat Sink
<i>p4</i> : Y Tension Belt	<i>p11</i> : Y Stepper Motor	<i>p18</i> : Nozzle Fan
<i>p5</i> : PEI Surface Print Bed	<i>p12</i> : Z Stepper Motor	<i>p19</i> : Part Fan
<i>p6</i> : Rambo Board	<i>p13</i> : Extruder Stepper Motor	<i>p20</i> : Filament
<i>p7</i> : Bearing	<i>p14</i> : Heat Bed Cable	
Service Components		
<i>s1</i> : Parameter Configuring	<i>s3</i> : Quality Checking	<i>s5</i> : Inventory Management
<i>s2</i> : Printing Tracking	<i>s4</i> : Maintenance Scheduling	<i>s6</i> : Payment Selection

Table 7. Context features considered in this example

Context Feature	Context Class	Context Values			
<i>c1</i> : Nozzle Temperature	Physical Context	-1: < 170 °C	0: 170-220 °C	1: > 220 °C	
<i>c2</i> : Extrusion Speed	Physical Context	-1: < 40 mm/s	0: 40-60 mm/s	1: > 60 mm/s	
<i>c3</i> : Layer Height	Physical Context	-1: < 0.14 mm	0: 0.14-0.38 mm	1: > 0.38 mm	
<i>c4</i> : Clogging	Operational Context	/	0: No Issue	1: Nozzle Clogged	
<i>c5</i> : String	Operational Context	/	0: No Issue	1: Filament Stringing	
<i>c6</i> : Second-hand status	Social Context	/	0: Brand New	1: Second-handed	
<i>c7</i> : User type (Experience)	User Context	0: N.A.	1: Novel (< 30h)	2: Ordinary (30 – 100h)	3: Expert (> 100h)

5.2 Implementation of the four steps on reconfiguring Smart 3D printer

Based on our previous research outcomes (Zheng et al., 2019a; Wang et al., 2019a, b; Li et al., 2020), this section illustrates the PDCA process of the four-step inner loop on a reconfiguration example on the Smart 3D printer, and aims to validate the feasibility of the process and the reasonability of the results.

5.2.1 Plan step: Elicit user requirements for the 3D printer

To implement the first step of requirement elicitation, 85 recent threads (Jun 2019 – Aug 2019) of user discussions were downloaded from *3Dhubs.com*, a famous online platform for 3D printing services and technical communication. With one-hot encoding, the content in each thread was mapped to the corresponding value of each context feature in Table 7 and forms an encoded scenario. The product and service mentioned in each thread were also annotated with the components listed in Table 6, thus generating the tuple of $req = \langle \{p\}, \{s\}, sn \rangle$. Based on the tuples, edges of $p-s$, $p-p$, $s-s$, $p-sn$ and $s-sn$ were defined, and a requirement graph was hence established. As shown in Figure 7, it visualized the interrelationship among all possible scenarios (red nodes) and the product/service components (orange and blue nodes).

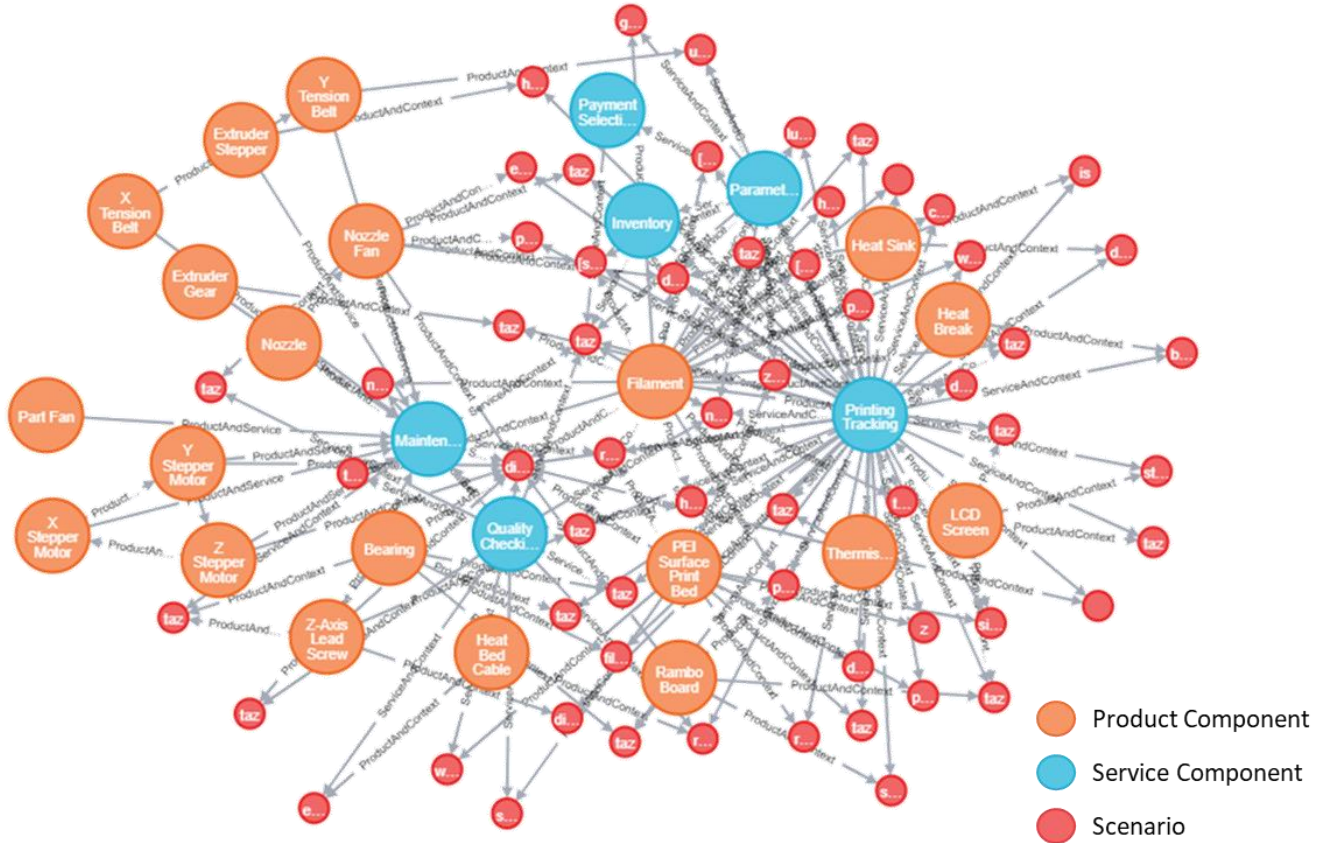


Figure 7. Requirement graph for the 3D printer product-service system

To extract meaningful requirements with context-awareness, top-3 frequently encountered scenarios were selected, and 5 product/service components predicted with the highest appearance probabilities by SkipGram algorithm (Wang et al., 2019b) were fetched to present the user requirements, as reported in Table 8. For example, requirement *R1* was elicited under an encoded scenario [-1, -1, 0, 1, 0, 0, 2]. According to the context features listed in Table 7, it indicated a perceived scenario of ‘Low temperature for certain filament’ (i.e., Nozzle Temperature < 170 °C, Extrusion Speed < 40 mm/s, Layer Height 0.14-0.38 mm, Nozzle Clogged, No filament stringing issue, Brand new printer and Ordinary user). Meanwhile, according to the collected user discussions, the product components of Filament, Nozzle Fan, and Thermistor, and the service components of Parameter Configuring and Maintenance Scheduling, were mostly mentioned. Hence, a piece of user requirement of improving these components under the perceived scenario was elicited.

Table 8. Top 3 user requirements elicited from requirement graph

Requirements	Encoded <i>sn</i>	Description of <i>sn</i>	Predicted <i>p</i> and <i>s</i>	Probability
<i>R1</i>	[-1, -1, 0, 1, 0, 0, 2]	Low temperature for certain filament	<i>p20</i> : Filament	0.950
			<i>p18</i> : Nozzle Fan	0.925
			<i>s1</i> : Parameter Configuring	0.847
			<i>p15</i> : Thermistor	0.810
			<i>s4</i> : Maintenance Scheduling	0.775
<i>R2</i>	[0, 0, 1, 0, 1, 0, 1]	Shifting layers with poor support	<i>s1</i> : Parameter Configuring	0.967
			<i>p5</i> : PEI Surface Print Bed	0.873
			<i>p20</i> : Filament	0.804
			<i>p4</i> : Y Tension Belt	0.722
			<i>p3</i> : X Tension Belt	0.722
<i>R3</i>	[0, -1, 0, 0, 0, 1, 2]	Extrusion failure after repair	<i>s4</i> : Maintenance Scheduling	0.942
			<i>p20</i> : Filament	0.918
			<i>p1</i> : Nozzle	0.903
			<i>s3</i> : Quality Checking	0.774
			<i>p8</i> : Extruder Gear	0.715

5.2.2 Do step: Recommend solution using 3D printer maintenance records

Aiming to solve the elicited requirements, 1802 maintenance records (repair/replace/upgrade logs) of 3D printers of the same model were collected and pre-processed for the second step of solution recommendation. As shown in Table 9, the scenario set encoded a real maintenance scenario with the context features in Table 7, and the decision set list the actual selection of product/service components under this scenario.

Table 9. A small portion of pre-processed historical records

Record No.	Encoded Scenario Set							Decision Set (repaired/replaced/upgraded product and service components)
	<i>c1</i>	<i>c2</i>	<i>c3</i>	<i>c4</i>	<i>c5</i>	<i>c6</i>	<i>c7</i>	
1	0	0	0	0	1	0	2	<i>p1</i> , <i>p8</i> , <i>p14</i> , <i>p15</i> , <i>s1</i> , <i>s4</i>
2	0	0	-1	0	0	1	1	<i>p7</i> , <i>p9</i> , <i>p12</i> , <i>p19</i> , <i>s2</i> , <i>s4</i>
3	-1	0	-1	1	1	0	1	<i>p5</i> , <i>p7</i> , <i>p8</i> , <i>p9</i> , <i>p12</i> , <i>p13</i> , <i>s2</i> , <i>s3</i> , <i>s4</i>
4	1	0	0	1	0	1	2	<i>p5</i> , <i>p14</i> , <i>p18</i> , <i>p19</i>
5	0	1	0	1	0	0	2	<i>p5</i> , <i>p14</i> , <i>s1</i> , <i>s4</i>
...

By conducting co-occurrence frequency analysis and Louvain community-partitioning algorithm (Zheng et al., 2019a), the product and service components in the 3D printer were divided into 5 clusters, as shown in Table 10. Then, a random-forest model was trained with 10-fold cross-validation on the existing dataset, and it was then leveraged to recommend solutions for the elicited user requirements, as shown in Table 11. For example, to solve *R1* (Low temperature for certain filament), solution *So1* recommended to replace the product components of

479 *Thermistor and Filament, and/or repair the product components of Heat break and Heat sink, and/or upgrade the*
 480 *service components of Parameter Configuring, Inventory Management, and Payment Selection.*

481 **Table 10.** Cluster division of the product and service components in the 3D printer

Cluster No.	Contained product and service components	Descriptions
<i>cl1</i>	<i>p1, p5, p7, p8, p13, p14, p18, p19, s4</i>	Extruding modules
<i>cl2</i>	<i>p2, p6, s2</i>	Printing tracking modules
<i>cl3</i>	<i>p3, p4, p9, p10, p11, p12, s3</i>	Movement modules
<i>cl4</i>	<i>p15, p16, p17, s1</i>	Heating modules
<i>cl5</i>	<i>p20, s5, s6</i>	Consumable management modules

482 **Table 11.** Recommended solutions for the elicited user requirements

Req.	Encoded <i>sn</i>	Probability of selection	Decision	Repaired/replaced/upgraded <i>p</i> and <i>s</i> in the recommended solution
	[<i>c1, c2, c3, c4, c5, c6, c7</i>]	[<i>P(cl1), P(cl2), P(cl3), P(cl4), P(cl5)</i>]	[<i>cl1, cl2, cl3, cl4, cl5</i>]	
<i>R1</i>	[-1, -1, 0, 1, 0, 0, 2]	[0.036, 0.112, 0.014, 0.765, 0.634]	[0, 0, 0, 1, 1]	<i>So1: p15, p16, p17, p20, s1, s5, s6</i>
<i>R2</i>	[0, 0, 1, 0, 1, 0, 1]	[0.171, 0.131, 0.724, 0.782, 0.240]	[0, 0, 1, 1, 0]	<i>So2: p3, p4, p9, p10, p11, p12, p15, p16, p17, s1, s3</i>
<i>R3</i>	[0, -1, 0, 0, 0, 1, 2]	[0.918, 0.003, 0.280, 0.196, 0.315]	[1, 0, 0, 0, 0]	<i>So3: p1, p5, p7, p8, p13, p14, p18, p19, s4</i>

483 5.2.3 Check step: Evaluate the cost-efficiency of the solutions

484 To evaluate the cost-efficiency of the recommended solutions, the third step of solution evaluation was
 485 conducted. Experimental data of each evolved prototype was collected to measure the 5 evaluation indicators via
 486 Eqs. 1-5. To maintain the confidentiality of company information, only the normalized evaluation results were
 487 reported, while the raw data of the component's price, specification, lifespan, and user rating was hidden. As for
 488 the weights w_1-w_4 in Eq. 6, they were identified through an online 5-point Likert Scale-based questionnaire on a
 489 panel of 7 novel users (i.e. in Table 7, $c7 = 1$) and 11 ordinary users ($c7 = 2$), which were [0.571, 0.714, 0.893,
 490 0.821] and [0.886, 0.841, 0.727, 0.591] respectively.

491 With the evaluated cost-efficiency of the solutions reported in Table 12, *So1* and *So3* were rather acceptable
 492 for the ordinary users, which replaced the thermistor and the filament to solve the low temperature for certain
 493 filament (*R1*), and repaired nozzle motors and upgraded the maintenance scheduling service to solve the extrusion
 494 failure after repair (*R3*). These two solutions were also approved by the experts in 3D printing. However, even
 495 though rather good performance in improving the quality (Q) and user satisfaction (US), a low CE was achieved by
 496 *So2* due to the rather high cost (C). Therefore, this reconfiguration solution needed to be further optimized according
 497 to the experts' suggestions, before its implementation to the novel users. For example, reconsider the necessity of
 498 each component that was recommended for repairing, replacing, and/or upgrading.

Table 12. Solution evaluation on the recommended solutions

Solution No.	Evaluation indicators					Indicators' weights	CE
	Q	US	LS	VC	C	$[w_1, w_2, w_3, w_4]$	
<i>So1</i>	0.922	0.758	0.750	0.633	2.79	[0.886, 0.841, 0.727, 0.591]	0.851
<i>So2</i>	0.978	0.958	0.364	0.545	3.78	[0.571, 0.714, 0.893, 0.821]	0.533
<i>So3</i>	0.824	0.962	0.529	0.511	2.35	[0.886, 0.841, 0.727, 0.591]	0.947

5.2.4 Adjust step: Evolve the 3D printing knowledge

After solution evaluation, the last step was to evolve the knowledge with four heuristic strategies. For example, in implementing *So1*, *filament (p20)* was required to be replaced to solve *R1*, and hence the related knowledge, *feed filament (p20) to the nozzle (p1)*, needed to be accordingly revised. Under this situation, $C \rightarrow C$ operator could be conducted on the concept of *filament*. A sub-concept, *polycaprolactone filament (p20_1)*, was hence derived with the appropriate attribute of *melting temperature 58 °C*. Using this derived concept, $C \rightarrow K$ operator could propose a novel knowledge, *feed polycaprolactone filament (p20_1) to the nozzle (p1) when the nozzle temperature is less than 170°C (i.e. $c1 = -1$) and the user type is ordinary user ($c7 = 2$)*. As no logical conflict to other 3D printing knowledge was observed, this novel knowledge could update the original one in the subsequent knowledge reuse (i.e., $K \rightarrow C$ operator). Besides, it could establish logical relations with other knowledge via $K \rightarrow K$ operator and hence generate a complex logical chain, like a piece of compound knowledge, *updating parameter configuring service (s1) for the ordinary user ($c7 = 2$) to change the nozzle temperature to less than 170°C ($c1 = -1$), when feeding polycaprolactone filament (p20_1) to the nozzle (p1)*.

Reflected on the knowledge base supporting the Smart 3D printer, these evolvments resulted in a novel sub-node of *polycaprolactone filament* linked to the existing node of *filament* in the domain ontology, and a novel formatted record of $rec = \{sn = [-1, 0, 0, 0, 0, 0, 2], d = \langle p1, p20_1, s1 \rangle\}$ added to the historical dataset. When another four-step loop started again in the subsequent development process, the data-driven flows in the first three steps would be correspondingly affected by the evolved knowledge.

5.3 Discussion

5.3.1 A brief comparison to the usual process

From the above description with the illustrative example, one can find that the proposed framework for Sustainable Smart PSS development still follows several basic ideations that are widely adopted in the usual reversible processes (e.g. 4R) for improving sustainability, namely, (1) extending the lifespan of the whole PSS by reconfiguring limited numbers of components (*environmental sustainability*); (2) exploiting the potential values under multiple scenarios by involving massive users into a co-development process (*social sustainability*); and (3) enhancing the effectiveness of solutions, by considering the cost-benefit criteria rather than only pursuing higher

values in solution evaluation (*economical sustainability*). However, beyond these ideations, there existing several novelties enabled by considering the key features of Sustainable Smart PSS in the proposed framework.

Firstly, beyond the traditional sustainability concerns for product design/development, which mainly focus on the reallocation of tangible resources in the physical space (Alcayaga et al., 2019), the proposed framework broadens the scope of sustainability to the cyber space and stresses the value of reusing intangible resources. In the showcase, the four-step inner loop provided an information/knowledge management manner to use and reuse the real-time and historical user-generated comments and operation logs, and predicted the requirements in Table 8 and recommended the solutions for evolving product/service components in Table 11. With these data-driven solutions, the conduction of the reconfiguration strategy could be timely supported. Therefore, instead of investigating sustainable solutions for an implicit requirement, continuously receiving valuable informed-decisions could prevent the high cost and unexpected failures in the business of pursuing sustainability (Kerin and Pham, 2019).

Secondly, different from the previous reversible strategies, which separately concentrate on one or a few specific lifecycle stages, the data-driven flow in the proposed framework is operating on multiple stages, even the whole lifecycle. Reflected in the showcase, even though it targeted at the reconfiguration that mainly conducted in the design and usage stage, whether to repair/replace/upgrade a product/service component depended on the logs and feedbacks collected in multiple stages of design, manufacturing, usage, or even end-of-life, and these hybrid records did impact the decision-making processes and results, for example, determining *CE* in the cost-benefit evaluation (Table 12). From a systematic perspective, the unified processes for representing and mapping requirements and solutions in the proposed framework are capable to connect the ‘*isolated islands of data*’ generated by separately implementing the smart sustainability strategies. Therefore, the proposed framework is more flexible to be applied and implemented in a user-oriented development process, and provides more comprehensive business intelligence for the development of Sustainable Smart PSS.

Thirdly, the processing of context-awareness runs through the whole data-driven loop in the proposed framework. Compared to the usual process, it will differentiate the generated solutions in the development process. Actually, due to the diverse groups of users and operating conditions, it is more rational and realistic that the same solution for sustainability will possess different effectiveness under various scenarios. Therefore, with the involvement of context-awareness in the framework, the provided solutions for product-service evolvement are better aligned with the user’s personalized needs. Besides, it also facilitates the Sustainable Smart PSS to self-recognize the opportunities and necessities for self-evolving (i.e., when perceiving an unusual scenario), which levels up the autonomy and timeliness in the development process.

5.3.2 Limitations of the proposed framework

Despite the above-mentioned advantages, there are still two limitations of the proposed framework. Firstly, the ‘cold start’ issue is observed in the data-driven framework, where each step can operate well only if enough user-

generated and product-sensed data are collected and annotated. For example, to guarantee the performance of the machine learning algorithm in solution recommendation, enough repair/replace/upgrade logs (~1000 records, inferred from this example) should be fetched to train and cross-validate the model. However, this criterion of data quality and quantity might be hard for a newly-designed PSS to reach. To mitigate this issue, a crowd-sourcing technique with a monetary or service-based incentive mechanism is recommended, to improve the involvement of stakeholders. Also, reinforcement learning and transfer learning manners can be integrated into the current framework, so as to train the decision-making model with rather few data.

Secondly, although the proposed framework demonstrates potentials in Sustainable Smart PSS development, it still has more research to be conducted on the specialized implementations of the four-step inner loop on the five sustainable/circularity strategies in the outer loop. Taking the solutions recommended in Table 11 as an instance, more technical details for repairing/replacing/upgrading should be attached, and the corresponding impacts to the surrounding cyber-physical environment should be further analyzed. Also, more implications to the remanufacturing/recycling scenarios should be offered. To solve these issues, a series of external or open-source knowledge base storing abundant transdisciplinary domain knowledge and common knowledge can be leveraged to provide a more solid and informative guide for the smart sustainable/circularity practice (Li et al., 2020).

6 Conclusion and future work

Aiming to lengthen the product lifespan and fulfill customers' uprising requirements with fewer un-renewable resource consumptions and environmental impacts, Smart Circular System and Smart PSS can provide useful insights integrally. A meeting-point of these two concepts, Sustainable Smart PSS, is about to emerge and flourish. It shows the promise of a smarter circular system manner and reveals a better performance in its sustainable processes throughout the whole lifecycle. As few studies reported in this novel area, this paper proposes a data-driven reversible framework for Sustainable Smart PSS development, based on the comprehensive summarization and discussion on its key features.

The main contributions of this paper can be concluded into three points:

(1) *Broadened the scope of sustainability to the management of cyber-physical resources.* In pursuit of sustainable cyber-physical resources holistically, a clear distinction between the conventional perspective in product lifecycle management and the proposed one was hence depicted as the additional consideration of exploiting and maximizing the value of reallocating information/knowledge resources.

(2) *Summarized the key features in developing Sustainable Smart PSS.* Based on the trinary intersection of sustainable strategy, smart technology and PSS, the concept of Sustainable Smart PSS was further elaborated with four compound features in its development process concluded.

(3) *Proposed a data-driven reversible framework to evolve the Sustainable Smart PSS.* With the flow of user-generated data and product-sensed data keep running in the framework, this paper showed the capabilities of leveraging these datasets to continuously deliver value in the extended or circular lifecycle.

As an explorative study, this paper highlighted the systematic development framework for Sustainable Smart PSS, while many detailed processes and algorithms for its development and implementation are oversimplified. Therefore, it is recommended that future work can investigate into the following aspects: (1) introduce few-shot machine learning methods and incentive mechanisms, to solve the ‘cold start’ issue for a newly-developed Sustainable Smart PSS; (2) update the adopted data analytics and context-awareness manner with advanced natural language processing and computer vision techniques, and hence leverage more sorts and types of data generated in the development process, and (3) to better support sustainable strategies in the outer loop under multiple scenarios, import transdisciplinary domain knowledge and common knowledge into the knowledge base, thus enabling a more solid logical inference and achieving higher autonomy in the development of Sustainable Smart PSS.

Acknowledgement

The authors wish to acknowledge the financial support from the National Research Foundation (NRF) Singapore and Delta Electronics International (Singapore) Pte Ltd., under the Corporate Laboratory@ University Scheme (Ref. SCO-RP1; RCA-16/434) at Nanyang Technological University, Singapore. The authors also acknowledge the funding support from the Start-up Fund for New Recruits (1-BE2X) and the Departmental General Research Fund (G-UAHH) at The Hong Kong Polytechnic University, China.

Reference

- Alcayaga, A., Wiener, M., Hansen, E.G. (2019) Towards a framework of smart-circular systems: An integrative literature review. *Journal of Cleaner Production* 221, 622-634. doi:10.1016/j.jclepro.2019.02.085
- Blondel, V.D., Guillaume, J.-L., Lambiotte, R., Lefebvre, E. (2008) Fast unfolding of communities in large networks. *Journal of Statistical Mechanics: Theory and Experiment* 2008. doi:10.1088/1742-5468/2008/10/p10008
- Bressanelli, G., Adrodegari, F., Perona, M., Saccani, N. (2018) Exploring how usage-focused business models enable circular economy through digital technologies. *Sustainability* 10, 639. doi:10.3390/su10030639
- Chang, M., Ong, S., Nee, A. (2017) AR-guided product disassembly for maintenance and remanufacturing. *Procedia CIRP* 61, 299-304. doi:10.1016/j.procir.2016.11.194
- Cooper, D.R., Gutowski, T.G. (2017) The Environmental Impacts of Reuse: A Review. *Journal of Industrial Ecology* 21, 38-56. doi:10.1111/jiec.12388

620 Damirchi Loo, L., Mahdavinejad, M. (2018) Analysis of Design Indicators of Sustainable Buildings with an
621 Emphasis on Efficiency of Energy Consumption (Energy Efficiency). *Civil Engineering Journal* 4.
622 doi:10.28991/cej-0309142

623 Diallo, C., Venkatadri, U., Khatab, A., Bhakthavatchalam, S. (2016) State of the art review of quality, reliability
624 and maintenance issues in closed-loop supply chains with remanufacturing. *International Journal of*
625 *Production Research* 55, 1277-1296. doi:10.1080/00207543.2016.1200152

626 Gianmarco Bressanelli, F.A., Marco Perona and Nicola Saccani (2018) Exploring How Usage-Focused Business
627 Models Enable Circular Economy through Digital Technologies. *Sustainability* 10. doi:10.3390/su10030639

628 Hatchuel, A., Weil, B. (2009) C-K design theory: an advanced formulation. *Research in Engineering Design* 19,
629 181-192. doi:10.1007/s00163-008-0043-4

630 Hu, Y., Liu, S., Zhang, H. (2015) Remanufacturing Decision Based on RUL Assessment. *Procedia CIRP* 29, 764-
631 768. doi:10.1016/j.procir.2015.01.027

632 Iacovidou, E., Purnell, P., Lim, M.K. (2018) The use of smart technologies in enabling construction components
633 reuse: A viable method or a problem creating solution? *Journal of environmental management* 216, 214-223.
634 doi:10.1016/j.jenvman.2017.04.093

635 Jiao, J., Helander, M.G. (2006) Development of an electronic configure-to-order platform for customized product
636 development. *Computers in Industry* 57, 231-244. doi:10.1016/j.compind.2005.12.001

637 Kerin, M., Pham, D.T. (2019) A review of emerging industry 4.0 technologies in remanufacturing. *Journal of*
638 *Cleaner Production* 237. doi:10.1016/j.jclepro.2019.117805

639 Kuhlenkötter, B., Wilkens, U., Bender, B., Abramovici, M., Süße, T., Göbel, J., Herzog, M., Hypki, A., Lenkenhoff,
640 K. (2017) New Perspectives for Generating Smart PSS Solutions – Life Cycle, Methodologies and
641 Transformation. *Procedia CIRP* 64, 217-222. doi:10.1016/j.procir.2017.03.036

642 Lee, J., Bagheri, B., Kao, H.-A. (2015) A Cyber-Physical Systems architecture for Industry 4.0-based
643 manufacturing systems. *Manufacturing Letters* 3, 18-23. doi:10.1016/j.mfglet.2014.12.001

644 Li, A.Q., Found, P. (2017) Towards Sustainability: PSS, Digital Technology and Value Co-creation. *Procedia CIRP*
645 64, 79-84. doi:10.1016/j.procir.2017.05.002

646 Li, J., Tao, F., Cheng, Y., Zhao, L. (2015) Big Data in product lifecycle management. *The International Journal of*
647 *Advanced Manufacturing Technology* 81, 667-684. doi:10.1007/s00170-015-7151-x

648 Li, X., Chen, C.-H., Zheng, P., Wang, Z., Jiang, Z., Jiang, Z. (2020) A Knowledge Graph-Aided Concept-
649 Knowledge Approach for Evolutionary Smart Product-Service System Development. *Journal of Mechanical*
650 *Design* 142. doi:10.1115/1.4046807

651 Li, X., Jiang, Z., Guan, Y., Li, G., Wang, F. (2019) Fostering the transfer of empirical engineering knowledge under
652 technological paradigm shift: An experimental study in conceptual design. *Advanced Engineering Informatics*
653 41. doi:10.1016/j.aei.2019.100927

654 Li, X., Jiang, Z., Liu, L., Song, B. (2018) A novel approach for analysing evolutionary motivation of empirical
 655 engineering knowledge. *International Journal of Production Research* 56, 2897-2923.
 656 doi:10.1080/00207543.2017.1421785
 657 Li, X., Jiang, Z., Song, B., Liu, L. (2017) Long-term knowledge evolution modeling for empirical engineering
 658 knowledge. *Advanced Engineering Informatics* 34, 17-35. doi:10.1016/j.aei.2017.08.001
 659 Liu, A., Teo, I., Chen, D., Lu, S., Wuest, T., Zhang, Z., Tao, F. (2019a) Biologically Inspired Design of Context-
 660 Aware Smart Products. *Engineering* 5, 637-645. doi:10.1016/j.eng.2019.06.005
 661 Liu, B., Zhang, Y., Zhang, G., Zheng, P. (2019b) Edge-cloud orchestration driven industrial smart product-service
 662 systems solution design based on CPS and IIoT. *Advanced Engineering Informatics* 42.
 663 doi:10.1016/j.aei.2019.100984
 664 Liu, L., Song, W., Han, W. (2020a) How sustainable is smart PSS? An integrated evaluation approach based on
 665 rough BWM and TODIM. *Advanced Engineering Informatics* 43. doi:10.1016/j.aei.2020.101042
 666 Liu, Z., Ming, X., Qiu, S., Qu, Y., Zhang, X. (2020b) A framework with hybrid approach to analyse system
 667 requirements of smart PSS toward customer needs and co-creative value propositions. *Computers & Industrial*
 668 *Engineering* 139. doi:10.1016/j.cie.2019.03.040
 669 Liu, Z., Ming, X., Song, W. (2019c) A framework integrating interval-valued hesitant fuzzy DEMATEL method to
 670 capture and evaluate co-creative value propositions for smart PSS. *Journal of Cleaner Production* 215, 611-
 671 625. doi:10.1016/j.jclepro.2019.01.089
 672 Luscuere, L., Mulhall, D., (2018) Circularity information management for buildings: The example of materials
 673 passports, Designing for the Circular Economy. Routledge, pp. 369-380.
 674 Maleki, E., Belkadi, F., Boli, N., van der Zwaag, B.J., Alexopoulos, K., Koukas, S., Marin-Perianu, M., Bernard,
 675 A., Mourtzis, D. (2018) Ontology-Based Framework Enabling Smart Product-Service Systems: Application
 676 of Sensing Systems for Machine Health Monitoring. *IEEE Internet of Things Journal* 5, 4496-4505.
 677 doi:10.1109/jiot.2018.2831279
 678 Michelini, G., Moraes, R.N., Cunha, R.N., Costa, J.M.H., Ometto, A.R. (2017) From Linear to Circular Economy:
 679 PSS Conducting the Transition. *Procedia CIRP* 64, 2-6. doi:10.1016/j.procir.2017.03.012
 680 Miranda, J., Pérez-Rodríguez, R., Borja, V., Wright, P.K., Molina, A. (2017) Sensing, smart and sustainable product
 681 development (S3 product) reference framework. *International Journal of Production Research* 57, 4391-4412.
 682 doi:10.1080/00207543.2017.1401237
 683 Murray, A., Skene, K., Haynes, K. (2017) The Circular Economy: An Interdisciplinary Exploration of the Concept
 684 and Application in a Global Context. *Journal of Business Ethics* 140, 369-380. doi:10.1007/s10551-015-2693-
 685 2
 686 Niu, B., Xie, F. (2020) Incentive alignment of brand-owner and remanufacturer towards quality certification to
 687 refurbished products. *Journal of Cleaner Production* 242. doi:10.1016/j.jclepro.2019.118314

688 Rymaszewska, A., Helo, P., Gunasekaran, A. (2017) IoT powered servitization of manufacturing—an exploratory
689 case study. *International Journal of Production Economics* 192, 92-105. doi:10.1016/j.ijpe.2017.02.016

690 Savarino, P., Abramovici, M., Göbel, J.C., Gebus, P. (2018) Design for reconfiguration as fundamental aspect of
691 smart products. *Procedia CIRP* 70, 374-379. doi:10.1016/j.procir.2018.01.007

692 Shen, J., Erkoyuncu, J.A., Roy, R., Wu, B. (2017) A framework for cost evaluation in product service system
693 configuration. *International Journal of Production Research* 55, 6120-6144.
694 doi:10.1080/00207543.2017.1325528

695 Sousa-Zomer, T.T., Cauchick Miguel, P.A. (2018) Sustainable business models as an innovation strategy in the
696 water sector: An empirical investigation of a sustainable product-service system. *Journal of Cleaner*
697 *Production* 171, S119-S129. doi:10.1016/j.jclepro.2016.07.063

698 Taguchi, G. (1995) Quality engineering (Taguchi methods) for the development of electronic circuit technology.
699 *IEEE Transactions on Reliability* 44, 225-229. doi:10.1109/24.387375

700 Thoroe, L., Knothe, B.d., Raabe, K., Schumann, M. (2011) Impacts of item-level RFID on packaging waste
701 recycling: exploratory study of the industry's expectations in Germany. *International Journal of Innovation*
702 *and Sustainable Development* 5, 358-370. doi:10.1504/IJISD.2011.043323

703 Tietze, F., Hansen, E.G., (2013) To own or to use? How product service systems facilitate eco-innovation behavior,
704 2013 Academy of Management Conference, Orlando, Florida.

705 Tukker, A. (2015) Product services for a resource-efficient and circular economy – a review. *Journal of Cleaner*
706 *Production* 97, 76-91. doi:10.1016/j.jclepro.2013.11.049

707 Tukker, A., Tischner, U. (2006) Product-services as a research field: past, present and future. Reflections from a
708 decade of research. *Journal of Cleaner Production* 14, 1552-1556. doi:10.1016/j.jclepro.2006.01.022

709 Valencia, A., Mugge, R., Schoormans, J., Schifferstein, H. (2015) The design of smart product-service systems
710 (PSSs): An exploration of design characteristics. *International Journal of Design* 9.

711 Vazquez-Martinez, G.A., Gonzalez-Compean, J.L., Sosa-Sosa, V.J., Morales-Sandoval, M., Perez, J.C. (2018)
712 CloudChain: A novel distribution model for digital products based on supply chain principles. *International*
713 *Journal of Information Management* 39, 90-103. doi:10.1016/j.ijinfomgt.2017.12.006

714 Wang, Z., Chen, C.-H., Zheng, P., Li, X., Khoo, L.P. (2019a) A graph-based context-aware requirement elicitation
715 approach in smart product-service systems. *International Journal of Production Research*, 1-17.
716 doi:10.1080/00207543.2019.1702227

717 Wang, Z., Chen, C.-H., Zheng, P., Li, X., Khoo, L.P. (2019b) A novel data-driven graph-based requirement
718 elicitation framework in the smart product-service system context. *Advanced Engineering Informatics* 42.
719 doi:10.1016/j.aei.2019.100983

720 Westkämper, E., Alting, Arndt (2000) Life Cycle Management and Assessment: Approaches and Visions Towards
721 Sustainable Manufacturing (keynote paper). *CIRP Annals* 49, 501-526. doi:10.1016/s0007-8506(07)63453-2

- 722 Whitmore, A., Agarwal, A., Da Xu, L. (2014) The Internet of Things—A survey of topics and trends. *Information*
723 *Systems Frontiers* 17, 261-274. doi:10.1007/s10796-014-9489-2
- 724 Zhang, Y., Ren, S., Liu, Y., Sakao, T., Huisingh, D. (2017) A framework for Big Data driven product lifecycle
725 management. *Journal of Cleaner Production* 159, 229-240. doi:10.1016/j.jclepro.2017.04.172
- 726 Zheng, P., Chen, C.-H., Shang, S. (2019a) Towards an automatic engineering change management in smart product-
727 service systems – A DSM-based learning approach. *Advanced Engineering Informatics* 39, 203-213.
728 doi:10.1016/j.aei.2019.01.002
- 729 Zheng, P., Lin, T.-J., Chen, C.-H., Xu, X. (2018a) A systematic design approach for service innovation of smart
730 product-service systems. *Journal of Cleaner Production* 201, 657-667. doi:10.1016/j.jclepro.2018.08.101
- 731 Zheng, P., Lin, Y., Chen, C.-H., Xu, X. (2018b) Smart, connected open architecture product: an IT-driven co-
732 creation paradigm with lifecycle personalization concerns. *International Journal of Production Research* 57,
733 2571-2584. doi:10.1080/00207543.2018.1530475
- 734 Zheng, P., Wang, Z., Chen, C.-H., Pheng Khoo, L. (2019b) A survey of smart product-service systems: Key aspects,
735 challenges and future perspectives. *Advanced Engineering Informatics* 42, 100973.
736 doi:10.1016/j.aei.2019.100973
- 737 Zheng, P., Xu, X., Chen, C.-H. (2020) A data-driven cyber-physical approach for personalised smart, connected
738 product co-development in a cloud-based environment. *Journal of Intelligent Manufacturing* 31, 3-18.
739 doi:10.1007/s10845-018-1430-y

740

A Data-driven Reversible Framework for Achieving Sustainable Smart Product-Service Systems

Abstract: Higher sustainability with extended product lifecycle is a tireless pursuit in companies’ product design/development endeavours. In this regard, two prevailing concepts, namely the smart circular system and smart product-service system (Smart PSS), have been introduced, respectively. However, most existing studies only focus on the sustainability of physical materials and components, without considering the cyber-physical resources as a whole, let alone an integrated strategy towards the so-called Sustainable Smart PSS. To fill the gap, this paper discusses the key features in Sustainable Smart PSS development from a broadened scope of cyber-physical resources management. A data-driven reversible framework is hereby proposed to sustainably exploit high-value and context-dependent information/knowledge in the development of Sustainable Smart PSS. A four-step context-aware process in the framework, including requirement elicitation, solution recommendation, solution evaluation, and knowledge evolvment, is further introduced to support the decision-making and optimization along the extended or circular lifecycle. An illustrative example is depicted in the sustainable development of a smart 3D printer, which validates the feasibility and advantages of the proposed framework. As an explorative study, it is hoped that this work provides useful insights for Smart PSS development with sustainability concerns in a cyber-physical environment.

Keywords: smart product-service system; sustainability; knowledge management; reversible design; context-awareness

Nomenclature

Smart PSS	Smart Product-Service System	CE	Circular Economy
ICT	Information and Communication Technology	IoT	Internet-of-Things
CPS	Cyber-Physical System	DT	Digital Twin
AR/VR	Augmented Reality/Virtual Reality	KG	Knowledge Graph
ML/DL	Machine Learning/Deep Learning	PLM	Product Lifecycle Management
4V Data	High Volume, Variety, Veracity, and Velocity Data	SCP	Smart, Connected Product
4R	Re-design, Remanufacturing, Reuse, and Recycle	RUL	Remaining Useful Life
DIKW	Data-Information-Knowledge-Wisdom	C-K Model	Concept-Knowledge Model

1 Introduction

Sustainable development is the main theme of today’s production systems, and has gained increasing attention among academia, practitioners, and policymakers (Gianmarco Bressanelli, 2018). Responding to a call for “*doing more with less material*” (Westkämper et al., 2000) in CE, one prevailing concept for promoting sustainability, i.e. circular system, was introduced by transforming the linear system of production (produce, sale, and dispose after

use) to a circular one with reversible strategies (e.g. re-design, remanufacturing, reuse and recycle). Hence, it can effectively reduce un-renewable resource consumptions and mitigating environmental impact (Murray et al., 2017). Another concept, termed product-service system (PSS), proposed a paradigm that tightly couples products and add-on services to fulfil customized requirements. Extending the lifespan with product reconfiguration and service innovation, PSS also promotes sustainability by “*doing more*” (Tukker, 2015; Tukker and Tischner, 2006).

Owing to the recent rapid development of advanced ICT infrastructure, digitalization technology and AI techniques, these two concepts individually evolve to be smarter, as the so-called Smart Circular System and Smart PSS, respectively. For the former, the increasing usage of IoT allows a higher level of traceability of materials and products in the circulation (Whitmore et al., 2014), and the leveraging of big data analytics techniques provides ever sufficient product lifecycle information (e.g. degradation status, remaining useful life) for decision-making (Bressanelli et al., 2018; Li et al., 2015; Zhang et al., 2017). For Smart PSS, the novel techniques provide capabilities to collect and transmit sensed-data and user-generated data among various SCPs and multi-stakeholders (Zheng et al., 2018a; Zheng et al., 2018b; Zheng et al., 2020), and also enable a rapid (even real-time) reconfiguration solution of hardware and software with requirement-orientation and context-awareness (Wang et al., 2019b; Zheng et al., 2019a).

Note that Smart Circular System provides competitive advantages for Smart PSS with cost reductions and new revenue potentials in commercialization (Michelini et al., 2017), and Smart PSS revealed great built-in-flexibility and self-adaptability to implement the lifecycle management of Smart Circular System (Zheng et al., 2018b). A meeting-point of the two prevailing concepts, so-called Sustainable Smart PSS (or Smart Circular PSS), is about to emerge. By collecting and analysing the meaningful product-sensed and user-generated data, Sustainable Smart PSS can better perform its sustainable use/reuse, maintenance, reconfigure, and recycle processes throughout the whole lifecycle. This provides a promising manner to enable sustainable development in the production system.

However, to the authors’ knowledge, only a few qualitative studies have proposed the potential of Sustainable Smart PSS (Alcayaga et al., 2019; Li and Found, 2017), while little research has further discussed its development process or realized it. More importantly, most existing studies still restrain themselves in a conventional perspective of product lifecycle management, which only considers the sustainability of tangible materials and components along the 4R process (Zheng et al., 2019b). Since the value-creation of products/services relies on massive operation datasets and effective data analytics manners, the discussion of sustainability is required to be extended to the cyber space and consider the cyber-physical resources as a whole. Rather than the well-known reversible strategies for material circularity, a novel perspective of sustainable information/knowledge management needs to be emphasized via the digital servitization business model (Kuhlenkötter et al., 2017). It will maximize the value of exploiting and reallocating cyber-physical resources in the development of Sustainable Smart PSS.

Aiming to fill the abovementioned gaps, this paper will first discuss the key features of Sustainable Smart PSS in a cyber-physical environment, and then propose a data-driven reversible development framework, and finally

validate the proposed framework with an illustrative example. The remainder of this paper is organized as follows. Section 2 briefly introduces the key terms and approaches for sustainability strategies and Smart PSS development. Section 3 discusses the key features in Sustainable Smart PSS development. The overall framework for its development process is presented in Section 4, with each module illustrated in detail. Section 5 provides an illustrative example of a smart 3D printer development to further validate the proposed framework towards smart sustainability. At last, the conclusion and future work are highlighted in Section 6.

2 Terms and approaches for sustainability and Smart PSS development

2.1 Reversible strategies for achieving higher sustainability

In order to balance economic development with environment and resource protection, the report of UN Environment Programme (UNEP) in 2006 initially outlined *sustainability* in the production system as “*restorative or regenerative by intention and design*”, and generically proposed the criterion of *low consumption of energy*, *low emission of pollutants*, and *high efficiency* (Murray et al., 2017). It was then derived and clarified for product development and product lifecycle management (PLM) into three aspects, namely, *environmental sustainability* (less material/fuel consumption, carbon emission, air/water pollution), *economical sustainability* (allowing an upgrade of components, reducing transportations) and *social sustainability* (shared value, customer loyalty, human well-beings improvement) (Li and Found, 2017; Liu et al., 2020a).

Originated from PLM, typical reversible strategies for achieving higher sustainability in product development includes *Re-design*, *Remanufacturing*, *Reuse*, and *Recycle* (4R), which reform the linear system of product lifecycle stages (design, manufacturing, distribution, usage, and disposal) to a circular system (Alcayaga et al., 2019; Zheng et al., 2019b). As shown in Figure 1, *Re-design* bridges customer experience in the usage stage and the end-product with an inverse-design principle and ‘configure-to-order’ manner (Jiao and Helander, 2006). Rather than start from scratch, it selects the appropriate components/modules from the existing product family to rapidly offer an upgraded design solution, thus providing higher flexibility and fewer un-renewable resource consumptions (Miranda et al., 2017). *Remanufacturing* is a series of manufacturing steps on a used product, to return or restore it to at least equivalent or better performance than that of the newly manufactured product (Diallo et al., 2016). Several techniques are leveraged under this generic definition, like remaining useful life (RUL) assessment (Hu et al., 2015), predictive maintenance (Kerin and Pham, 2019), refurbishing or reassembly (Niu and Xie, 2020). *Reuse* is regarded as a non-destructive process that allows additional lifecycle cycles of the whole or partial of product in an alternative scenario, without changing their original state. It is widely adopted in the industrial sectors of construction, packaging, and textiles (Cooper and Gutowski, 2017; Damirchi Loo and Mahdavinejad, 2018). *Recycle* aims at extracting raw materials or useful components from end-of-life products, and typically consists of three main phases: collection, sorting and recycling processing (Thoroe et al., 2011). Since the recycled materials and components are

usually leveraged in the strategies of *Re-design*, *Remanufacturing*, and *Reuse* and start another loop of the product lifecycle, *Recycle* is often considered as an ultimate closing-step in the circular system.

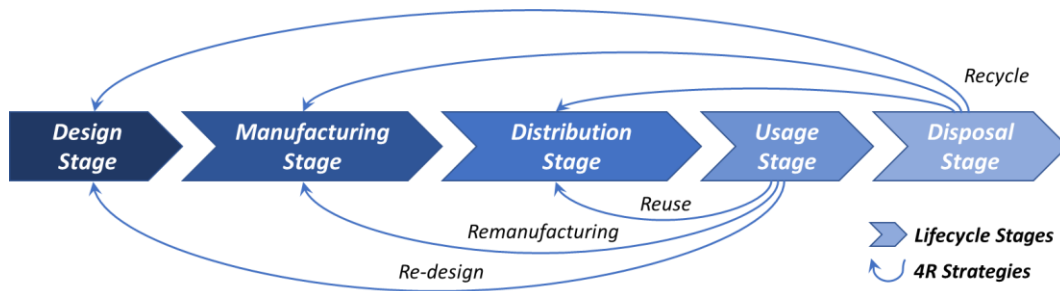


Figure 1. 4R strategies in product lifecycle stages

With the advanced ICT infrastructures (e.g. IoT, smart sensors, cloud computing), digitalization technologies (e.g. CPS, DT, AR/VR) and AI techniques (e.g. machine/deep learning, 4V Data mining and large-scale KG), the reversible strategies have become smarter. Typical studies are listed in Table 1. Generally, the smartness of the strategies is usually achieved by IoT-enabled product lifecycle data collection, Big data-supported decision making, and CPS-based simulation and operation, and it hence outperforms its predecessor in increasing resource efficiency, extending lifespan and closing the circulation (Alcayaga et al., 2019; Bressanelli et al., 2018). However, due to an inheritance from PLM, only tangible materials and components are considered in the majority of reversible strategies. Data itself, as well as the high-value information/knowledge mined from it, is often dismissed in the sustainability considerations due to intangibility and context-dependency, which sometimes contributes to the high cost and unexpected failures in adopting these smart strategies (Kerin and Pham, 2019).

Table 1 Typical smart strategies for achieving higher sustainability via reverse engineering

Strategies	Representative Studies	Specifications / Applications	Smart Techniques
Smart Re-design	(Savarino et al., 2018)	Adaptable product with context-aware modules	IoT, Smart sensors
	(Bressanelli et al., 2018)	Remote product upgrade to postpone replacement	Big data mining
Smart	(Chang et al., 2017)	Virtual disassembly platform for remanufacturing (and recycle)	AR/VR, CPS
Remanufacturing	(Zhang et al., 2017)	Lifecycle-data-driven decision-making for remanufacturing	Big data mining, ML
	(Alcayaga et al., 2019)	IoT-enabled remanufacturing planning and real-time monitoring	IoT, Smart sensors
Smart Reuse	(Zhang et al., 2017)	Lifecycle-data-driven decision-making for reuse	Big data mining, ML
	(Iacovidou et al., 2018)	Reusable materials/components evaluating, tracking and tracing	IoT, CPS
	(Bressanelli et al., 2018)	Usage data supported decision-making for reuse	IoT, Big data mining
Smart Recycle	(Zhang et al., 2017)	Lifecycle-data-driven decision-making for recycle	Big data mining, ML
	(Luscuere and Mulhall, 2018)	IoT-enabled mechanism to collect, process and report lifecycle data	IoT, Big data mining

2.2 Smart PSS and its development

It is widely accepted that Smart PSS fundamentally composed of Smart, connected product (SCP) and its generated digital services (Kuhlenkötter et al., 2017; Valencia et al., 2015; Zheng et al., 2018a). Compared to conventional PSS, the smartness is reflected in two aspects, namely, *online smartness* and *offline smartness*. *Online smartness* is implemented by intelligent algorithms and customized analytic tools, which leverage a huge amount of multi-source, heterogonous data generated from the communications of SCPs to deliver valuable insights for design, manufacturing, distribution, usage and disposal (Rymaszewska et al., 2017; Zheng et al., 2018b). On the other hand, *Offline smartness* is that Smart PSS can perceive a specific user scenario with context-awareness, and then adjust itself with built-in-flexibility hardware and self-learning software (Zheng et al., 2019a; Zheng et al., 2020). Based on these two aspects of smartness, Smart PSS is capable of following the sustainable business model with an ever-evolving manner (Sousa-Zomer and Cauchick Miguel, 2018). Specifically, novel digital services can be innovated to continuously meet customers' requirements, while the physical components can be adaptively reconfigured with changeable modules or open architectures to extend their lifespan.

To develop an evolving Smart PSS and continuously deliver value in its lifetime, several manners are proposed and tentatively implemented. Systematically, the development processes fall into two categories: (1) data-driven platform-based approach and (2) multi-stakeholder value-cocreation approach. The first approach follows a hierarchical flow of data-information-knowledge-wisdom (DIKW). It firstly collects massive user-generated data and product-sensed data through SCPs, and then analyses them in a service platform, and finally provides requirement-oriented solutions for product upgrade and service innovation (Wang et al., 2019a, b; Zheng et al., 2019a). The second approach investigates Smart PSS development from a value-driven perspective and depicts a co-evolvment process with the engagement of multiple stakeholders (end-user/designer/manufacture/service provider). Four phases, namely, requirement co-generation, function co-design, process co-implementation, and performance co-monitor, composes the co-development process of Smart PSS (Liu et al., 2020b; Liu et al., 2019c).

Although several studies attempt to develop an evolving Smart PSS, there is still a rather long way to go before a true Sustainable Smart PSS that coordinates the principles of CE can be realized. Two factors need to be further considered in development. Firstly, the objectives of Sustainable Smart PSS development should be promoted to 'develop for circularity', instead of 'develop for fail' (Tietze and Hansen, 2013). Extending the product-service portfolio may lengthen the lifetime, but it does not lead to the reduction of resource consumption. A reversible development method, which places emphasis on the organization of materials/information flows and reuses them as possible, is the fundamental solution to increase resource efficiency in CE (Michelini et al., 2017). Secondly, implementing Sustainable Smart PSS development requires moving the business model towards service and retaining long-lasting customer relationships (Alcayaga et al., 2019). In this ever-evolving value proposition process, stakeholder requirements vary frequently due to the changing contexts/scenarios, which directly affect the

performance of the product-service bundles (Wang et al., 2019a). Therefore, improving customer experience with context-awareness will be an indispensable consideration in Sustainable Smart PSS development.

2.3 Knowledge gaps addressed by this paper

As reviewed in section 2.1 and 2.2, most existing studies have been dispersed in two separate directions, namely, enabling reversible strategies with smartness via the advanced ICT and AI techniques, and improving the sustainability of Smart PSS by ever-evolving product development and service innovation. As the first gap, few studies have attempted to merge the two directions together via an integrated concept of Sustainable Smart PSS, not to mention a comprehensive summarization of the key features and systematic methodical support for its development process.

Moreover, inherited from product lifecycle management, many previous studies mainly concentrated on the sustainability of tangible components and resources in the product lifecycle, and thus emphasized more on the aspects of *environmental sustainability* and *economical sustainability* in sustainability evaluation and optimization (Liu et al., 2020a). Actually, with growing concerns on digital servitization to further improve *social sustainability*, increasing amounts of personalized data/information/knowledge leveraged and generated in Smart PSS development. However, due to the innate characteristic of context-dependency in these heterogeneous datasets collected from historical Smart PSS design, usage and disposal (Zheng et al., 2019b), there is still a lack of comprehensive sustainable/circularity strategies to ‘reuse’ or ‘recycle’ these intangible but equally-important resources in the cyber space, serving as the second gap.

To fill these two gaps in this paper, key features in Sustainable Smart PSS are firstly synthesized and analyzed (Section 3), and a data-driven reversible framework for Sustainable Smart PSS development is then established based on the context-awareness (Section 4).

3 Key features in Sustainable Smart PSS development

After reviewing the related literature on sustainable/circularity strategies and Smart PSS in section 2.1 and 2.2, and identifying the knowledge gaps in section 2.3, this section discusses the fundamental of Sustainable Smart PSS and then accordingly propose the key features in its development process.

3.1 The fundamental of Sustainable Smart PSS

Inspired by Alcayaga et al. (2019), the concept of Sustainable Smart PSS can be regarded as the trinary intersection of sustainable strategy, smart technology, and PSS, as illustrated in Figure 2. It can be further elaborated in three perspectives:

- From the perspective of sustainable strategy, Sustainable Smart PSS achieves extended product lifespan by better reallocating tangible and intangible resources in a cost-efficient manner (*economical sustainability*) with less environmental impact (*environmental sustainability*), and it moves forward to maintaining long-lasting customer relationships with ever-evolving manners (*social sustainability*).
- From the perspective of smart technology, Sustainable Smart PSS is enabled with *ubiquitous connectivity* to collect and transmit lifecycle big data via IoT infrastructure. Supported by massive internal information retrieved from these product-sensed and user-generated data, and explained with transdisciplinary external domain-specific and common knowledge, Sustainable Smart PSS is capable to self-learn the surrounding environment and self-configure itself under various contexts for better performance (*autonomous*).
- From the perspective of PSS, Sustainable Smart PSS still follows the business paradigm of value co-creation, while further enhances the openness of its hardware and software via open-architecture and open-source, and improves the involvement of its massive users via service-based incentive mechanism, thus achieving user-oriented *open-innovation* and continuously deliver value in its extended or circular lifecycle.

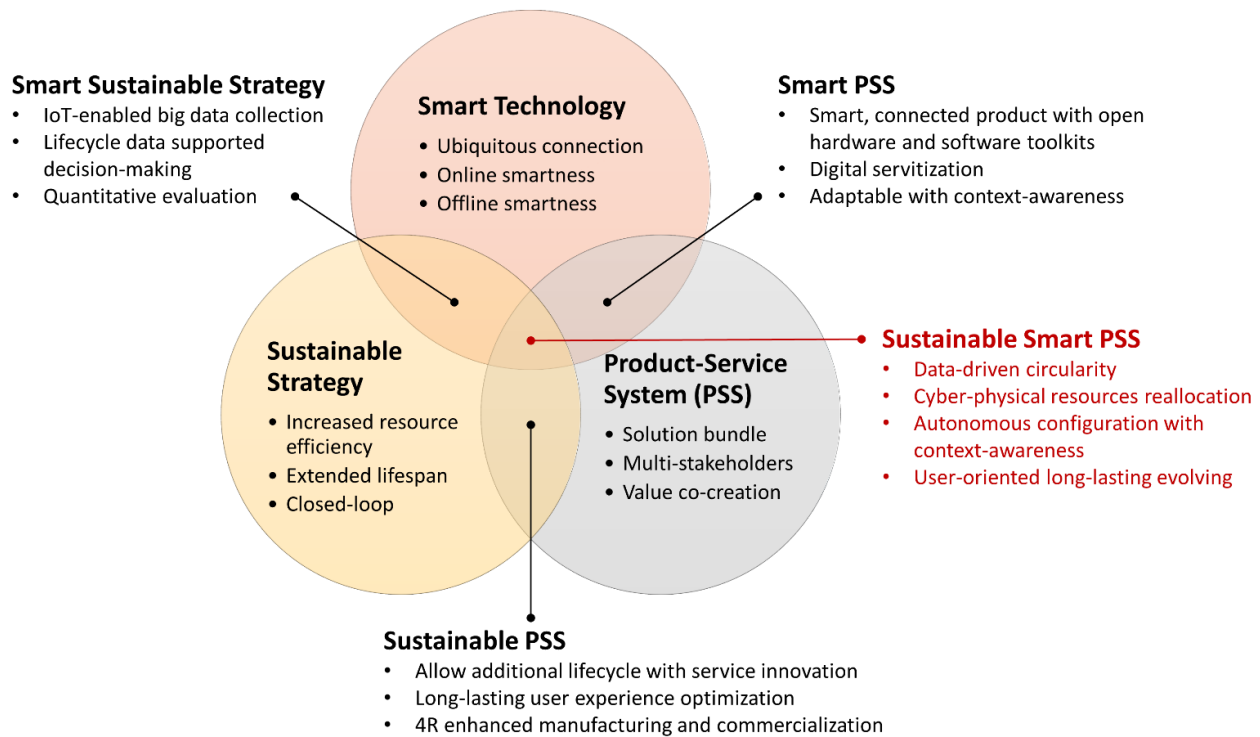


Figure 2. Sustainable Smart PSS: the trinary intersection of sustainable strategy, smart technology, and PSS

3.2 Key features in the development process

A systematic development process is determinant to the final success of implementing Sustainable Smart PSS, of which the key features can be summarized into four aspects, namely, *data-driven circularity* as its essence, *cyber-*

1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60
61
62
63
64
65

physical resource reallocation as its methodology, *autonomous configuration with context-awareness* as its manifestation, and *user-oriented long-lasting evolving* as its motivation.

Data-driven circularity follows the hierarchical flow of *DIKW*, where massive product-sensed and user-generated data in all lifecycle stages are incrementally acquired via IoT-enabled sensing devices (e.g. smart sensors, smart meters) and social sensors (e.g. web crawler, event-listener) (Zheng et al., 2019a). With universal models (e.g. regression, classification, clustering) and/or domain-specific models (e.g. ontology, UML diagram), the status information of the Sustainable Smart PSS itself (e.g. reusability, reconfigurability) and the dependent enablers/ecosystems (e.g. third-party service availability, logistics capability) is dynamically mined, integrated and traced (Alcayaga et al., 2019). This further contributes to extracting more precise lifecycle management rules and empirical knowledge, thus supporting the circularity decision-makings in the development process (e.g. remanufacturing process optimization, service capability upgrade) with a more solid basis but shorten latency (Liu et al., 2019b; Zhang et al., 2017).

Cyber-physical resource reallocation aims to achieve the goal of sustainability in both physical and cyber spaces in the development process. In the physical space, tangible resources of materials and components in Sustainable Smart PSS are reallocated in the circular production systems via 4R strategies, as referred in the previous studies (Alcayaga et al., 2019; Zheng et al., 2019b). More critically, in the cyber space, the intangible resources of collected dataset, annotated information, and mined knowledge are also reallocated in the process of product upgrade and service innovation via an information/knowledge management mechanism, where the previous concepts and propositions are reused or re-organized to offer a novel but cost-effective solution (i.e. knowledge transfer (Li et al., 2019)).

Autonomous configuration with context-awareness reflects the highest level of smartness and connectedness in the 5C level architecture (Lee et al., 2015). Relying on the PSS-related knowledge as well as other common knowledge, the contexts in the development process are perceived and the informed circularity decisions are self-made. According to these decisions, it is capable to self-configure the product/service components under different physical/social/user/operational contexts in real-time for better performance and higher sustainability.

User-oriented long-lasting evolving is critical to fulfilling the ever-changing user's requirements in the development process to continuously meet their satisfaction and maintain a long-lasting relationship (Liu et al., 2020b). With a higher degree of innovation flexibility enabled by open-architecture hardware and open-source software, massive users can originate the development process in its extended or circular lifecycle. Therefore, the achieved functionality and the delivered value may far beyond the originally designed propose (Zheng et al., 2018b), and reverse processes that start from the usage/disposal stages and end at the design/manufacturing/distribution stages (e.g. 4R) will be the mainstream in the long-lasting development process.

4 Data-driven reversible framework for Sustainable Smart PSS development

4.1 Overall framework

Based on the features summarized in section 3.2, this paper proposes a conceptual framework for Sustainable Smart PSS development, as shown in Figure 3. Considering the cyber-physical resources as a whole, two closed-loops separately describe the reversible development process in physical space and cyber space.

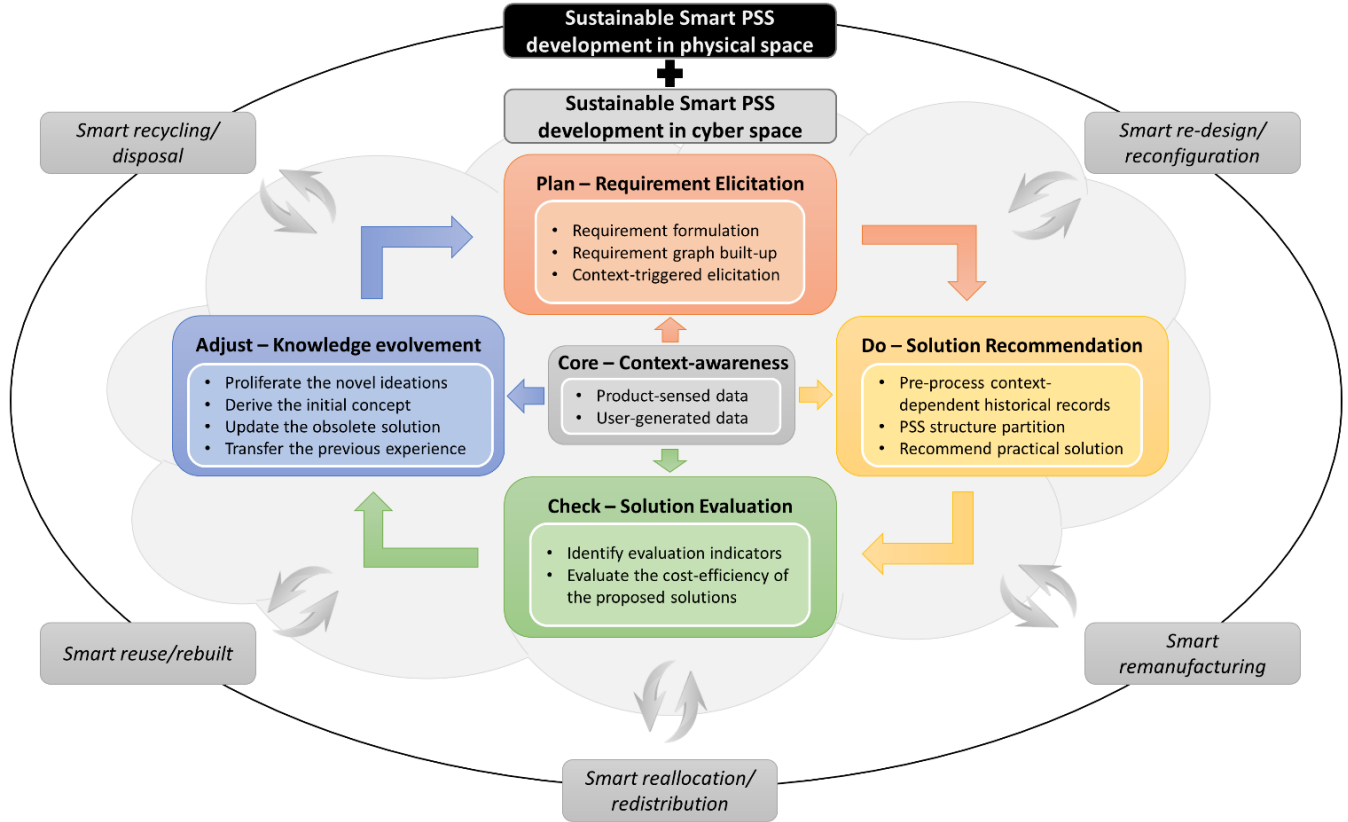


Figure 3. Data-driven reversible framework for Sustainable Smart PSS development

4.1.1 The outer loop: smart reversible strategies for product/service lifecycle management

Referring to previous studies regarding the reversible strategies (i.e. 4R) and Smart PSS lifecycle management (Alcayaga et al., 2019; Zheng et al., 2019b), the outer loop in the framework comprises five lifecycle-data-driven sustainability strategies, i.e., smart re-design/reconfiguration (e.g. automated engineering change management), smart remanufacturing (e.g. predictive maintenance), smart reallocation/redistribution (e.g. smart logistics and packaging), smart reuse/rebuilt (e.g. smart rental/second-hand system), and smart recycling/disposal (e.g. smart sorting and disassembly). Applying these strategies, the reallocation of the physical resource can be achieved in the development process.

Note that each smart sustainability strategy in the outer loop possesses individual characteristics regarding the frequency in the lifecycle stage and the type of lifecycle data analytics, as briefly summarized in Table 2. To handle these multi-source, heterogeneous datasets generated, collected, stored, and leveraged in conducting these strategies with higher cost-efficiency and running fluency, a generic process is further prescribed, namely, the inner closed-loop designed for the reallocation of the cyber resources.

Table 2. Smart sustainability strategies for Sustainable Smart PSS

Strategies	Specifications and functionalities	Frequency in the lifecycle stages	Type of lifecycle data analytics	References
Smart re-design/reconfiguration	Engineering change management; Product-service reconfiguration	Constantly in both design stage and usage stage	Online and all the time; Requires data about product/service design parameters, product/service operational status	(Zheng et al., 2019a)
Smart remanufacturing	Predictive and proactive maintenance; Production process plan and control	Regularly in both manufacturing stage and usage stage	Online and many times; Requires data about maintenance history, product/service operational status, disassembly and reassembly	(Maleki et al., 2018)
Smart reallocation/redistribution	Smart logistics; Smart packaging	Rarely in the logistic stage	On request and few times; Requires data about location of product, and availability of service	(Vazquez-Martinez et al., 2018)
Smart reuse/rebuilt	Smart rental; Smart second-hand system; Real-time performance assessment	Regularly in the usage stage	On request and many times; Requires product/service operational status, location of product, and availability of service	(Alcayaga et al., 2019)
Smart recycling/disposal	Smart sorting; Smart disassembly	Rarely in the disposal stage, design stage and manufacturing stage	On request and one time; Requires data about product/service operational status, dismantling process, and material parameters	(Alcayaga et al., 2019)

4.1.2 The inner loop: four-step context-aware process

Aiming to achieve the reallocation of the high context-dependent cyber resource in the development of Sustainable Smart PSS, a four-step context-aware process is proposed as the inner closed-loop in the conceptual framework. The core of the inner loop is context-awareness, which perceives the scenarios from product-sensed data and user-generated data collected in different lifecycle stages and encodes them with multiple context features. Then, inspired by an iterative four-step management method leveraged for continuous improvement, PDCA (plan-do-check-adjust) cycle, the inner loop is composed of four steps, namely, requirement elicitation, solution recommendation, solution evaluation, and knowledge evolvment. Based on these four context-aware steps, data-driven solutions for the development of Sustainable Smart PSS are generated. Details of the core and four steps in the inner loop will be further described in Section 4.2.

4.1.3 The interrelationship between the inner loop and the outer loop

Regarding the interaction between the inner loop and the outer loop, the four-step context-aware process in the inner loop can be universally leveraged to support each smart sustainability strategy in the outer loop, as listed in the interaction matrix of Table 3.

Table 3. Interaction matrix between the four-step context-aware process and five smart sustainability strategies

Interactions	Requirement Elicitation	Solution Recommendation	Solution Evaluation	Knowledge Evolvment
Smart re-design/ reconfiguration (Zheng et al., 2019a)	Functional requirement capture	Engineering change management	Feasibility analysis	Design concepts and principles
Smart remanufacturing (Maleki et al., 2018)	Re-production planning and maintenance planning	Work-in-progress and maintenance schedules	Re-production/ maintenance capacity assessment	Knowledge of re-processing/maintenance techniques
Smart reallocation/ redistribution (Vazquez-Martinez et al., 2018)	Logistic demand and supply forecasting	Warehouse and transportation management	Time/cost analysis	Information about supply chain
Smart reuse/rebuilt (Alcayaga et al., 2019)	Potential requirement extraction	Rental/second-hand market orders	Performance assessment	Usage records and Kansei knowledge
Smart recycling/disposal (Alcayaga et al., 2019)	Recycling demand estimation	Sorting features and disassembly sequences	Recycling capability and environmental impact assessment	Information on structure, dismantling, and materials

Taking smart re-design (Zheng et al., 2019a) as an example, the user's latent requirements for the current product/service functionalities under a specific context are elicited from the recent usage data as the start-up. Considering the historical engineering change records (e.g. update log), reconfiguration solutions on the design parameters and/or modularity correlations are recommended. After evaluating the feasibility of the solutions under the target context, product/service modules are reconfigured with all the corresponding design concepts and principles updated in the knowledge base.

Seen from Tables 2 and 3, one can find that the inner loop will drive and advise the outer loop in the whole lifecycle stages, by offering multiple data-driven and context-aware solutions. Specifically, relying on the use/reuse of valuable but context-dependent cyber resources, it recommends a decision-making solution of what and how product/service components need to be reconfigured, remanufactured, reallocated, reused, or recycled under a specific scenario. With this informatics-based guidance, the material/components circularity processes in the sustainable strategies of the outer loop can be conducted more smoothly and cost-efficiently.

Since this paper aims to highlight the sustainability in the cyber space, rather than its well-known connotations in the physical space, detailed sustainable processes of material circularity in each lattice in Table 3 will not be

further specialized. Only a general flow of the four-step context-aware process in the inner loop will be elaborated in the following subsections.

4.2 The process of the inner loop

Concentrating on the flow of the four-step context-aware process in the inner loop, this subsection elaborates on the data analytics manners and information/knowledge management processes. As shown in Figure 4, data analytics manners for mapping the requirement sets and solution sets are proposed based on the product-sensed and user-generated data, and an evolvement mechanism with four management strategies is also established to update the supportive information and knowledge in Sustainable Smart PSS development.

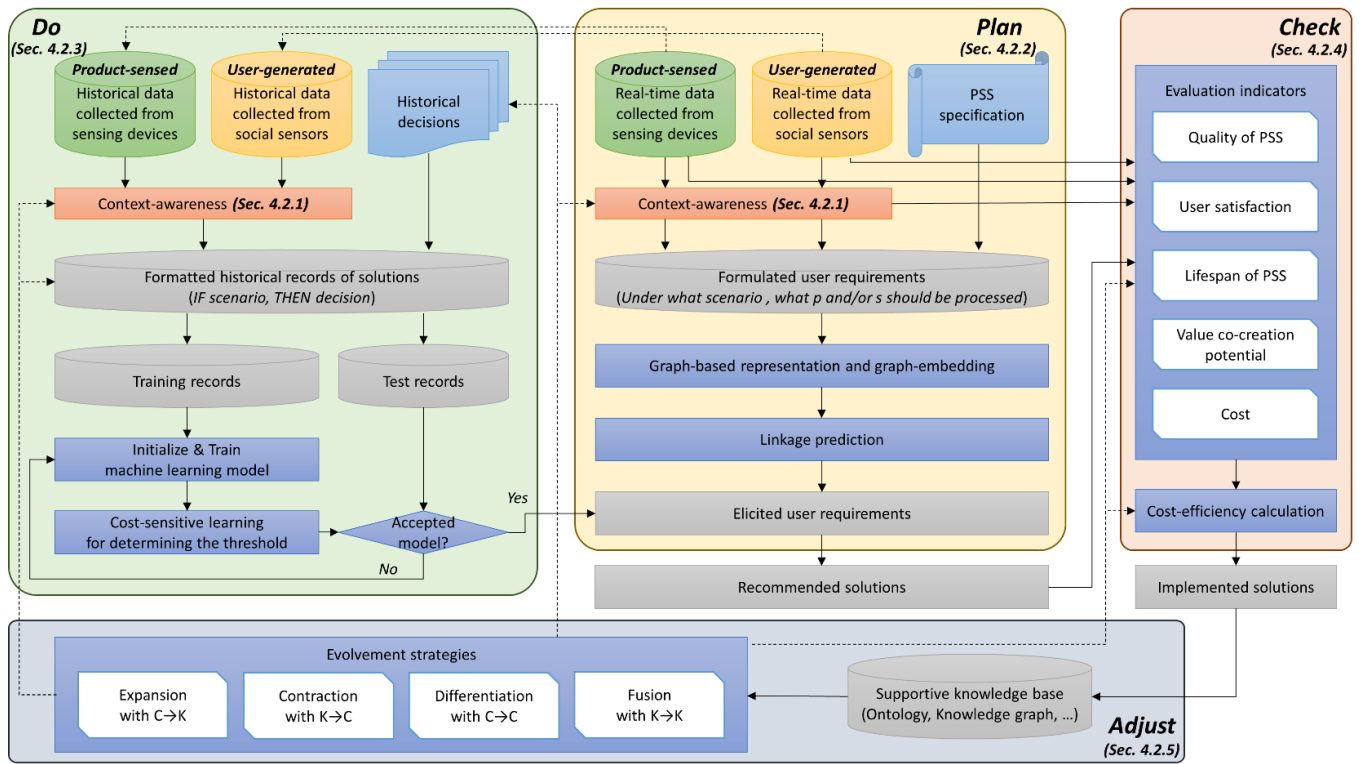


Figure 4. The flowchart of the four-step context-aware process in the inner closed-loop

4.2.1 Core of the inner loop: Context-awareness

As the core of the loop, context-awareness aims to model the multifarious scenarios in massive user-generated data and product-sensed data. Considering the sorts and contents that can be cost-effectively perceived via IoT-enabled sensing devices and social sensors, context features in Sustainable Smart PSS development are firstly categorized into four domain-independent classes (Liu et al., 2019a): (1) *Physical context* (information about the surrounding environment), (2) *Social context* (information about the nearby products and services), (3) *User context* (information about the users and user-PSS interactions), and (4) *Operational context* (information about the

operational status of PSS). Table 4 lists some examples of context features in each class for the development of Sustainable Smart PSS, and more features can be added if necessary and available. Based on these context features, a specific scenario in the dataset can be encoded with key-value modeling. Specifically, for each context feature c_i in k -elements set $C = \{c_i\}_k$, a corresponding value v_i is determined, and then forms a k -dimensional vector for the scenario, namely, $sn = [v_1, v_2, \dots, v_k] \in \mathbb{R}^k$, as illustrated in Figure 5. Note that the datasets generated and collected in the development process are heterogeneous, Table 5 also lists out the frequently used data analysis manners for typical data sources and types in context value determination.

Table 4. Perceived context features in the development of Sustainable Smart PSS

Context classes	Example context features
Physical Context	Date; Time; Location; Direction; Temperature; Humidity; Odor; Air/Water quality; Weather.....
Social Context	Peer products; Third-party service provider; Available recycler; Resource supply; Second-hand market orders.....
User Context	User demographics; User mood/health; User knowledge/profession; User preference/habit; Usage type
Operational Context	Power/energy; Software version; Maintenance history; Portability/Wearability; Computing power.....

Context No.	Context Type	Context Name	Values
C1	Social Context	Product Number	0: N.A. 1: Jet Fusion 500 2: Jet Fusion 520 3: Jet Fusion 3000 ...
C2	Physical Context	Location	0: N.A. 1: Factory 2: Studio 3: Home ...
C3	User Context	Client's Type	0: N.A. 1: New Customer 2: Regular Customer ...
C4	User Context	Client's Profession	0: N.A. 1: Manufacturer 2: Designer 3: Student ...
C5	User Context	Client's age	0: N.A. 1: Young 2: Middle-aged 3: Elderly ...
...

Description:
'The young students prefer to use Jet Fusion 520 at home'

Encoded Scenario:
 $sn = [2, 3, 0, 3, 1, \dots]$

Figure 5. Encoding the scenarios based on context features

Table 5. Data analysis manners in context value determination

Data sources & types	User-generated data			Product-sensed data
	Structural text	Natural language	Numerical value	Numerical value
Frequently used	Table headers & elements	Keyword extraction	Use domain knowledge	Pattern recognition
data analysis	Formal concept analysis	Named-entity recognition	Use common knowledge	Use domain knowledge
manners	Schema-based annotation	Syntax analysis	Fuzzy rules	Fuzzy rules
	Predefined template	Sentiment analysis	Rough sets	Rough sets

4.2.2 Plan step in the inner loop: Requirement elicitation

As the *plan* step in the loop, requirement elicitation aims to detect and model requirements of end-user in a distributed IoT-enabled environment (e.g. a cloud-based on-demand sharing platform). Under this context, implicit

user requirements are extracted in a data-driven manner, and then serve as the guidance for the following product-service solution innovation.

Datasets used for requirement elicitation mainly come from two resources, user-contributed feedbacks from mobile/ social networking (e.g. ratings, comments, Q&A threads) and signal data collected by embedded sensor devices (e.g. position, acceleration, angular velocity, temperature). To consider the context-dependency in these datasets, a formulation template is proposed for Sustainable Smart PSS development, namely, “*given a certain scenario, what product structures and/or service modules should be changed/updated/reused/recycled*” (Wang et al., 2019a, b). A piece of requirement is hence denoted as a tuple $req = \langle \{p\}, \{s\}, sn \rangle$, where $p \in P$ and $s \in S$ are decomposed components in the system (i.e. $PSS = P \cup S, P \cap S = \emptyset$), and $sn \in SN$ is encoded by the k -dimensional vector in context-awareness. In this data-driven situation, requirement elicitation is transformed into exploring the co-occurrence relationship among product, service and scenario information, and a graph-based approach is suitable for solving this issue when tackling massive data. Specifically, a requirement graph, $RG = \langle V, E \rangle$, is built, where the vertex set $V = P \cup S \cup SN$ and the edge set E refers to the co-occurrence relations mined from the dataset (e.g. two entities appear simultaneously in a piece of comment). Moreover, RG can be incrementally expanded with new product, service and scenario information, if more data are generated and collected in the development of Sustainable Smart PSS.

Based on the representation of RG , the elicitation of novel user requirements in the development process follows the model of linkage prediction. When a particular scenario is perceived, top K p - sn / s - sn edges which have the highest appearance probabilities predicted by graph-embedding algorithms (e.g. SkipGram, DeepWalk) can be selected to form an explicit user requirement. It is then leveraged as the user-oriented guidance for the subsequent PSS provision upgrade.

4.2.3 Do step in the inner loop: Solution recommendation

Since requirement elicitation is conducted from the user’s perspective, instead of a designer/manufacturer/supplier/operator/recycler’s perspective, it is regardless of some practical constraints in the development process. Therefore, solution recommendation, as the *do* step in the loop, is conducted to offer a more feasible solution from massive historical records accumulated in Sustainable Smart PSS development.

Similar to the data-driven situation, the historical records can be regarded as an empirical knowledge base storing the cases about “*IF a scenario occurs, THEN change/update/reuse/recycle the selected product/service components*”. Here, the scenario concerns the constraints in the sustainable processes, which are encoded by the context features shown in Table 4 and Figure 5. A typical format of a historical record can hence be partitioned into two parts, namely, $rec = \langle sn, d \rangle$, where sn also indicates a specific scenario with a k -dimensional vector, and $d = \langle \{p\}, \{s\} \rangle$ is the historical decision of selecting product and service components. Obviously, if a particular

scenario re-occurs in the elicited user requirement, stored empirical knowledge can be directly reused to rapidly offer a practical solution by changing/updating/reusing/recycling the previously mentioned components in the corresponding cases. However, when a novel scenario with an unknown combination of context feature values is perceived, the previous solutions need to be automatically revised before recommendation, and hence a machine learning manner can be adopted (e.g. Random Forest, Naïve Bayes, SVM). Specifically, a prediction model is trained with a large volume of historical records, which is partitioned into a matrix of context feature values (scenario set) and a corresponding matrix of the selected product/service components (decision set). After the training process, the occurrence probability of each product/service component in the recommended solution is separately predicted for the scenario in the test set, thus evaluating the performance of machine learning manner with the classification error. Besides, in order to determine the possibility threshold for selecting the product/service component in the recommended solution, a teaching cost for the classification of boundary region is also considered in a cost-sensitive training (Zheng et al., 2019a).

For a complex PSS possessing increasing numbers of product/service components and exponentially growing combinations of decisions, the precision of prediction may be deteriorated if only a relatively small training dataset is available. To handle this, clustering methods can be leveraged to effectively reduce the dimensions in the learning process. A co-occurrence matrix can be generated with the historical records, where each lattice in the matrix depicts the co-occurrence frequency of two components in the total records. Communities in PSS can be detected and partitioned with the calculation of modularity via community-partitioning algorithms (Blondel et al., 2008). The decision set in the historical records can be updated to the component-cluster level, before conducting the abovementioned machine-learning-based prediction, thus further improve the practicableness of this data-driven solution recommendation step in the loop.

4.2.4 Check step in the inner loop: Solution evaluation

To retain the competitiveness in the fierce market, only cost-effective solutions will be adopted in the development of Sustainable Smart PSS, rather than blindly pursuing better performance, longer lifespan or higher user satisfaction. Therefore, as the *check* step in the loop, solution evaluation aims to balance the cost and benefits by measuring and optimizing the cost-efficiency of the proposed solutions.

Based on the previous studies (Liu et al., 2020a; Shen et al., 2017), 5 criteria are firstly proposed for solution evaluation, considering value-proposition capability via product/service innovation, the long-lasting customer relationship, and the cost in the development process, namely, (1) maximize the quality of PSS (Q); (2) maximize the user satisfaction (US); (3) maximize the lifespan of PSS (LS); (3) maximize value co-creation potential (VC); and (5) minimize the cost for evolvement (C). They can be measured with Eq. 1-5.

$$Q = 1 - \alpha_1 \sum_{PSB} k (performance - goal)^2 \quad (\text{Eq. 1})$$

$$US = \frac{\alpha_2}{|PSB|} \sum_{PSB} (\overline{rate} - \overline{rate}_0) \quad (\text{Eq. 2})$$

$$LS = \alpha_3 \frac{\overline{lifespan}_{PSB} - \overline{lifespan}_0}{\overline{lifespan}_0} \quad (\text{Eq. 3})$$

$$VC = \frac{\alpha_4}{|PSB|} \sum_{PSB} Score_{potential} \quad (\text{Eq. 4})$$

$$C = \alpha_5 \sum_{PSB} (C_P + C_S + C_H + C_I) \quad (\text{Eq. 5})$$

Q in Eq.1 is calculated as a remaining quality after subtracting Taguchi's quality loss (Taguchi, 1995), and the loss is accumulated with the normalized deviations for the goals caused by each product-service bundle (PSB). US in Eq. 2 indicates the average improvement of user satisfaction on each product-service bundle in the recommended solution, which can be quantified by conducting sentiment analysis and time-series analysis on the user-generated online ratings and/or sentiment-rich feedbacks. LS in Eq. 3 measures the extendibility of lifespan when a specific solution is implemented, which is estimated with the lifecycle data. VC in Eq. 4 represents a series of capabilities of product-service bundles (like smartness, connectedness and openness) that can be provided to the users in value-co-creation, which can be scored with predefined rules and models (e.g. 5C model (Lee et al., 2015)). As for C in Eq. 5, it includes the cost of physical resources C_P , service-related processing C_S , involved human resources C_H , and intellectual resources C_I , which can be collected from the multi-stakeholders. α_1 - α_5 in Eqs. 1-5 are five constant normalization coefficients that align the order of magnitude of Q , US , LS , VC , and C .

After the evaluation on each criterion, the cost-efficiency of the proposed solution can be calculated by Eq. 6, where w_1 - w_4 are four dynamic and personalized weights that can be valued and adjusted by the user preference in the extended or circular lifecycle. Obviously, for a group of recommended solutions, the feasible ones with higher CE will be further implemented for a particular scenario in the development of Sustainable Smart PSS.

$$CE = \frac{w_1 * Q + w_2 * US + w_3 * LS + w_4 * VC}{C} \quad (\text{Eq. 6})$$

4.2.5 Adjust step in the inner loop: Knowledge evolvement

When a novel product-service solution is verified and implemented, the product/service components have been partially or wholly changed/updated/reused/recycled. Correspondingly, the related knowledge accumulated in the whole lifecycle stages, like design principles, manufacturing methodology, logistic constraints, usage manners, and dismantling information, also needs evolvement. Hence, as the *adjust* step in the loop, knowledge evolvement aims to manage these modifications and close the loop in the cyber space. It guarantees the consistency in the knowledge base of the Sustainable Smart PSS during the long-lasting development process.

Inspired by the four patterns recognized in the long-term knowledge evolvement (Li et al., 2018; Li et al., 2017) and the four operators proposed in Concept-Knowledge theory (Hatchuel and Weil, 2009), four heuristic strategies

are proposed to trigger the knowledge evolvement, and an information/knowledge management mechanism is hence established with these strategies to periodically modify the nodes and relations in the knowledge base (e.g. ontology, knowledge graph).

➤ *Expansion Strategy with $C \rightarrow K$ operator: Proliferate the novel ideations.*

$C \rightarrow K$ operator indicates a process of linking and re-organizing the concepts to form a novel knowledge. Based on this operator, an expansion strategy can be proposed to establish a ‘knowledge family’ based on the implemented innovative solutions. Namely, by linking the concepts leveraged in these solutions via default inference, a group of proliferated propositions can be generated, if no logical conflict to other existing knowledge is observed.

➤ *Contraction Strategy with $K \rightarrow C$ operator: Update the obsolete solution.*

As a symmetrical process for $C \rightarrow K$ operator, $K \rightarrow C$ operator introduces new properties and imported the specialized concepts from the existing knowledge, which guarantees the logical consistency in the evolvement. In this situation, obsolete solutions that leverage original concepts need to be accordingly updated, and the chances for adopting these solutions in the subsequent development process is hence reduced with a contraction strategy.

➤ *Differentiation Strategy with $C \rightarrow C$ operator: Derive the initial concept.*

$C \rightarrow C$ operator also discovers novel attributes to propose a new concept, but it aims to differentiate the definition and scope of for an existing generic concept in the new scenarios. Inheriting this idea, the differentiation strategy will seek for a derived concept in PSS-related entities with the considerations of unusual context features, thus providing the alternative options for self-adaptation in different scenarios.

➤ *Fusion Strategy with $K \rightarrow K$ operator: Transfer the previous experience.*

$K \rightarrow K$ operator establishes the logical relationship between newly generated knowledge and the existing one with all classic types of reasoning (classification, deduction, abduction, inference). Based on the logical chain established in this fusion process, reusing of previous experience generated in other scenarios is enabled, thus generating a wholly or partially transferred solution under the new scenarios.

5 An illustrative example

5.1 Background and pre-processing

In order to demonstrate the performance of the proposed framework, an illustrative example of a 3D printer is presented in this section. 3D printer is widely recognized as an eco-friendly product with high sustainability in the physical space, which is able to rapidly reconfigure and remanufacture itself with reusable/recyclable materials and components. Coupling with a digital twin in the cyber space, 3D printer can be bundled with multiple customized services, like remote printing monitoring, maintenance scheduling, and inventory management. In this regard, 3D printer possesses a *Cyber level* of smartness and connectedness in the 5C architecture (Lee et al., 2015), i.e.,

possessing the capabilities of gathering, storing, transmitting, and analyzing massive data to provide preliminary insights for production.

Although these features indicate great potentials for the 3D printer as a Sustainable Smart PSS, due to the poor exploitation of high context-dependent information/knowledge mined during its lifecycle, current 3D printer doesn't contribute much to improving sustainability in cyber space. Hence, an illustrative example of the application of the proposed data-driven reversible framework is presented for this situation, and this example was conducted on a cyber-physical smart 3D printer prototype, as shown in Figure 6.

Due to the complexity of realizing every aspect along its whole lifecycle, this example only showcased the implementation of the inner loop on the reconfiguration, which is an outer loop's sustainable strategy constantly-used in the design and usage stage. The structure of the 3D printer was also accordingly simplified to 20 product components and 6 service components, as listed in Table 6. To enable context-awareness with high feasibility and reliability, 7 context features were selected in this example according to the recommendation from the experts in 3D printing, as listed in Table 7. These experts were also invited to evaluate the reasonability of the reconfiguration solutions, and hence validate the proposed framework.

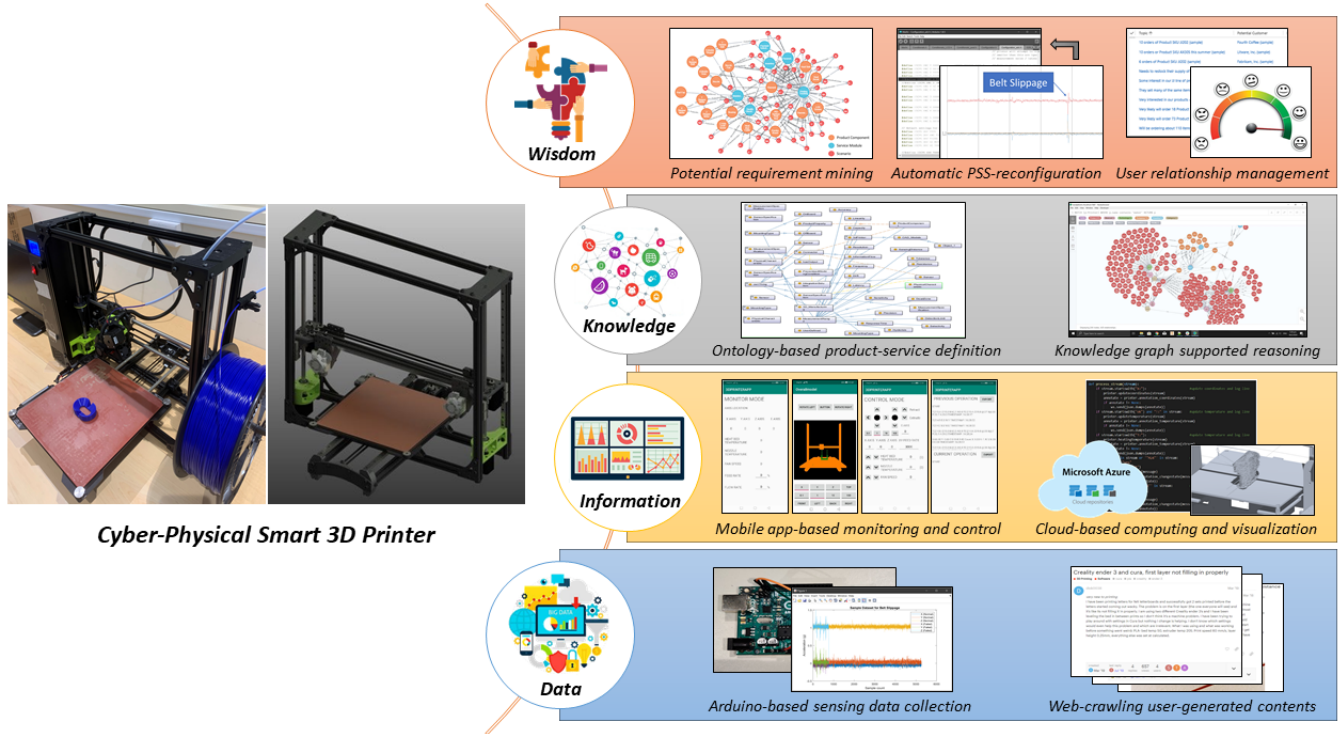


Figure 6. Cyber-physical smart 3D printer prototype

Table 6. Product components and service components of the smart 3D printer

Product Components		
<i>p1</i> : Nozzle	<i>p8</i> : Extruder Gear	<i>p15</i> : Thermistor
<i>p2</i> : LCD Screen	<i>p9</i> : Z-Axis Lead Screw	<i>p16</i> : Heat Break
<i>p3</i> : X Tension Belt	<i>p10</i> : X Stepper Motor	<i>p17</i> : Heat Sink
<i>p4</i> : Y Tension Belt	<i>p11</i> : Y Stepper Motor	<i>p18</i> : Nozzle Fan
<i>p5</i> : PEI Surface Print Bed	<i>p12</i> : Z Stepper Motor	<i>p19</i> : Part Fan
<i>p6</i> : Rambo Board	<i>p13</i> : Extruder Stepper Motor	<i>p20</i> : Filament
<i>p7</i> : Bearing	<i>p14</i> : Heat Bed Cable	
Service Components		
<i>s1</i> : Parameter Configuring	<i>s3</i> : Quality Checking	<i>s5</i> : Inventory Management
<i>s2</i> : Printing Tracking	<i>s4</i> : Maintenance Scheduling	<i>s6</i> : Payment Selection

Table 7. Context features considered in this example

Context Feature	Context Class	Context Values			
<i>c1</i> : Nozzle Temperature	Physical Context	-1: < 170 °C	0: 170-220 °C	1: > 220 °C	
<i>c2</i> : Extrusion Speed	Physical Context	-1: < 40 mm/s	0: 40-60 mm/s	1: > 60 mm/s	
<i>c3</i> : Layer Height	Physical Context	-1: < 0.14 mm	0: 0.14-0.38 mm	1: > 0.38 mm	
<i>c4</i> : Clogging	Operational Context	/	0: No Issue	1: Nozzle Clogged	
<i>c5</i> : String	Operational Context	/	0: No Issue	1: Filament Stringing	
<i>c6</i> : Second-hand status	Social Context	/	0: Brand New	1: Second-handed	
<i>c7</i> : User type (Experience)	User Context	0: N.A.	1: Novel (< 30h)	2: Ordinary (30 – 100h)	3: Expert (> 100h)

5.2 Implementation of the four steps on reconfiguring Smart 3D printer

Based on our previous research outcomes (Zheng et al., 2019a; Wang et al., 2019a, b; Li et al., 2020), this section illustrates the PDCA process of the four-step inner loop on a reconfiguration example on the Smart 3D printer, and aims to validate the feasibility of the process and the reasonability of the results.

5.2.1 Plan step: Elicit user requirements for the 3D printer

To implement the first step of requirement elicitation, 85 recent threads (Jun 2019 – Aug 2019) of user discussions were downloaded from *3Dhubs.com*, a famous online platform for 3D printing services and technical communication. With one-hot encoding, the content in each thread was mapped to the corresponding value of each context feature in Table 7 and forms an encoded scenario. The product and service mentioned in each thread were also annotated with the components listed in Table 6, thus generating the tuple of $req = \langle \{p\}, \{s\}, sn \rangle$. Based on the tuples, edges of $p-s$, $p-p$, $s-s$, $p-sn$ and $s-sn$ were defined, and a requirement graph was hence established. As shown in Figure 7, it visualized the interrelationship among all possible scenarios (red nodes) and the product/service components (orange and blue nodes).

Table 8. Top 3 user requirements elicited from requirement graph

Requirements	Encoded <i>sn</i>	Description of <i>sn</i>	Predicted <i>p</i> and <i>s</i>	Probability
<i>R1</i>	[-1, -1, 0, 1, 0, 0, 2]	Low temperature for certain filament	<i>p20</i> : Filament	0.950
			<i>p18</i> : Nozzle Fan	0.925
			<i>s1</i> : Parameter Configuring	0.847
			<i>p15</i> : Thermistor	0.810
			<i>s4</i> : Maintenance Scheduling	0.775
<i>R2</i>	[0, 0, 1, 0, 1, 0, 1]	Shifting layers with poor support	<i>s1</i> : Parameter Configuring	0.967
			<i>p5</i> : PEI Surface Print Bed	0.873
			<i>p20</i> : Filament	0.804
			<i>p4</i> : Y Tension Belt	0.722
			<i>p3</i> : X Tension Belt	0.722
<i>R3</i>	[0, -1, 0, 0, 0, 1, 2]	Extrusion failure after repair	<i>s4</i> : Maintenance Scheduling	0.942
			<i>p20</i> : Filament	0.918
			<i>p1</i> : Nozzle	0.903
			<i>s3</i> : Quality Checking	0.774
			<i>p8</i> : Extruder Gear	0.715

5.2.2 Do step: Recommend solution using 3D printer maintenance records

Aiming to solve the elicited requirements, 1802 maintenance records (repair/replace/upgrade logs) of 3D printers of the same model were collected and pre-processed for the second step of solution recommendation. As shown in Table 9, the scenario set encoded a real maintenance scenario with the context features in Table 7, and the decision set list the actual selection of product/service components under this scenario.

Table 9. A small portion of pre-processed historical records

Record No.	Encoded Scenario Set							Decision Set (repaired/replaced/upgraded product and service components)
	<i>c1</i>	<i>c2</i>	<i>c3</i>	<i>c4</i>	<i>c5</i>	<i>c6</i>	<i>c7</i>	
1	0	0	0	0	1	0	2	<i>p1</i> , <i>p8</i> , <i>p14</i> , <i>p15</i> , <i>s1</i> , <i>s4</i>
2	0	0	-1	0	0	1	1	<i>p7</i> , <i>p9</i> , <i>p12</i> , <i>p19</i> , <i>s2</i> , <i>s4</i>
3	-1	0	-1	1	1	0	1	<i>p5</i> , <i>p7</i> , <i>p8</i> , <i>p9</i> , <i>p12</i> , <i>p13</i> , <i>s2</i> , <i>s3</i> , <i>s4</i>
4	1	0	0	1	0	1	2	<i>p5</i> , <i>p14</i> , <i>p18</i> , <i>p19</i>
5	0	1	0	1	0	0	2	<i>p5</i> , <i>p14</i> , <i>s1</i> , <i>s4</i>
...

By conducting co-occurrence frequency analysis and Louvain community-partitioning algorithm (Zheng et al., 2019a), the product and service components in the 3D printer were divided into 5 clusters, as shown in Table 10. Then, a random-forest model was trained with 10-fold cross-validation on the existing dataset, and it was then leveraged to recommend solutions for the elicited user requirements, as shown in Table 11. For example, to solve *R1* (*Low temperature for certain filament*), solution *So1* recommended to replace the product components of

Thermistor and Filament, and/or repair the product components of Heat break and Heat sink, and/or upgrade the service components of Parameter Configuring, Inventory Management, and Payment Selection.

Table 10. Cluster division of the product and service components in the 3D printer

Cluster No.	Contained product and service components	Descriptions
<i>cl1</i>	<i>p1, p5, p7, p8, p13, p14, p18, p19, s4</i>	Extruding modules
<i>cl2</i>	<i>p2, p6, s2</i>	Printing tracking modules
<i>cl3</i>	<i>p3, p4, p9, p10, p11, p12, s3</i>	Movement modules
<i>cl4</i>	<i>p15, p16, p17, s1</i>	Heating modules
<i>cl5</i>	<i>p20, s5, s6</i>	Consumable management modules

Table 11. Recommended solutions for the elicited user requirements

Req.	Encoded <i>sn</i>	Probability of selection	Decision	Repaired/replaced/upgraded <i>p</i> and <i>s</i> in the recommended solution
	[<i>c1, c2, c3, c4, c5, c6, c7</i>]	[<i>P(cl1), P(cl2), P(cl3), P(cl4), P(cl5)</i>]	[<i>cl1, cl2, cl3, cl4, cl5</i>]	
<i>R1</i>	[-1, -1, 0, 1, 0, 0, 2]	[0.036, 0.112, 0.014, 0.765, 0.634]	[0, 0, 0, 1, 1]	<i>So1: p15, p16, p17, p20, s1, s5, s6</i>
<i>R2</i>	[0, 0, 1, 0, 1, 0, 1]	[0.171, 0.131, 0.724, 0.782, 0.240]	[0, 0, 1, 1, 0]	<i>So2: p3, p4, p9, p10, p11, p12, p15, p16, p17, s1, s3</i>
<i>R3</i>	[0, -1, 0, 0, 0, 1, 2]	[0.918, 0.003, 0.280, 0.196, 0.315]	[1, 0, 0, 0, 0]	<i>So3: p1, p5, p7, p8, p13, p14, p18, p19, s4</i>

5.2.3 Check step: Evaluate the cost-efficiency of the solutions

To evaluate the cost-efficiency of the recommended solutions, the third step of solution evaluation was conducted. Experimental data of each evolved prototype was collected to measure the 5 evaluation indicators via Eqs. 1-5. To maintain the confidentiality of company information, only the normalized evaluation results were reported, while the raw data of the component's price, specification, lifespan, and user rating was hidden. As for the weights w_1 - w_4 in Eq. 6, they were identified through an online 5-point Likert Scale-based questionnaire on a panel of 7 novel users (i.e. in Table 7, $c7 = 1$) and 11 ordinary users ($c7 = 2$), which were [0.571, 0.714, 0.893, 0.821] and [0.886, 0.841, 0.727, 0.591] respectively.

With the evaluated cost-efficiency of the solutions reported in Table 12, *So1* and *So3* were rather acceptable for the ordinary users, which replaced the thermistor and the filament to solve the low temperature for certain filament (*R1*), and repaired nozzle motors and upgraded the maintenance scheduling service to solve the extrusion failure after repair (*R3*). These two solutions were also approved by the experts in 3D printing. However, even though rather good performance in improving the quality (Q) and user satisfaction (US), a low CE was achieved by *So2* due to the rather high cost (C). Therefore, this reconfiguration solution needed to be further optimized according to the experts' suggestions, before its implementation to the novel users. For example, reconsider the necessity of each component that was recommended for repairing, replacing, and/or upgrading.

Table 12. Solution evaluation on the recommended solutions

Solution No.	Evaluation indicators					Indicators' weights	CE
	Q	US	LS	VC	C	$[w_1, w_2, w_3, w_4]$	
<i>So1</i>	0.922	0.758	0.750	0.633	2.79	[0.886, 0.841, 0.727, 0.591]	0.851
<i>So2</i>	0.978	0.958	0.364	0.545	3.78	[0.571, 0.714, 0.893, 0.821]	0.533
<i>So3</i>	0.824	0.962	0.529	0.511	2.35	[0.886, 0.841, 0.727, 0.591]	0.947

5.2.4 Adjust step: Evolve the 3D printing knowledge

After solution evaluation, the last step was to evolve the knowledge with four heuristic strategies. For example, in implementing *So1*, *filament (p20)* was required to be replaced to solve *R1*, and hence the related knowledge, *feed filament (p20) to the nozzle (p1)*, needed to be accordingly revised. Under this situation, **C**→**C** operator could be conducted on the concept of *filament*. A sub-concept, *polycaprolactone filament (p20_1)*, was hence derived with the appropriate attribute of *melting temperature 58 °C*. Using this derived concept, **C**→**K** operator could propose a novel knowledge, *feed polycaprolactone filament (p20_1) to the nozzle (p1) when the nozzle temperature is less than 170°C (i.e. $c1 = -1$) and the user type is ordinary user ($c7 = 2$)*. As no logical conflict to other 3D printing knowledge was observed, this novel knowledge could update the original one in the subsequent knowledge reuse (i.e., **K**→**C** operator). Besides, it could establish logical relations with other knowledge via **K**→**K** operator and hence generate a complex logical chain, like a piece of compound knowledge, *updating parameter configuring service (s1) for the ordinary user ($c7 = 2$) to change the nozzle temperature to less than 170°C ($c1 = -1$), when feeding polycaprolactone filament (p20_1) to the nozzle (p1)*.

Reflected on the knowledge base supporting the Smart 3D printer, these evolvments resulted in a novel sub-node of *polycaprolactone filament* linked to the existing node of *filament* in the domain ontology, and a novel formatted record of $rec = \{sn = [-1, 0, 0, 0, 0, 0, 2], d = \langle p1, p20_1, s1 \rangle\}$ added to the historical dataset. When another four-step loop started again in the subsequent development process, the data-driven flows in the first three steps would be correspondingly affected by the evolved knowledge.

5.3 Discussion

5.3.1 A brief comparison to the usual process

From the above description with the illustrative example, one can find that the proposed framework for Sustainable Smart PSS development still follows several basic ideations that are widely adopted in the usual reversible processes (e.g. 4R) for improving sustainability, namely, (1) extending the lifespan of the whole PSS by reconfiguring limited numbers of components (*environmental sustainability*); (2) exploiting the potential values under multiple scenarios by involving massive users into a co-development process (*social sustainability*); and (3) enhancing the effectiveness of solutions, by considering the cost-benefit criteria rather than only pursuing higher

values in solution evaluation (*economical sustainability*). However, beyond these ideations, there existing several novelties enabled by considering the key features of Sustainable Smart PSS in the proposed framework.

Firstly, beyond the traditional sustainability concerns for product design/development, which mainly focus on the reallocation of tangible resources in the physical space (Alcayaga et al., 2019), the proposed framework broadens the scope of sustainability to the cyber space and stresses the value of reusing intangible resources. In the showcase, the four-step inner loop provided an information/knowledge management manner to use and reuse the real-time and historical user-generated comments and operation logs, and predicted the requirements in Table 8 and recommended the solutions for evolving product/service components in Table 11. With these data-driven solutions, the conduction of the reconfiguration strategy could be timely supported. Therefore, instead of investigating sustainable solutions for an implicit requirement, continuously receiving valuable informed-decisions could prevent the high cost and unexpected failures in the business of pursuing sustainability (Kerin and Pham, 2019).

Secondly, different from the previous reversible strategies, which separately concentrate on one or a few specific lifecycle stages, the data-driven flow in the proposed framework is operating on multiple stages, even the whole lifecycle. Reflected in the showcase, even though it targeted at the reconfiguration that mainly conducted in the design and usage stage, whether to repair/replace/upgrade a product/service component depended on the logs and feedbacks collected in multiple stages of design, manufacturing, usage, or even end-of-life, and these hybrid records did impact the decision-making processes and results, for example, determining *CE* in the cost-benefit evaluation (Table 12). From a systematic perspective, the unified processes for representing and mapping requirements and solutions in the proposed framework are capable to connect the ‘*isolated islands of data*’ generated by separately implementing the smart sustainability strategies. Therefore, the proposed framework is more flexible to be applied and implemented in a user-oriented development process, and provides more comprehensive business intelligence for the development of Sustainable Smart PSS.

Thirdly, the processing of context-awareness runs through the whole data-driven loop in the proposed framework. Compared to the usual process, it will differentiate the generated solutions in the development process. Actually, due to the diverse groups of users and operating conditions, it is more rational and realistic that the same solution for sustainability will possess different effectiveness under various scenarios. Therefore, with the involvement of context-awareness in the framework, the provided solutions for product-service evolvement are better aligned with the user’s personalized needs. Besides, it also facilitates the Sustainable Smart PSS to self-recognize the opportunities and necessities for self-evolving (i.e., when perceiving an unusual scenario), which levels up the autonomy and timeliness in the development process.

5.3.2 Limitations of the proposed framework

Despite the above-mentioned advantages, there are still two limitations of the proposed framework. Firstly, the ‘cold start’ issue is observed in the data-driven framework, where each step can operate well only if enough user-

generated and product-sensed data are collected and annotated. For example, to guarantee the performance of the machine learning algorithm in solution recommendation, enough repair/replace/upgrade logs (~1000 records, inferred from this example) should be fetched to train and cross-validate the model. However, this criterion of data quality and quantity might be hard for a newly-designed PSS to reach. To mitigate this issue, a crowd-sourcing technique with a monetary or service-based incentive mechanism is recommended, to improve the involvement of stakeholders. Also, reinforcement learning and transfer learning manners can be integrated into the current framework, so as to train the decision-making model with rather few data.

Secondly, although the proposed framework demonstrates potentials in Sustainable Smart PSS development, it still has more research to be conducted on the specialized implementations of the four-step inner loop on the five sustainable/circularity strategies in the outer loop. Taking the solutions recommended in Table 11 as an instance, more technical details for repairing/replacing/upgrading should be attached, and the corresponding impacts to the surrounding cyber-physical environment should be further analyzed. Also, more implications to the remanufacturing/recycling scenarios should be offered. To solve these issues, a series of external or open-source knowledge base storing abundant transdisciplinary domain knowledge and common knowledge can be leveraged to provide a more solid and informative guide for the smart sustainable/circularity practice (Li et al., 2020).

6 Conclusion and future work

Aiming to lengthen the product lifespan and fulfill customers' uprising requirements with fewer un-renewable resource consumptions and environmental impacts, Smart Circular System and Smart PSS can provide useful insights integrally. A meeting-point of these two concepts, Sustainable Smart PSS, is about to emerge and flourish. It shows the promise of a smarter circular system manner and reveals a better performance in its sustainable processes throughout the whole lifecycle. As few studies reported in this novel area, this paper proposes a data-driven reversible framework for Sustainable Smart PSS development, based on the comprehensive summarization and discussion on its key features.

The main contributions of this paper can be concluded into three points:

(1) *Broadened the scope of sustainability to the management of cyber-physical resources.* In pursuit of sustainable cyber-physical resources holistically, a clear distinction between the conventional perspective in product lifecycle management and the proposed one was hence depicted as the additional consideration of exploiting and maximizing the value of reallocating information/knowledge resources.

(2) *Summarized the key features in developing Sustainable Smart PSS.* Based on the trinary intersection of sustainable strategy, smart technology and PSS, the concept of Sustainable Smart PSS was further elaborated with four compound features in its development process concluded.

(3) *Proposed a data-driven reversible framework to evolve the Sustainable Smart PSS.* With the flow of user-generated data and product-sensed data keep running in the framework, this paper showed the capabilities of leveraging these datasets to continuously deliver value in the extended or circular lifecycle.

As an explorative study, this paper highlighted the systematic development framework for Sustainable Smart PSS, while many detailed processes and algorithms for its development and implementation are oversimplified. Therefore, it is recommended that future work can investigate into the following aspects: (1) introduce few-shot machine learning methods and incentive mechanisms, to solve the ‘cold start’ issue for a newly-developed Sustainable Smart PSS; (2) update the adopted data analytics and context-awareness manner with advanced natural language processing and computer vision techniques, and hence leverage more sorts and types of data generated in the development process, and (3) to better support sustainable strategies in the outer loop under multiple scenarios, import transdisciplinary domain knowledge and common knowledge into the knowledge base, thus enabling a more solid logical inference and achieving higher autonomy in the development of Sustainable Smart PSS.

Acknowledgement

The authors wish to acknowledge the financial support from the National Research Foundation (NRF) Singapore and Delta Electronics International (Singapore) Pte Ltd., under the Corporate Laboratory@ University Scheme (Ref. SCO-RP1; RCA-16/434) at Nanyang Technological University, Singapore. The authors also acknowledge the funding support from the Start-up Fund for New Recruits (1-BE2X) and the Departmental General Research Fund (G-UAHH) at The Hong Kong Polytechnic University, China.

Reference

- Alcayaga, A., Wiener, M., Hansen, E.G. (2019) Towards a framework of smart-circular systems: An integrative literature review. *Journal of Cleaner Production* 221, 622-634. doi:10.1016/j.jclepro.2019.02.085
- Blondel, V.D., Guillaume, J.-L., Lambiotte, R., Lefebvre, E. (2008) Fast unfolding of communities in large networks. *Journal of Statistical Mechanics: Theory and Experiment* 2008. doi:10.1088/1742-5468/2008/10/p10008
- Bressanelli, G., Adrodegari, F., Perona, M., Saccani, N. (2018) Exploring how usage-focused business models enable circular economy through digital technologies. *Sustainability* 10, 639. doi:10.3390/su10030639
- Chang, M., Ong, S., Nee, A. (2017) AR-guided product disassembly for maintenance and remanufacturing. *Procedia CIRP* 61, 299-304. doi:10.1016/j.procir.2016.11.194
- Cooper, D.R., Gutowski, T.G. (2017) The Environmental Impacts of Reuse: A Review. *Journal of Industrial Ecology* 21, 38-56. doi:10.1111/jiec.12388

- Damirchi Loo, L., Mahdavinejad, M. (2018) Analysis of Design Indicators of Sustainable Buildings with an Emphasis on Efficiency of Energy Consumption (Energy Efficiency). *Civil Engineering Journal* 4. doi:10.28991/cej-0309142
- Diallo, C., Venkatadri, U., Khatib, A., Bhakthavatchalam, S. (2016) State of the art review of quality, reliability and maintenance issues in closed-loop supply chains with remanufacturing. *International Journal of Production Research* 55, 1277-1296. doi:10.1080/00207543.2016.1200152
- Gianmarco Bressanelli, F.A., Marco Perona and Nicola Saccani (2018) Exploring How Usage-Focused Business Models Enable Circular Economy through Digital Technologies. *Sustainability* 10. doi:10.3390/su10030639
- Hatchuel, A., Weil, B. (2009) C-K design theory: an advanced formulation. *Research in Engineering Design* 19, 181-192. doi:10.1007/s00163-008-0043-4
- Hu, Y., Liu, S., Zhang, H. (2015) Remanufacturing Decision Based on RUL Assessment. *Procedia CIRP* 29, 764-768. doi:10.1016/j.procir.2015.01.027
- Iacovidou, E., Purnell, P., Lim, M.K. (2018) The use of smart technologies in enabling construction components reuse: A viable method or a problem creating solution? *Journal of environmental management* 216, 214-223. doi:10.1016/j.jenvman.2017.04.093
- Jiao, J., Helander, M.G. (2006) Development of an electronic configure-to-order platform for customized product development. *Computers in Industry* 57, 231-244. doi:10.1016/j.compind.2005.12.001
- Kerin, M., Pham, D.T. (2019) A review of emerging industry 4.0 technologies in remanufacturing. *Journal of Cleaner Production* 237. doi:10.1016/j.jclepro.2019.117805
- Kuhlenkötter, B., Wilkens, U., Bender, B., Abramovici, M., Süße, T., Göbel, J., Herzog, M., Hypki, A., Lenkenhoff, K. (2017) New Perspectives for Generating Smart PSS Solutions – Life Cycle, Methodologies and Transformation. *Procedia CIRP* 64, 217-222. doi:10.1016/j.procir.2017.03.036
- Lee, J., Bagheri, B., Kao, H.-A. (2015) A Cyber-Physical Systems architecture for Industry 4.0-based manufacturing systems. *Manufacturing Letters* 3, 18-23. doi:10.1016/j.mfglet.2014.12.001
- Li, A.Q., Found, P. (2017) Towards Sustainability: PSS, Digital Technology and Value Co-creation. *Procedia CIRP* 64, 79-84. doi:10.1016/j.procir.2017.05.002
- Li, J., Tao, F., Cheng, Y., Zhao, L. (2015) Big Data in product lifecycle management. *The International Journal of Advanced Manufacturing Technology* 81, 667-684. doi:10.1007/s00170-015-7151-x
- Li, X., Chen, C.-H., Zheng, P., Wang, Z., Jiang, Z., Jiang, Z. (2020) A Knowledge Graph-Aided Concept–Knowledge Approach for Evolutionary Smart Product–Service System Development. *Journal of Mechanical Design* 142. doi:10.1115/1.4046807
- Li, X., Jiang, Z., Guan, Y., Li, G., Wang, F. (2019) Fostering the transfer of empirical engineering knowledge under technological paradigm shift: An experimental study in conceptual design. *Advanced Engineering Informatics* 41. doi:10.1016/j.aei.2019.100927

- 1
- 2
- 3
- 4 Li, X., Jiang, Z., Liu, L., Song, B. (2018) A novel approach for analysing evolutionary motivation of empirical
5 engineering knowledge. *International Journal of Production Research* 56, 2897-2923.
6 doi:10.1080/00207543.2017.1421785
- 7
- 8 Li, X., Jiang, Z., Song, B., Liu, L. (2017) Long-term knowledge evolution modeling for empirical engineering
9 knowledge. *Advanced Engineering Informatics* 34, 17-35. doi:10.1016/j.aei.2017.08.001
- 10
- 11 Liu, A., Teo, I., Chen, D., Lu, S., Wuest, T., Zhang, Z., Tao, F. (2019a) Biologically Inspired Design of Context-
12 Aware Smart Products. *Engineering* 5, 637-645. doi:10.1016/j.eng.2019.06.005
- 13
- 14 Liu, B., Zhang, Y., Zhang, G., Zheng, P. (2019b) Edge-cloud orchestration driven industrial smart product-service
15 systems solution design based on CPS and IIoT. *Advanced Engineering Informatics* 42.
16 doi:10.1016/j.aei.2019.100984
- 17
- 18 Liu, L., Song, W., Han, W. (2020a) How sustainable is smart PSS? An integrated evaluation approach based on
19 rough BWM and TODIM. *Advanced Engineering Informatics* 43. doi:10.1016/j.aei.2020.101042
- 20
- 21 Liu, Z., Ming, X., Qiu, S., Qu, Y., Zhang, X. (2020b) A framework with hybrid approach to analyse system
22 requirements of smart PSS toward customer needs and co-creative value propositions. *Computers & Industrial*
23 *Engineering* 139. doi:10.1016/j.cie.2019.03.040
- 24
- 25 Liu, Z., Ming, X., Song, W. (2019c) A framework integrating interval-valued hesitant fuzzy DEMATEL method to
26 capture and evaluate co-creative value propositions for smart PSS. *Journal of Cleaner Production* 215, 611-
27 625. doi:10.1016/j.jclepro.2019.01.089
- 28
- 29 Luscuere, L., Mulhall, D., (2018) Circularity information management for buildings: The example of materials
30 passports, Designing for the Circular Economy. Routledge, pp. 369-380.
- 31
- 32 Maleki, E., Belkadi, F., Boli, N., van der Zwaag, B.J., Alexopoulos, K., Koukas, S., Marin-Perianu, M., Bernard,
33 A., Mourtzis, D. (2018) Ontology-Based Framework Enabling Smart Product-Service Systems: Application
34 of Sensing Systems for Machine Health Monitoring. *IEEE Internet of Things Journal* 5, 4496-4505.
35 doi:10.1109/jiot.2018.2831279
- 36
- 37 Michelini, G., Moraes, R.N., Cunha, R.N., Costa, J.M.H., Ometto, A.R. (2017) From Linear to Circular Economy:
38 PSS Conducting the Transition. *Procedia CIRP* 64, 2-6. doi:10.1016/j.procir.2017.03.012
- 39
- 40 Miranda, J., Pérez-Rodríguez, R., Borja, V., Wright, P.K., Molina, A. (2017) Sensing, smart and sustainable product
41 development (S3 product) reference framework. *International Journal of Production Research* 57, 4391-4412.
42 doi:10.1080/00207543.2017.1401237
- 43
- 44 Murray, A., Skene, K., Haynes, K. (2017) The Circular Economy: An Interdisciplinary Exploration of the Concept
45 and Application in a Global Context. *Journal of Business Ethics* 140, 369-380. doi:10.1007/s10551-015-2693-
46 2
- 47
- 48 Niu, B., Xie, F. (2020) Incentive alignment of brand-owner and remanufacturer towards quality certification to
49 refurbished products. *Journal of Cleaner Production* 242. doi:10.1016/j.jclepro.2019.118314
- 50
- 51
- 52
- 53
- 54
- 55
- 56
- 57
- 58
- 59
- 60
- 61
- 62
- 63
- 64
- 65

- Rymaszewska, A., Helo, P., Gunasekaran, A. (2017) IoT powered servitization of manufacturing—an exploratory case study. *International Journal of Production Economics* 192, 92-105. doi:10.1016/j.ijpe.2017.02.016
- Savarino, P., Abramovici, M., Göbel, J.C., Gebus, P. (2018) Design for reconfiguration as fundamental aspect of smart products. *Procedia CIRP* 70, 374-379. doi:10.1016/j.procir.2018.01.007
- Shen, J., Erkoyuncu, J.A., Roy, R., Wu, B. (2017) A framework for cost evaluation in product service system configuration. *International Journal of Production Research* 55, 6120-6144. doi:10.1080/00207543.2017.1325528
- Sousa-Zomer, T.T., Cauchick Miguel, P.A. (2018) Sustainable business models as an innovation strategy in the water sector: An empirical investigation of a sustainable product-service system. *Journal of Cleaner Production* 171, S119-S129. doi:10.1016/j.jclepro.2016.07.063
- Taguchi, G. (1995) Quality engineering (Taguchi methods) for the development of electronic circuit technology. *IEEE Transactions on Reliability* 44, 225-229. doi:10.1109/24.387375
- Thoroe, L., Knothe, B.d., Raabe, K., Schumann, M. (2011) Impacts of item-level RFID on packaging waste recycling: exploratory study of the industry's expectations in Germany. *International Journal of Innovation and Sustainable Development* 5, 358-370. doi:10.1504/IJISD.2011.043323
- Tietze, F., Hansen, E.G., (2013) To own or to use? How product service systems facilitate eco-innovation behavior, 2013 Academy of Management Conference, Orlando, Florida.
- Tukker, A. (2015) Product services for a resource-efficient and circular economy – a review. *Journal of Cleaner Production* 97, 76-91. doi:10.1016/j.jclepro.2013.11.049
- Tukker, A., Tischner, U. (2006) Product-services as a research field: past, present and future. Reflections from a decade of research. *Journal of Cleaner Production* 14, 1552-1556. doi:10.1016/j.jclepro.2006.01.022
- Valencia, A., Mugge, R., Schoormans, J., Schifferstein, H. (2015) The design of smart product-service systems (PSSs): An exploration of design characteristics. *International Journal of Design* 9.
- Vazquez-Martinez, G.A., Gonzalez-Compean, J.L., Sosa-Sosa, V.J., Morales-Sandoval, M., Perez, J.C. (2018) CloudChain: A novel distribution model for digital products based on supply chain principles. *International Journal of Information Management* 39, 90-103. doi:10.1016/j.ijinfomgt.2017.12.006
- Wang, Z., Chen, C.-H., Zheng, P., Li, X., Khoo, L.P. (2019a) A graph-based context-aware requirement elicitation approach in smart product-service systems. *International Journal of Production Research*, 1-17. doi:10.1080/00207543.2019.1702227
- Wang, Z., Chen, C.-H., Zheng, P., Li, X., Khoo, L.P. (2019b) A novel data-driven graph-based requirement elicitation framework in the smart product-service system context. *Advanced Engineering Informatics* 42. doi:10.1016/j.aei.2019.100983
- Westkämper, E., Alting, Arndt (2000) Life Cycle Management and Assessment: Approaches and Visions Towards Sustainable Manufacturing (keynote paper). *CIRP Annals* 49, 501-526. doi:10.1016/s0007-8506(07)63453-2

- 1
- 2
- 3
- 4
- 5 Whitmore, A., Agarwal, A., Da Xu, L. (2014) The Internet of Things—A survey of topics and trends. *Information*
- 6 *Systems Frontiers* 17, 261-274. doi:10.1007/s10796-014-9489-2
- 7
- 8 Zhang, Y., Ren, S., Liu, Y., Sakao, T., Huisingh, D. (2017) A framework for Big Data driven product lifecycle
- 9 management. *Journal of Cleaner Production* 159, 229-240. doi:10.1016/j.jclepro.2017.04.172
- 10
- 11 Zheng, P., Chen, C.-H., Shang, S. (2019a) Towards an automatic engineering change management in smart product-
- 12 service systems – A DSM-based learning approach. *Advanced Engineering Informatics* 39, 203-213.
- 13 doi:10.1016/j.aei.2019.01.002
- 14
- 15 Zheng, P., Lin, T.-J., Chen, C.-H., Xu, X. (2018a) A systematic design approach for service innovation of smart
- 16 product-service systems. *Journal of Cleaner Production* 201, 657-667. doi:10.1016/j.jclepro.2018.08.101
- 17
- 18 Zheng, P., Lin, Y., Chen, C.-H., Xu, X. (2018b) Smart, connected open architecture product: an IT-driven co-
- 19 creation paradigm with lifecycle personalization concerns. *International Journal of Production Research* 57,
- 20 2571-2584. doi:10.1080/00207543.2018.1530475
- 21
- 22 Zheng, P., Wang, Z., Chen, C.-H., Pheng Khoo, L. (2019b) A survey of smart product-service systems: Key aspects,
- 23 challenges and future perspectives. *Advanced Engineering Informatics* 42, 100973.
- 24 doi:10.1016/j.aei.2019.100973
- 25
- 26 Zheng, P., Xu, X., Chen, C.-H. (2020) A data-driven cyber-physical approach for personalised smart, connected
- 27 product co-development in a cloud-based environment. *Journal of Intelligent Manufacturing* 31, 3-18.
- 28 doi:10.1007/s10845-018-1430-y
- 29
- 30
- 31
- 32
- 33
- 34
- 35
- 36
- 37
- 38
- 39
- 40
- 41
- 42
- 43
- 44
- 45
- 46
- 47
- 48
- 49
- 50
- 51
- 52
- 53
- 54
- 55
- 56
- 57
- 58
- 59
- 60
- 61
- 62
- 63
- 64
- 65

Xinyu Li: Conceptualization, Methodology, Investigation, Writing - Original Draft.

Zuoxu Wang: Data Curation, Software, Visualization.

Chun-Hsien Chen: Validation, Supervision, Writing - Review & Editing, Project administration.

Pai Zheng: Conceptualization, Writing - Review & Editing.