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Value creation and retention through re-servitization: Product service system for prescription medication dispensing in homecare

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ABSTRACT

Product-service systems (PSS) typically assume that users determine the value of the service and take responsibility for deciding when to start and discontinue use. However, without visibility to organizational value such as fleet-level operational gains, PSS users are ill-equipped to make such decisions. In this study, we examine a PSS for dispensing prescription medication to memory-impaired homecare clients of a municipal healthcare organization. Robot dispensers provided by a PSS operator automate medication adherence duties, streamlining workflows and reducing nursing staff needed during morning peaks. However, neither the memory-impaired client nor the homecare provider have visibility to the service's value. Collaborating with the operator and the healthcare organization, we discovered that the main problem was the value that was lost when the dispenser was deployed and redeployed too late. As a solution design, we propose detection of lost value opportunity and dynamic capture of the available value using smart and connected product technology for the robotic dispenser and its simpler precursor alternative. With these changes, the PSS operator can continuously re-servitize, i.e. use the PSS to actively guide the deployment and redeploy the robotic dispensers for improved value impact. Our contribution to the innovation management is highlighting the role of re-servitization in unlocking the potential operational value of a PSS in dynamic environments, such as healthcare.

1. Introduction

Product Service System (PSS) is a type of servitized product where a system operator (also called provider) delivers value to the customer using the product as the means of service delivery (Reim et al., 2015). The operational focus of a PSS operator is the provision of value to the customer, which contrasts with an original equipment manufacturer's operational focus of delivering a physical product, which customer then uses (c.f., Baines et al., 2007; Baines et al., 2017). In challenging settings, such as healthcare, retaining the value of the PSS over time requires not only the operational engagement of the customer, but the management of an innovation ecosystem (Talmar et al., 2020; Kapoor et al., 2022).

The primary design objective of the PSS operator is to effectively deliver the functional value of the product to the customer. PSS designs are often enabled by innovative use of digital technologies for service delivery, such as automated monitoring of customer-product interactions (Kohtamäki et al., 2021, 2022), as well as autonomously operating products (Porter and Heppelmann, 2014). As an operational design, PSS provides a transition path from linear operations focused on product delivery to circular operations focused on value creation and retention (Reim et al., 2015), extending life cycles and increasing product reuse. However, reuse might not retain value when users have limited visibility to the value, and the value of product's use varies between users, evolves dynamically, and is fleeting. This makes rethinking and adapting how and when the product is used and reused—i.e. re-servitized (Reike et al., 2018, p. 257)—essential.

In this paper, we operationalize re-servitization for retaining the value of the PSS in a dynamic operational environment and elaborate on the implications for PSS innovation management. We do this by studying how a fleet of medicine dispensing robots can be effectively deployed to

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provide prescription medications to memory-impaired elderly clients in their homes. Using mixed methods (e.g., Tashakkori, 1998) and inspired by the design science approach (Holmström et al., 2009), we collaborated in two publicly funded research projects over eight years with a PSS operator. We developed the service operations for a fleet of dispensing robots, focusing on the reorganization of care to the elderly by a homecare organization. Our study goes beyond reporting the value of the dispensing robot for improved medication adherence for the homecare client, reported in the clinical study of Rantanen et al. (2017). Leveraging the reliable dispensing for the clients, we investigated the PSS's value creation and retention for the homecare organization responsible for the clients (Lyly-Yrjänäinen et al., 2017). We focus in our study on how the PSS provider can use a fleet of dispensing robots to improve the productivity of the homecare organization. The research setting adds the PSS and its operator as new actors in the homecare innovation ecosystem (Talmar et al., 2020), alongside clients, nurses, physicians, and pharmacies.

Our theoretical contribution relies on the conceptual elaboration and operationalization of re-servitization. ***Re-servitization*** was originally defined by Reike et al. (2018, p. 257) as "rethinking and adapting services and the development of product service systems (PSS) – as part of [circular economy] business models.". Illustrated by changes such as shorter circular economy loops, the idea behind this concept is the redesign of PSS to redesign how products are deployed to maximize the value they provide and redeployed when the value starts to diminish. We operationalize re-servitization as the detection, capture, and re-capture of value-creation opportunities for a product in use by the PSS operator. Our analysis of the evolution of value creation in homecare highlights the need for active management of functional value creation and retention through timely (re)deployment.

We contribute to the innovation management of PSS (Lafuente et al., 2023). Our study shows how determining how and when value is created and lost operationally can become key to unlocking the potential of a PSS. In our study, we learned how value was created and lost, uncovering latent (hidden) needs (Wang et al., 2022). Addressing these uncovered needs, we use the smart product as the platform for effectively achieving the service objectives (Kapoor et al., 2022). We propose how, through a combination of functional extensions relying on smart connected products, the PSS design can include actionable measures of value creation (loss), and the operational procedures for re-servitization based on those measures.

2. Literature review

From the innovation management perspective, the challenge of PSS development is not just identifying the latent needs of the customer (Wang et al., 2022), but also understanding how the needs change. Thus, detecting changes in value creation becomes an operational task, with implications for the design of the PSS. To remain competitive, a PSS provider needs to develop re-servitization to effectively use available technological means to retain value (Kohtamäki et al., 2021). Next, we review literature on dynamic value creation and measurement, and management of PSS's value creation.

2.1. Dynamic value creation and the problem of actionable measurement

The value of a product can be considered based on whether the users find it useful or not; a product is valuable if it is in use, and once the user no longer uses the product, it becomes obsolete (den Hollander et al., 2017; Mellal, 2020). Obsolescence can be triggered technically (by the product lagging behind alternatives technologically or economically), functionally (by the product physically deteriorating to a point where it no longer is able to provide the intended value), and psychologically (by the user no longer finding the product attractive, even if it remains functional) (Mellal, 2020). In this situation, the value of the product or its materials can be retained by finding a new user and/or new uses for an obsolete product (den Hollander et al., 2017; Reike et al., 2018). However, the idea of obsolescence as an indicator of value is rooted in consumer setting with the user defining what kind of value is desirable and whether such value is created (cf. Grönroos and Voima, 2013; den Hollander et al., 2017; Mellal, 2020). Problems arise concerning the visibility, motivation, and communication of desired value when users (as employees) are also creating operational value for the organization (Kleinaltenkamp et al., 2017).

Operationally, value retention through reuse is challenging due to the dynamic nature of value, which is both created and destroyed during a product's lifecycle (Grönroos and Voima, 2013). Value in service provision is conceptualized as collaborative, emphasizing customer involvement and supplier-customer interaction (Grönroos, 2008, 2011; Grönroos and Helle, 2010; Grönroos and Voima, 2013). Despite the dynamic conceptualization, determination of value are often studied separately from operations, typically relying on surveys of customer satisfaction (e.g., Lee et al., 2015). The research challenge is developing actionable value creation metrics to enable effective re-servitization, prevent missed opportunities, and optimize resource allocation among alternative uses.

2.2. Product-service systems, servitization, and operations

PSS is closely associated with digitalization and value creation on the servitization research agenda (e.g., Kapoor et al., 2022; Kohtamäki et al., 2021; Reim et al., 2015). Despite an understanding of the operational barriers and transient conditions affecting the value creation in PSSs (Sjödin et al., 2017), the design of operational processes to sustain value creation (through measurement and management of value) remains largely unchartered (Baines et al., 2017). Grönroos and Voima (2013, p. 147), for example, highlight that "… to support customers' value creation, instead of creating value-destructing effects, are additional areas that need further research."

Continuous evaluation and management of value have mainly been discussed in two contexts in PSS research: production equipment in manufacturing plants and upgradable consumer PSS. The performance of the equipment can be purposefully managed by the PSS operator to maintain high overall equipment effectiveness and fulfill its purpose and role as part of the manufacturing system (e.g., Basak et al., 2022). The upgradable consumer PSS is not an operational concept, but a value proposal to consumers; its feasibility and potential impact have been evaluated in consumer and manufacture representative focus groups (Pialot et al., 2017). Their proposed PSS replaces repair when needed (broken), with upgrades for the user to purchase to prevent technological and functional obsolescence (cf. Mellal, 2020) and retain value by maintaining performance and improving functionality (Pialot et al., 2017).

Products that are deployed and redeployed can be thought of as a product fleet. Fleet management is a well-established topic in transportation literature (e.g., Pedraza Martinez et al., 2011). The field focuses on decisions such as determining optimal fleet size and mix (P. Wu et al., 2005), optimizing the utilization-residual value trade-off (Eftekhar and Van Wassenhove, 2016), and keeping each asset in the fleet operational until obsolescence (den Hollander et al., 2017). Ideas from circular economy have started to influence also this research. For example, Wu and Ryan (2014) proposed fleet management models that approach fleet optimization from a product life cycle perspective. Likewise, den Hollander et al. (2017) have conceptualized how products are remanufactured and redeployed to the same customers, resulting in multiple product life cycles within the same product use cycle. However, what is missing in the fleet management literature is the perspective of how to manage the value of the deployed fleet to improve operations, especially when such value is transient.

2.3. Theoretical framing and research gap

We apply Reike et al.'s (2018) concept of re-servitization to address the problem of value-retention over time on PSS. This concept generally refers to the rethinking and adapting of the provided services as part of the business models but lacks an operational definition. Indeed, the literature lacks sufficient focus on dynamic value creation and loss in PSS design for long-term value retention. There's also a shortage of actionable measurements for innovation ecosystem actors, necessary for effective PSS re-servitization. In practice, PSS operators lack both the understanding and solutions to dynamically identify value creation opportunities and effectively deploy products to achieve service objectives.

In practice, PSS has developed into a business model used for medical equipment (Xing et al., 2017). For medical equipment Adeogun et al. (2010) identify PSS as a promising model for providing point of care services, such as glucose testing for diabetics. Research has investigated how to design a PSS for extended life-cycles, as well as for minimizing waste in the end-of-life (Damha et al., 2019). However, there is a lack of understanding on how to design a PSS for value retention when value is fleeting. There is an assumption that use equals value creation, but when this is not the case (e.g., due to limited user visibility to organizational value), we lack understanding of how the PSS could be designed to detect and recapture value creation opportunities (re-servitization).

3. Research context and methods

Including re-servitization in the design of a PSS requires addressing a set of research problems: How do we determine the value of the PSS for the homecare organization?; What are the dynamic situations where value needs to be operationally managed as part of the product-service design?; And, what are the needed functionality enabling re-servitization of the PSS? We address these research problems for robotic dispensing of prescription medication, a novel technology-based product-service in healthcare, drawing inspiration from the design science approach (Holmström et al., 2009; Dimov et al., 2023). The approach is appropriate for the research problem (Romme and Holmström, 2023), guiding us in the exploration and implementation of the solutions available to the PSS operator for creating and retaining value for the homecare organization using a fleet of products.

Our research utilizes mixed methods; we combine scholarly engagement and quantitative modeling to develop solutions for determining value and managing value creation. More specifically, we utilize Regression Discontinuity Design (RDD) and Latent Profile Analysis (LPA) to validate the value potential and identify the characteristics of this operational value, which serves as the basis for our re-servitization design. By determining value and identifying how it is created and lost, our proposed re-servitization design is based on evidence (van Aken et al., 2016). Even though the re-servitization proposal is not yet implemented, the PSS of which it is to be a part is.

Before presenting results on the value of introducing the innovative PSS in the homecare ecosystem, and the design of the operational re-servitization process, we will in this chapter first describe the context and methods. We will introduce how homecare is provided in Finland and the use of robot technology, identify medicine administration as a key challenge for cost effective homecare, and present the methods used for value determination.

3.1. Research study and context

This study is based on an eight-year research collaboration (research projects in 2014–2018 and 2018–2021) with a company during its start-up and scale-up phases providing a special-purpose robot for dispensing prescription medications for elderly homecare clients. The PSS operator (or PSS provider) leases a fleet of robots as a PSS to the homecare organizations providing the care for the elderly clients. Appendix A describes in more detail the technologies that were developed by the PSS operator, and the technologies that the solution relies on. Table 1 summarizes the development and the role of academic researchers in the process.[2]

In Finland, the aging of the population has been faster than in any other European country (Eurostat, 2022). To support the quality of life in old age, the elderly clients are encouraged to stay in their own homes with municipalities providing homecare services (e.g., Anderson, 2007). Compared to those in assisted-living facilities or hospitals, individuals who stay in their homes consume fewer health care resources; hence, provision of homecare services can also be considered as a cost containment strategy (e.g., Groop et al., 2017).

Finnish homecare organizations provide two types of services (Mielikäinen and Kuronen, 2019): (1) cleaning, delivering meals, and

Table 1
Overview of case company (PSS operator) operations and research collaboration.

Time period	PSS operator's operations	Research collaboration
2008–2013	Development of the PSS. Certification as Class I medical device (Medical Device Directive, MDD)	Clinical study of effects on health outcomes, conducted by another research team (Rantanen et al., 2017).
2014–2016	Launch with first customers in Finland, Sweden, and Norway, mainly small-scale pilots. Enhancing the PSS based on customer feedback and experience.	Initial contact between PSS operator and research team. Access to PSS operator and the first homecare organizations. Work with two public homecare organizations.
2017–2018	Ramping-up operations including first large-scale competitive tenderings. Clients started to move from pilot mindset towards continuous service mindset. Received the second largest start-up investment (20M EUR) in Finland (2017) enabling growth in Nordic countries. Helping existing customers grow their fleets.	Value determination: first attempt to measure value on operational efficiency and cost. Discovery of the work of Groop et al. (2017). Work with 7 homecare organizations (6 new organizations).
2019–2022	Articulating the value offered by the solution. Creating the operational organization and processes for delivering value. New majority owner enabling international scale-up. Helping customers manage their large PSS fleets. New product with video connection. Certification as Class I medical device (Medical Device Regulation, MDR).	Re-servitization: Design research with homecare organizations and the PSS operator operations. New approach for value determination based on Regression Discontinuity Design (RDD) and Latent Profile Analysis (LPA). Work with 8 home care organizations (5 new organizations).
2023–2024	Pursuing international growth and entering new markets outside homecare. Launch of a video-assisted medicine dispensing robot and acquisition of another medicine dispensing company. First cases of client-driven transitions from precursor technologies to successor technologies.	Solution design: Co-development of the design for smart connectivity-based actionable measures and for operational procedures of re-servitization.

[2] Initially, the research team consists of two field-researchers, next complemented with a co-author of previous study with high relevance for the operational impact of the product-service and then with a co-author who is an expert in quantitative methods in operations management research. The inventor of the robotic dispenser also co-authors this paper.

assisting with personal hygiene; and (2) blood sugar/pressure measurements, treating wounds, and administering medication, among other things (e.g., Lyly-Yrjänäinen et al., 2017). Typically, the former tasks are carried out by community nurses, whereas the latter tasks require a certified nurse. The administration of medication is a significant reason for frequent homecare visits, placing a burden especially on certified nurses. The medicine dispensing PSS introduced by the PSS operator aims to address this challenge by automating the administration of medication, thus streamlining homecare operations.

We were invited by the PSS operator to investigate the value proposition of the automated medicine dispensing solution to the homecare organizations. The value proposition to the homecare organization was ambiguous at the outset of the study. Managers of homecare organizations implementing the technology were interested in medication safety and adherence, yet at the same time, expected short-term efficiency improvements stemming from reduced homecare visits.

3.2. Data collection

The PSS operator provided us access to thirteen Finnish and Swedish municipalities either implementing or already using their service. In total, we have had 169 meetings (site visits and virtual meetings) and 1785 emails/calls with the PSS operator and the municipalities (summarized in Table 2). We also got access to datasets from multiple municipalities totaling 7 713 836 homecare visits to thousands of homecare clients, 825 of which have been using the dispensing robot.

Throughout the research project, we acted as a mediator in-between the PSS operator and their customers. By doing this, we were able to (1) identify challenges in achieving the desired operational value together with the homecare organizations, as well as (2) develop tools and fleet management approaches together with the PSS operator to support homecare in the realization of operational value. We started by observing training sessions for the lead users (how to set up the services for a client) and nurses (how to operate the robot in the field) as well as interviewing nurse teams implementing the service. We were also given an opportunity to visit 20 homecare clients before and after implementation of the robot service.

As collaboration progressed, we started to actively participate in client selection meetings and facilitate performance review sessions with the purpose of understanding the mechanisms of value creation, retention, and loss. In the client selection meetings, we shared knowledge about the mechanisms of the operational value to the homecare organization and emphasized the importance of goal-based deployments. The purpose of our activities there was to help nurses identify appropriate clients and help them deploy robots purposefully for the value that the homecare organization sought. For performance review sessions, we evaluated the operational value of the dispensing robots by analyzing the visit records with simple before-and-after analyses, which we used to facilitate the discussion about the success of the implementation, how future deployments should be targeted, and whether some deployments should be reconsidered.

In the data collection, we made notes about the homecare management and use of robots instead of recording and transcribing the sessions, as most meetings also included sensitive personal client information. This enabled us to refrain from gathering unnecessary sensitive data on the clients, streamlining the process needed to gain access to the homecare organizations and their data on operational performance.

Our analysis focuses on a single homecare case with the largest PSS robot fleet implementation in 2019, conducted in a homecare organization that had previously piloted a smaller fleet of robots in 2015–2017. An important consideration in the case selection was that decision makers in the homecare organization had already recognized the importance of the key operational value mechanism (morning peak hour reduction) and value retention (the need to redeploy robots) before deciding to increase the PSS deployment. The case homecare organization provided a dataset of 4 638 007 homecare visits from 17 124 homecare clients (424 dispenser users) over a 27-month period when the size of the PSS fleet was increased incrementally.

3.3. Methods for value determination

Four challenges make detecting operational value of the robotic medicine dispensing PSS difficult. First, the implementation is continuous, as well as temporary, with clients having their own individual and unique deployment (and redeployment) dates. Second, the service plans of clients vary in intensity and are updated when the condition of clients change. Third, the objectives of deployments also vary among clients, making it highly likely that the operational impact on the activity system also varies between clients. Fourth, the client base of homecare is constantly changing, with new clients coming in and others leaving to more work-intensive care, as well as clients temporarily assisted by home care. Therefore, we cannot just compare the operations at two different points of time to see if there is operational value, but instead, we needed a more advanced analysis method that would not be limited by these challenges.

To deal with these challenges and for analyzing the operational value we use Regression Discontinuity Design (RDD) and Latent Profile Analysis (LPA) (Masyn, 2013). The data are a sample of homecare visits, recording the time and duration of each client visit. Our analysis focuses on deployment of the fleet of dispensing robots. The dispensing robots are not deployed randomly but purposefully for clients who the homecare organization expects can benefit from the device. Thus, we decided to use a quasi-experimental RDD approach. RDD recognizes the robot deployment day as a clear cutoff point, enabling examining the operational value on a client level in a context where robots are continuously deployed as clients that can potentially benefit are identified. Since we did not have any information on the purpose for deployment to the clients, we used LPA to identify whether latent groups were visible in the data. More detailed information about the use of the two methods are provided in Appendix B.

3.4. Sample

In our sample, we had 4 638 007 observations of visits (N) of 17 124 homecare clients (n), including both robot users and non-robot users. We first trimmed the data to match our data about robot use, cleaned any errors in the data, removed virtual visits and phone calls, and excluded clients who did not use the robot during the sample. The resulting dataset included (N) 319 929 homecare visits (N) for 424 dispenser user clients (n). We then aggregated the data so that instead of days, each N represents a week (homecare typically cycles weekly). This way the representation of how the weekly workload changed throughout the sample, now with 39 501 weeks of data (N) for 424 clients (n). We then excluded any clients with missing data such as over 28-day absences, removed all weeks after robot redeployments, filtered out the relative weeks that had data from less than 10 clients, and excluded clients whose sample was less than 8 weeks (at least 4 weeks before and 4 weeks after). In the end, we had a dataset representing 26 601 weeks of workload (N) for 352 clients (n).

4. Value creation, retention and lost opportunity

Our first step was to identify the mechanisms of operational value, i. e., what kind of operational change would PSS deployment enable for the homecare organizations. The focus is on the operational value for the homecare organization. The value of robotic medicine dispensing to the client —i.e., effects using robots on client medicine adherence, usability,

Table 2
Interactions with the PSS operator, case homecare organization and other municipalities and organizations.

Organization	Type	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	Total
PSS operator	Meetings	1	9	2	5	11	27	6	18		2	2	**83**
	Calls/Emails	9	69	63	91	123	285	153	160	24	19	45	**1041**
Homecare organization (case)	Meetings		8	1	3		2	4	8				**26**
	Calls/Emails		50	74	9		54	79	41				**307**
Other municipalities and homecare organizations	Meetings			2	12	12	24	11	1	2			**64**
	Calls/Emails			13	67	94	186	113	23	5			**501**
Total	**Meetings**	**1**	**17**	**5**	**20**	**23**	**53**	**21**	**27**	**2**	**2**	**2**	**173**
	Calls/Emails	**9**	**119**	**150**	**167**	**217**	**525**	**345**	**224**	**29**	**19**	**45**	**1849**

and safety— are reported elsewhere. The results of the clinical study are presented in Rantanen et al. (2017) .[3]

While the improved and measurable medicine adherence of clients is a desirable outcome for the homecare organizations, not all homecare organizations have the financial capabilities to fund the PSS without offsetting cost savings in operations. Therefore, the PSS operator and the homecare organizations early on began to investigate whether and how the robots could be used to improve operational efficiency of the homecare organizations. These operational efficiency gains (i.e., operational value) would generate the required cost savings to preferably counter, but at least partially pay back the monthly cost of the robots. Next, we discuss (4.1) how such operational value by the PSS is created, (4.2) how the operational value can be determined, (4.3) how the value can be retained through operational re-servitization, and (4.4) how the timing of deployment of robots in the PSS fleet can result in value loss (i. e., operational value opportunity left uncaptured). To conclude we describe the operationalization of re-servitization by the PSS operator for the fleet of dispensers deployed in the homecare organization (4.5).

4.1. The mechanism for value creation in the homecare organization

We started by looking into the number of visits before and after the deployment of a robot. The mechanisms for creating value for the home care organization were initially assumed as follows: if the robot can be used to reduce enough visits per month, then the reduced visits would provide enough cost savings to pay back the monthly fee of each robot, at least partially. To evaluate if such visit reductions are possible, we did simple analyses on pilot deployments comparing the average monthly workload 8 weeks before the deployment of each robot with 8 weeks after the deployment. While the pilot implementations with around 10 to 20 robot users per municipality showed some fleet-level visit reductions, these were not enough to compensate for the cost of the robot fleet.

This initial mechanism for value creation raised other issues as well. First, the cost savings were calculated using the average cost of visits of around 40 Euros a visit that also included time not spent directly at a client. An activity-based costing exercise on limited information estimated that the direct salary costs of such visits would be lower at 10 to 20 Euros, reducing fleet-level value creation further. Second, the sum of these client-level cost savings seldom equaled the workload of one nurse. As nurses are salaried employees, this implied no cost savings on the organizational level. Third, on the client-level visit reductions in the pilots varied significantly, with a vast majority of clients not showing any change at all, prompting the homecare organizations to consider reducing the already small pilot fleet sizes. Finally, our discussions with homecare personnel and observations of the client selection meetings suggested that many robot deployments were not even aiming at a reduced number of visits, even if such reduction was one of the most important measures for the decision making. Overall, the reduction of medicine administration visits increased flexibility for timing visits, but the operational value of such flexibility remained unclear.

The work done by Groop et al. (2017) turned out to be a game changer for our study. Their findings prompted us to closely investigate the value creation potential for more flexible timing of visits, and more specifically the impact of reducing the morning peak hour. Groop et al. (2017) recognized how the reduction of the morning peak is an effective mechanism for cost reduction in the homecare organizations. Nurses tend to be very busy in the morning hours, yet once the morning rush hours are over, there is no longer enough direct client work to keep everyone in the nurse teams occupied (Lyly-Yrjänäinen et al., 2017). Here, a few eliminated (or rescheduled) visits from the morning peak can reduce the resource need of the whole organization. Fig. 1 shows a clear morning peak in the case homecare organization at the outset of the rollout with the difference in workload between the morning peak (7–10 a.m.) and afternoon peak (12 a.m.–2 p.m.) around 30 percent.

Whereas Groop et al. (2017) focused on moving non-time-critical visits from the morning peak to the afternoon, the robot dispenser PSS can be used to reduce the peak further by replacing time-critical morning visits for administration of the medication with administration by the PSS. If the client needs a bath, say three times a week, the bath can now be rescheduled to the afternoon non-peak hours.

The cost savings potential by reducing the peak hour constraint on the size of the nursing staff is much higher than by removing other visits. In the studied operations, eliminating just a few visits from the peak hours can bring the number of needed nurses down. While the average cost of a removed homecare visit was around 10 to 40 Euros, reducing the need for employing a nurse in a shift can save around 160 Euros per day per nurse. Importantly, the reduction in staffing directly reduces the bottom-line cost of the homecare organization, delivering the cost savings that the municipalities seek. In addition, reduction in the peak and the reductions in resources that this enables directly influence a key metric of homecare: the share of direct time spent at clients, making this value creating mechanisms also resonate with the quality of care objectives. Unlike one might assume, a reduction in the number of visits is perceived positively by many homecare clients. Homecare clients that prefer independent living, hence, welcome the reduction of visits (especially during the morning hours) and the hassle of quick medicine administration visits, called U-turn visits by the nurses. Similarly, instead of short daily visits, clients prefer less frequent but longer visits (enabling some socialization) during the non-peak hours. Finally, it is important to note that in the current situation in the Nordics, a reduction in the morning peak does not result in layoffs; there is a persistent shortage of nurses, number of homecare clients is constantly growing

[3] The study by Rantanen et al. (2017) shows that homecare clients were able to achieve around 99% medicine adherence using the robot and that 100% of patients found it easy to use. Moreover, in case of the 1% non-adherence, the robot will alert the care team, enabling them to make corrective actions appropriate for each situation. Thus, the robot has been recognized as an applicable solution for assisted medicine administration with positive health impacts for the clients.Without caregiver intervention, the actual level of medicine adherence remains unknown. Some studies estimate that as much as half of patients do not adhere with the medicine prescribed to their chronic diseases (Epstein and Cluss, 1982), even though medicine adherence has been linked with positive health impacts regardless of whether the treatment is real or placebo (Dimatteo et al., 2002; Epstein, 1984). Caregiver intervention can improve this adherence rate, but with the added cost of additional workload, typically during peak hours.

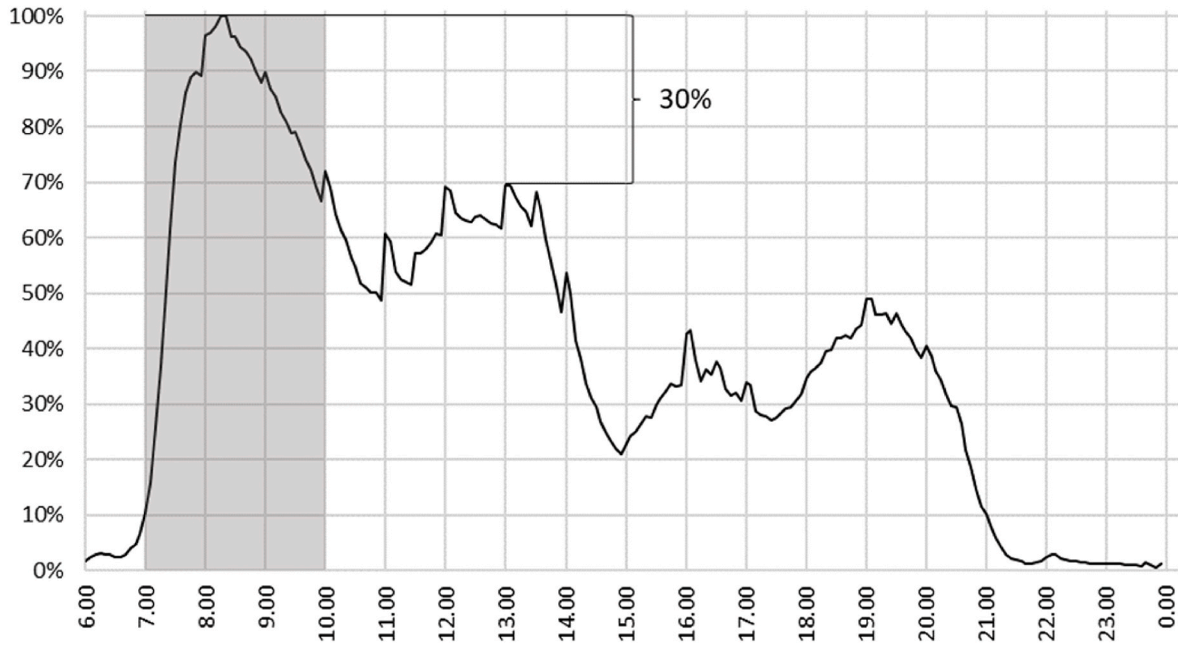

Fig. 1. Nurse workload distribution in home care organization – February 2018.

and hiring nurses is challenging.

> *"There are no more nurses, period. The situation has become horrible. We have had a vacancy for several months already without any potential candidates we could consider recruiting."* – Director of elderly care

A main challenge for addressing the morning peak constraint was that so far in our analyses, the pilot sizes had been rather small, and the client selection processes had prioritized 'easy' clients with whom nothing could go wrong even if the robots did not work as intended. The morning peak hour flexibility had been already recognized in home care, but it had not been a priority objective for deployments. This changed when the case homecare organization—that had already piloted the robots—decided to make a large-scale deployment of robots (scaling up from 20 robots to 301 robots in use by the end of March 2020) with morning peak reduction as one of the key objectives for the deployment.

4.2. Determining the operational value using RDD and LPA analyses

Next, the operational value of this large deployment is determined using RDD and LPA Analyses. See Appendix B for details of how the analyses were conducted.

4.2.1. RDD – determining operational value

We face three challenges in determining the operational value of the PSS for the case homecare organization. First, each client has a unique deployment date, since the robots are deployed whenever new clients are identified. Second, there is no stable alternative workload level useful for comparison, as the workload of elderly homecare clients varies among clients and change dynamically. Third, we cannot simply compare the morning peak for two points in time before and after deployments since deployments can be years apart and the client pool of the homecare organization is constantly changing (clients entering and leaving homecare).

Therefore, the remaining approach is to verify if a morning peak hour workload reduction can be identified on a client-level and then estimate what that client-level reduction would mean for the organization-level. Here, Regression Discontinuity Design (RDD), provides the means for verifying the operational value of the robot deployment on the morning workload. We ran the RDD analysis on both morning workload (as direct time spent at client during peak hours 7–10 a.m. in minutes) and morning visits (number of visits during morning peak hours 7–10 a.m.). The results of our RDD analysis are shown on Table 3 and the predicted model of workload and visits illustrated in Fig. 2.

The analysis identifies a statistically significant ($p < .001$) discontinuity of negative 13.2 min in the time spent at the client's home (or −0.96 visits, $p < .001$) per week during the morning rush hours. With statistically significant discontinuity we can make the causal link between deployment and morning workload reduction since the discontinuity is clearly visible in a visual test with binned plot of mean workloads. In practice, this means that for each client in our sample, the morning peak hour workload was 13.2 min or 0.96 visits less on the first week of robot use (treatment) than it was on the week before it (control). If we were to assume that the current clients all deployed the robot at the same time and scale this robot-level discontinuity to the fleet-level size of 301 concurrent dispensing robots, this would mean 9 h and 29 min of reduced peak hour workload per day (approximately 41 morning visits per day). While this reduction is shared among multiple homecare teams, it indicates the opportunity that PSS deployment creates for more efficient resource planning. This was recognized by a team leader who had had trouble finding suitable nurses to recruit for a vacancy that had been open for a long time.

Table 3
Coefficients and standard errors of the RDD analyses.

Coefficient	Morning workload		Morning visits	
	Estimate	Std. Error	Estimate	Std. Error
Discontinuity	−13.234***	1.536	−0.9551 ***	0.070
Week	0.008811	0.114	−0.005214	0.005
$Week^2$	−0.003750	0.003	−0.0001443	<0.001
$Week^3$	−0.00001696	<0.001	−0.00000008104	<0.001
D*Week	−0.5766 **	0.182	−0.05040 ***	0.008
D*$Week^2$	0.01546 **	0.005	0.001263 ***	<0.001
D*$Week^3$	−0.00001415	<0.001	−0.000003846 *	<0.001
R^2	0.0271		0.0886	

Note: *$p < .05$, **$p < .01$, ***$p < .001$.

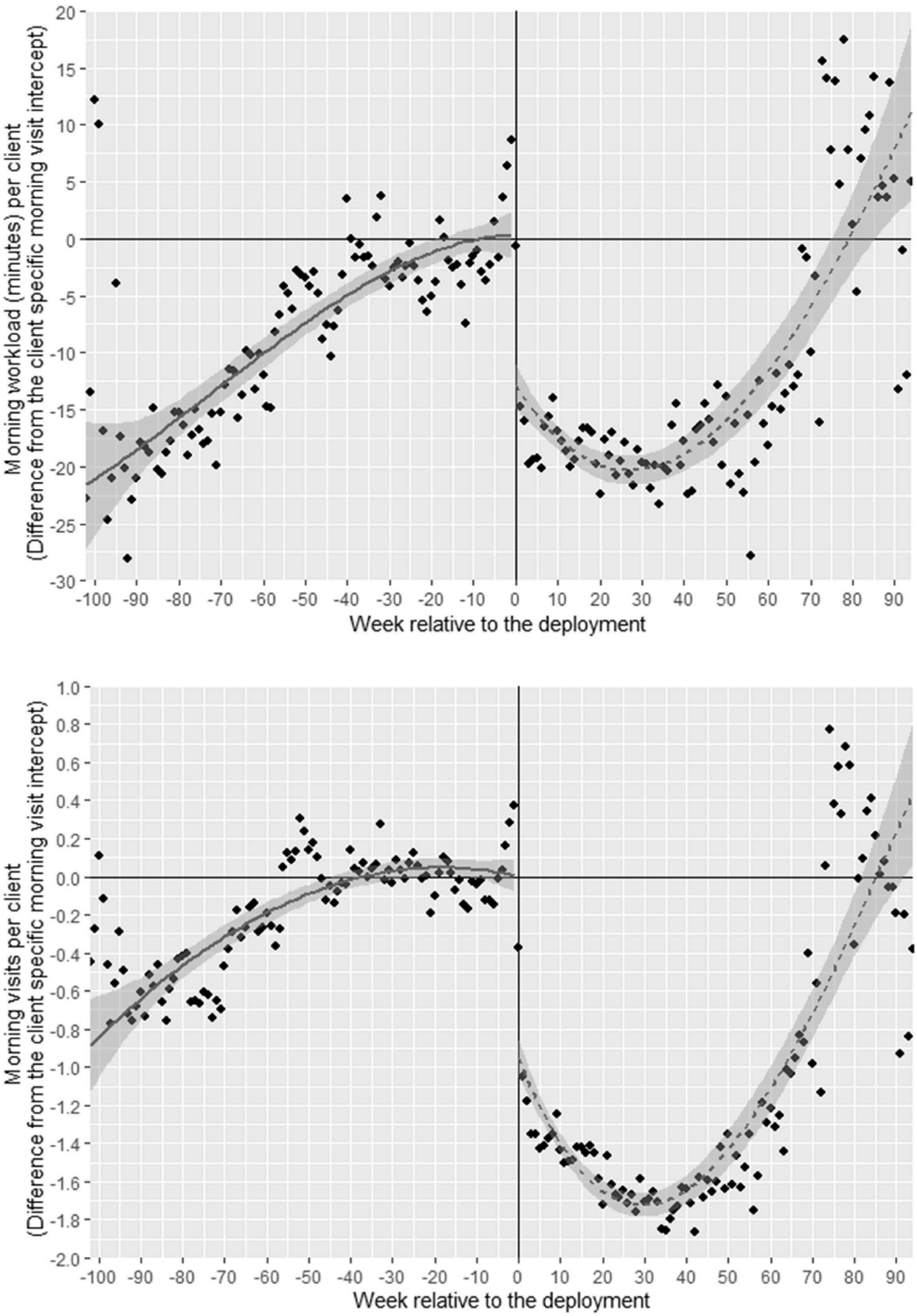

Fig. 2. Estimate plot of the RDD model including data points binned as the weekly mean workloads per client – minutes per client, and visits per client.

"The implementation of this robot technology has provided us concrete, tangible benefits. Thanks to the robot technology, our team made a decision not to fill one open nurse vacancy." – Homecare team leader

The slopes before and after the deployments are worth some thought as well. First, the workload development during the control group shows an incline, supporting our findings from talking with the homecare professionals that the workload of clients generally seems to increase over time (approximately 0.2 min per week on average). Intuitively, the point of reference for the value would be the workload level right before deployment, which in the model was set to zero. However, the trend right before deployment suggests that there might have been some incline in the workload if the robots had not been deployed. Thus, we have a nice point of reference right before the cutoff, but the value becomes harder to determine as time goes by.

Second, after the cutoff point there also seems to be a change in the slope of the treatment group, first declining for 30 weeks up to a 20-min lower workload on average than right before the deployment. Our prior findings suggest that the reduction of the visits seldom happens immediately after the deployment; the home care organization wishes to monitor whether the customer can manage their medication independently with robot assistance, hence explaining the delay of some days or even weeks.[4]

Third, the slope also increases after the 30 weeks and achieves the same morning workload level than before the cutoff point after 80 weeks. This supports our insights from discussions with homecare professionals that the operational value of the robots is only temporary, since at some point the condition of the elderly clients will deteriorate and they will either require support in using the robot, or other time-critical homecare activities that can only be done during the mornings. Moreover, we no longer know whether the reference point before deployment is valid, or if the trend of workload would have continued without the discontinuity enabled by the robots.

It is worth noting that the further away we move from the discontinuity on our running variable (x-axis), the less reliable the model becomes. On the other hand, the slopes provide some prediction on how the workload would have developed over the cutoff point, if there had not been any deployment. As such, the slopes expand the temporal view of the value indicating that value is in no way stable but evolves throughout the use cycle.

4.2.2. LPA – identifying different value profiles among clients

Our prior simple analyses and discussions with homecare personnel indicated that the operational value varied among clients. Therefore, we wanted to expand our operational value analysis to investigate if there were any contingencies for subgroups of clients whose morning peak hour workload evolution around the deployment shared similar characteristics. For this purpose, we used Latent Profile Analysis (LPA) to detect latent value profiles among the clients. In our analysis, the five-profile parametrization seemed to best differentiate latent subpopulations, without bringing unnecessary noise to the profiles. Fig. 3 shows a plot of the weekly mean workloads for each five latent profiles identified by the LPA.

The analysis clearly distinguishes five value profiles based on how the workload developed around the cutoff point. The identified profiles were similar to what we were expecting and had already observed among the clients of the homecare organization. The five operational value profiles in the order of measurable impact (1) 'Discontinuity Value, (2) 'Intercept Value', (3) 'Stability Value', (4) 'Proactive Value', as well as (5) 'Unrealized Value'.

First, 'Discontinuity Value' includes clients (n = 57, 16.2 % of the clients that had been using the robot) with a radical discontinuity after the robot deployment, where a daily visit reduces into a refill visit every second week. Second, 'Intercept Value' shows clients (n = 63, 17.9 % of the clients) with an increase in morning visits towards three visits per week before the deployment, followed by a radical decrease into refill visits every second week after deployment. Third, 'Stability Value' shows clients (n = 75, 21.3 % of the clients) whose visits were increasing towards daily visits before deployment which is intercepted by the dispensing robot and reduces slightly after the deployment. Fourth, the 'Proactive Value' includes the largest number of clients (n = 100, 28.4 % of the clients) with less than 1 occasional visits per week where the robots were deployed proactively to avoid an increase in visits. However, without any reference it is hard to say whether the timing of such proactive deployment was appropriate or too early. Fifth, 'Unrealized Value' includes clients (n = 57, 16.2 % of the clients) with daily visits that could not be reduced. With some of these clients, the inability to reduce visits was expected and other reasons justified the deployment. However, there are most likely also clients where the inability to reduce was unexpected.

To summarize, these two analyses show the peculiarities of the mechanisms of operational value creation. RDD analysis determines that the operational value is indeed present and shows that the value is not stable, but instead changes over time. However, LPA analyses expand this finding and show how the value differ among clients in five typical ways. These value profiles indicate that capturing operational value is contingent on the purposeful robot deployment. Finally, RDD model shows an increasing tail for the workload, supporting our field findings about the fleeting operational value. Therefore, there is a need to also consider when the care organization should take away the robots from clients and redeploy them with other clients. This reuse of robots is required to reintroduce the already diminished client-level operational value with another client to enable organization-level operational value retention. While decisions about reuse cannot be solely based on operational value,[5] knowledge about the operational value being diminished would support such decisions.

4.3. Retaining PSS operational value through operational Re-servitization

The previous chapter described the mechanisms of value creation, but in our further analysis, we will discuss four factors that indicate a need to for the PSS operator to actively manage the fleet-level value for the homecare organization. First, value in the context of homecare is not stable, but dynamic and needs to be actively managed. Second, there are no reliable data-based points of comparison, since we do not have a control group for the treatment group. This means that at best we can compare the workload in the treatment period with the last point of workload in the control period. Third, following the findings of the LPA analysis, the deployment of robots acts as an enabler for an operational value. It defines the value profiles that the care organization achieves with each client. Therefore, it is crucial that the nurses purposefully deploy the robots to the customers based on the intended value. Fourth, based on the tails of the RDD model, the value deteriorates over time. This means that the robots in the PSS fleet have to be redeployed with

[4] On a methodological note, we could apply a fuzzy approach, where not all clients achieve treatment status at the cutoff point, i.e., after robot deployment. However, in our case, it is not necessary since we know exactly who are using the robot and when. If we had the data when the care plan was redesigned after the dispensing robot deployment, we could utilize that as a cutoff point. However, again there could be several redesign points and these redesigns are not always documented making tracking them difficult. Thus, even if the discontinuity is not always exact at the deployment date, we can at least accurately pinpoint a clear cutoff point.

[5] On one hand, sometimes other value than operative—such as the improved medicine adherence, safety, and the autonomy these provide for the clients—justifies continuing use even if operational value is diminishing. O the other hand, another reason for redeployment is client's incapability of using the robot independently, triggered either by increased workload or increase in medicine administration related alarms.

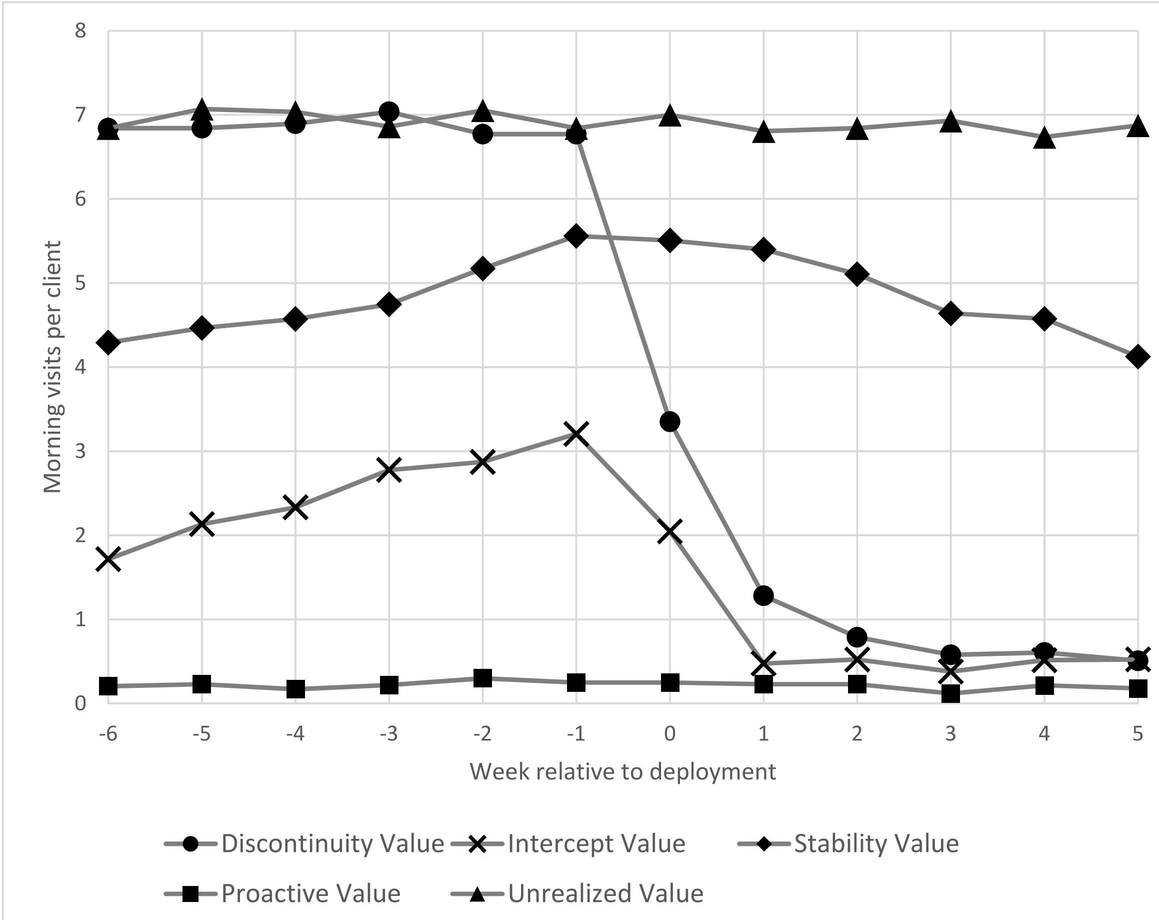

Fig. 3. LPA results with mean weekly workload for each operational value profile.

new potential clients, preferably as soon as operational value is no longer achieved. However, a practical design to achieve such a re-servitization is not a simple task for the PSS operator, or the homecare organization.

To operationally re-servitize to benefit the homecare organization, the robot that no more creates value should be redeployed to a client with identified value potential. It is the main task, as it is deployment and redeployment with clients that creates value on the organizational-level, and offsets the cost of the PSS. A challenge in the deployment task is that there are at least five variables affecting the client-robot fit and the expected operational value. First, as part of deployment, input from the nursing staff is needed to assess the feasibility of deployment with a client (e.g., considering positive attitude towards medication, sufficient cognitive capabilities). Second, the appropriate timing of deployment needs to be determined (e.g., Should the robot be deployed right away, or is the client a potential future client?). Third, nursing staff need to plan the redesign of care activities to enable the operational value (i.e., Can morning visits be reduced or rescheduled to decrease peak hour workload?). Fourth, the new plan needs to be implemented, if possible, immediately when the robot has been deployed. Fifth, if the deployment does not result in such expected care redesign, redeployment of the dispensing robot needs to be considered.

The need for redeployment raises when the robot is no longer feasible either cognitively (client no longer can use the dispensing robot independently) or from value perspective (removing the robot from a client would no longer have any operational effect). As the condition of the client deteriorates enough, they will most likely move forward to more work-intensive care (e.g., assisted living or nursing homes). There the robot is no longer feasible—at least from the morning peak hour value perspective—and should be removed and redeployed with another client. However, to retain the fleet-level value, it might be necessary to redeploy the robot even before the client exits home care. As shown in Fig. 2, when moving right after the discontinuity point the effect after the initial drop, gradually climbs back, indicating that the workload has returned to the level prior to deployment and the clear operational value has disappeared after around 80 weeks on average.[6]

Fig. 4 shows an example of value deterioration taking a client from 'Discontinuity Value' profile and operational value in managing the morning peak. In the graph, the y-axis shows the direct time spent at the client per day, x-axis the days in relation to the deployment and the colors differentiate between morning visits and visits done outside morning hours. As the graph shows, the client has recently become a homecare client with a short 10-to-20-min visit every morning (dark gray) and another visit outside morning hours. However, the daily visit could be removed after the deployment and the client was able to manage with a short meeting every two weeks, with some variation every now and then. The value, however, was only temporary; something happened after 23 weeks (about five months) when the client began to require longer, 15-to-30-min visits every day, though still outside the morning peak hours. One year and five months later the condition of the client—for whatever reason—quickly deteriorates and

[6] Value has disappeared in the sense of that the workload is considered to be on the same level as right before the deployment. It is worth noting that using the point before the deployment as reference is no longer valid after 83 weeks of use and —based on the trend in the control period—the reference point would be higher than before cutoff point.

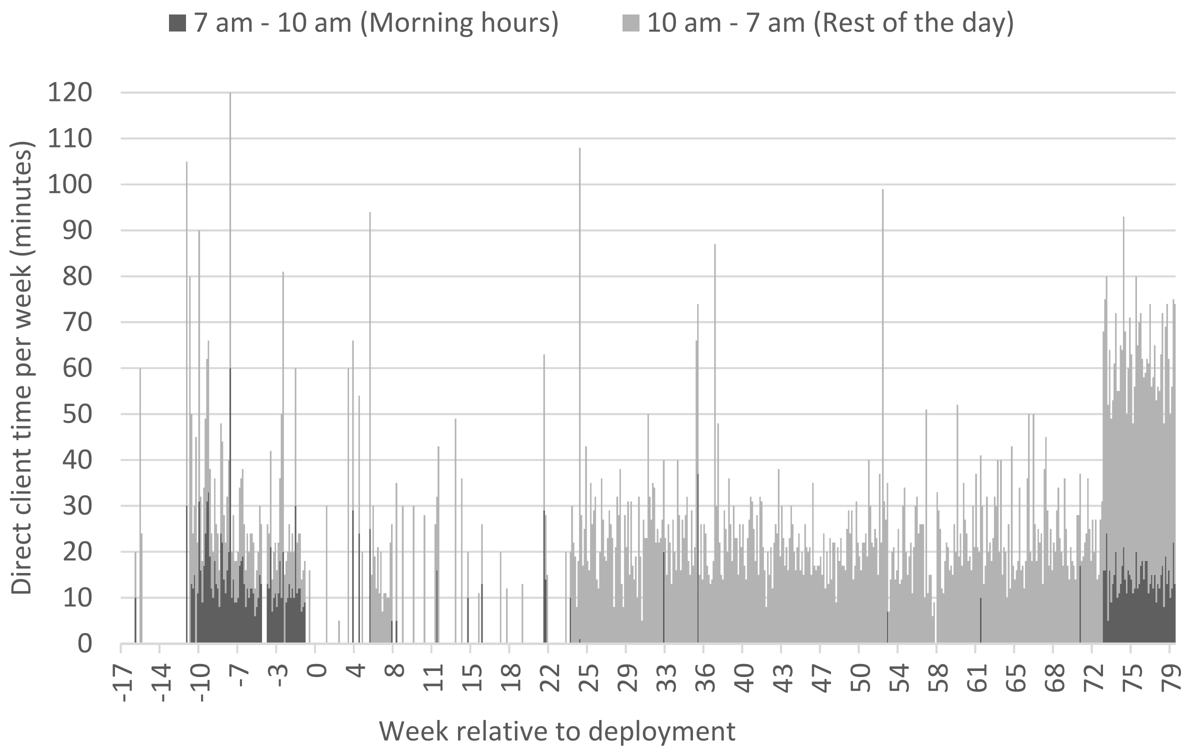

Fig. 4. An example client with value deterioration.

the workload almost triples with a daily 10-15-min morning visits and other daily visits with around 45 min of workload in total outside peak hours.

Even though the deployment was purposeful for managing morning peak hour workload and successful in achieving it, the above figure demonstrates how the achieved operational value is gradually diminished. Often the change of workload is not linear as it is based on a decision or reaction to changes in the client's condition. Client's condition can change either gradually or with drastic changes, for example, if the client falls and becomes injured. The eroding value provides an interesting insight for operational value retention, and furthermore for the PSS operator to include re-servitization in the design of the PSS. We will return to this topic in Section 4.5. below.

4.4. 'Lost opportunity' – the challenge of losing measurability by maximizing value

A typical transition from independent medicine administration to assisted administrations without a dispensing robot proceeds as follows. Initially, a client with good cognitive skills can administer and replenish their medication independently, requiring only few visits per month. Once the client's cognitive capabilities deteriorate, the first step is to distribute the client's medicines in a pill dispenser, still manageable with one or two non-time critical weekly homecare visit. With the cognitive capabilities deteriorating further, the homecare organization may no longer rely on the client to administer the medication appropriately using the pill dispenser and, as a result, must start scheduling visits according to the medication intervals. At some point, the condition changes again so that the client will require other morning activities, such as administration of liquid medicine or taking measurements, requiring even more time during morning peak hours. Even later, other health issues emerge, making it no longer possible for the client to manage at home—regardless of the number of nurse visits—and the client moves to a retirement home.

The transition process raises the question: what would be the best time to deploy the robot? However, before we can answer that question, we need to discuss how these value profiles relate to one another. Direct value shows the most promising discontinuity, based on the used evaluation method. However, such deployment—where the nurses already were visiting the premises of the clients to remind them in taking their medicine—does not capture the full value potential. If it were already possible to reduce morning peak hour visits by using the dispensing robot, then those visits should have been avoided with the robot deployed earlier. We refer to these avoidable visits as 'lost operational value opportunity'.

Then what part of the value potential is captured and what lost? Let us assume that there is a window of value potential for each client, some of which is captured through a purposeful deployment, and the remainder of which is lost due to the timing of the deployment and the redeployment. A deployment too late or a redeployment too early means that there remains value potential that could not be captured and is thus 'lost'. Moreover, a too early deployment or a too late redeployment also creates unnecessary costs outside the value opportunity window (i.e., the robot is being used without an operational value). Fig. 5 illustrates the lost and the captured value opportunity building upon our value model in Fig. 2. The lost opportunity is a share of the excess workload (i.e., the realized workload that surpasses the minimum level of workload after robot deployment) between the point with the lowest level of workload achievable after deployment (e.g., week 30) and the previous point before deployment when the same level of workload was achievable (e.g., week −100).

In Fig. 5, the lowest level of workload was approximately 20 min less than at the point of deployment, achieved around 30 weeks after deployment. The same level of workload was previously achieved around 100 weeks before deployment. If such level of workload is possible with the robot, and the condition of the clients is not getting better, then such level of workload should have been also possible earlier. Based on this logic, some part of the excess workload between weeks −95 and 30 should have been avoidable if the robots had been proactively deployed earlier or the learning curve between weeks 0 and 30 had been shortened. It should be noted, though, that this lost potential is client specific and most typical for clients in the 'Discontinuity

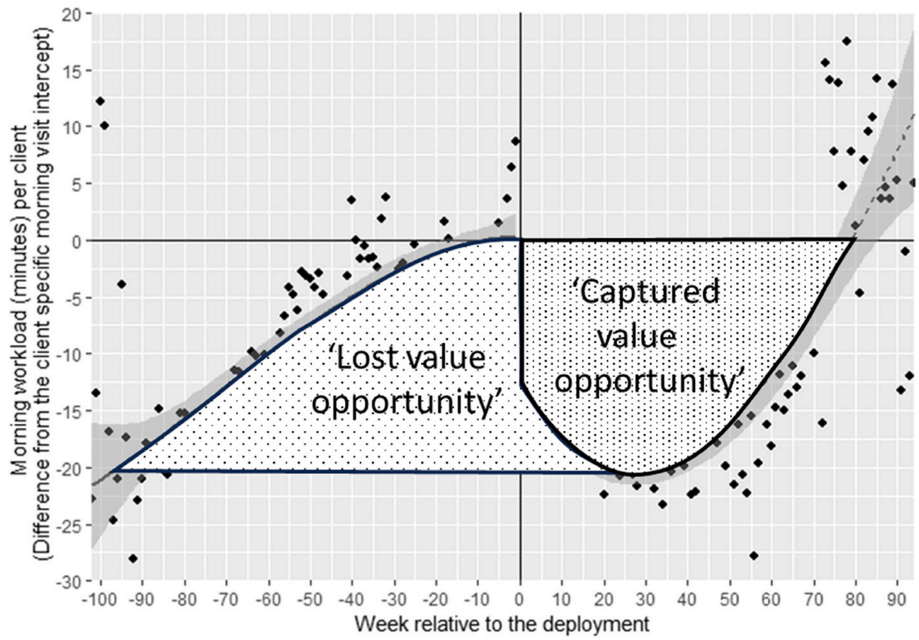

Fig. 5. The lost opportunity and captured value building upon the estimate plot in Fig. 2.

Value' profile.

Identifying the captured value is also difficult without a timelier point of comparison than the visit records. However, we can estimate the captured value following similar logic as previously. The statistically significant discontinuity suggests that the workload could be reduced with the robot, indicating that as long as the workload after deployment is below the point before deployment (i.e., zero), then some value should be captured. However, due to increasing trend of the slope in the control period, as well as the deteriorating conditions, it is likely that as time goes on, the workload without the robot would have been even higher than before deployment. Thus, a redeployment at week 80 might be too early, resulting in additional lost opportunity that we are unaware of.

In response to the question 'when is the best time to deploy the robot?', the value potential approach suggests that robots should be deployed preventively (i.e., according to the 'Proactive Value' profile) or as soon as possible when the workload starts to increase ('Intercept Value' profile). Similarly, the redeployment should be done right before the value opportunity window closes, so that the robots are not left with clients with whom the operational value opportunity is not realized ('Unrealized Value' profile). This way, we are able to also capture the opportunity that is lost if the deployment was done to achieve a Discontinuity Value. Here, the Discontinuity Value becomes counterintuitive, showing the largest value, but resulting in most lost opportunity. As such, Proactive Value deployment can capture more value, but with the expense of losing the measurability of the value. However, identifying these points in time is not simple, and the visit records might no longer be the best source of data to make such decisions.

4.5. Design proposition: smart product-based re-servitization of the PSS

The empirical analysis shown above reveals that choosing the optimal deployment and re-deployment times is a non-trivial task. For deploying, the challenge is to deploy early enough to capture value but not too early, wasting limited capacity. For re-deployment, the challenge is that there is no apparent client-level indicator for when the robot has stopped creating organization-level value. The client is unlikely to request the reallocation of the robot when the frequency of visits by nursing staff increases. It will also take some time for nurses to realize that a robot is redundant, as many different nurses visit the client. There is also no clear issue for a nurse with continuing the robot deployment even if the operational value diminishes; the nurse can do other activities while supervising that the robot administers the medicine as intended. Therefore, without some other actor actively managing redeployment, dispensing robots might remain deployed until the client exits homecare.

Next, we will examine how re-servitization (i.e., detection, capture, and re-capture of value creation opportunity for a product in use by the PSS operator) can be implemented for the robotic dispenser PSS in the examined homecare operations, where both deployment and redeployment are problematic. Ad hoc periodic analyses of the visit records (as done in this study) are ineffective in detecting and creating opportunities for the homecare organization. They do not help identify potential clients for the dispensers; even if they did, they would highlight potential clients too late, always resulting in some 'lost opportunity'. Automatic and continuous visit records data analysis with a threshold for changes in the workload of clients might be possible to identify the most value-creating deployment opportunities (i.e., achieve an Intercept Value profile). However, the PSS operator would have to get an access to visit records individually with each homecare organization, and the PSS does not currently collect any similar data that could be used to detect deployment and re-deployment opportunities, which depend on many factors related to the condition of clients.

We will now consider alternatives the PSS operator can use to determine deployment and redeployment opportunities for the homecare organization. For redeployment, autonomous detection of a nurse is an available alternative relying on the robot as a smart connected product (Porter and Heppelmann, 2014). The robots create operational value in the morning peak by replacing a nurse by administering the medicine. This operational value is not realized if a nurse is present during or near the administration time. Thus, the robot could be designed to detect if a nurse is present. For example, the robot could scan the room for nurses with a specific app on their smartphone. Autonomous detection of caregivers by the robot would enable the PSS operator to use the robots as the technological means to monitor operational value creation. With this approach, the PSS operator can inform the care organization of the diminishing value of robot deployment when nurses are present during medicine administration in the morning peak hours.

For deployment, the PSS operator could develop novel technologies such as machine learning. The technology could be used to automatically detect patterns in the workload, indicating that a deployment opportunity is approaching. However, the effectiveness of such technologies for monitoring and detection is limited by setup and implementation. With our help the PSS operator piloted an AI-based solution for identifying clients based on the short descriptions of visits (e.g., the AI solution would highlight clients who have morning visits with only a description of medicine administration). The pilot proved capable, but slower than experienced care teams, in identifying potential clients. However, the AI solution was deemed inefficient because of the required system implementation and other time-consuming set-up tasks. Implementation was too slow to support first deployments, where the nurse teams required the most assistance.

An alternative is to use a precursor solution. The robot cannot detect value creation opportunities before it is deployed with clients, but there may be a less expensive solution that can: including traditional pill dispensers in the PSS. The PSS operator deploys the precursor solution as a simpler and lower-cost dispensing solution, which then detects the need for the more advanced robot dispenser. In fact, use of a precursor solution utilizes the detection of the precursor solution's redeployment point as the trigger to detect deployment opportunity for the dispensing robot. In its simplest form, the precursor solution would be the addition of a QR code on conventional pill dispensers for the nurse to report that a client has not taken the prescribed medications. A more advanced precursor solution would be to enhance the design of conventional pill dispensers with sensors and connectivity to detect and report missed medications.

By developing and deploying autonomous detection based on smart product technology in the design of the robot dispenser and its precursor, the PSS operator can include re-servitization in the design of the PSS. This way it becomes possible to detect opportunities for robot dispenser deployment by monitoring medicine adherence for homecare clients with conventional dispensers, and opportunities for robot redeployment by monitoring nurse presence for clients with robot dispensers. To summarize, we propose an ***operational design for re-servitization of the PSS*** for dispensing prescription medication to homecare clients as follows:

For deployment the PSS operator develops **precursor solutions** to detect opportunities to create operational value for the use of the robots in the homecare organization. **For redeployment**, the PSS operator includes as a function of the robots the **autonomous detection of nurse visits**.

The PSS design enables re-servitization based on the combined use of smart conventional dispensers, as precursor products, and robot dispensers as the core products. Reduced medication adherence for clients using the precursor solution prompts deployment of the robot dispenser (and redeployment of the precursor solution), while the presence of a nurse during the dispensing of medicine flags decline in operational value and redeployment opportunity. With this combination of functional extensions, the PSS design improves the value of the robots and incorporates re-servitization of the PSS in the design of the PSS itself.

Moreover, by using the redeployment point of a precursor solution as the trigger for deployment of the more advanced technology, the medicine dispensing robot's redeployment could also be used to identify opportunities for deployment of successor solutions, such as the video assisted medicine dispensing robot recently developed by the PSS operator. As such, the re-servitization provides opportunities for the PSS provider for chaining appropriate solutions to capture the value creation opportunities as the needs of the clients change over time.

5. Discussion

In our study, re-servitization goes beyond reuse after obsolescence (den Hollander et al., 2017; Mellal, 2020; Reike et al., 2018) by accounting for the value creation of alternative deployments. The operationalization of re-servitization detects, captures, and recaptures value for a fleet of dispensing robots, deploying a limited set of resources to improve the performance of the homecare operations. We achieved this by framing the problem from the perspective of PSS operator to create and retain the value of the fleet of robot dispensers. Focusing on the use of the product to address the problem of actionable measurement, we propose an operational solution design for the deployment and redeployment of the PSS using smart connected products.

Measuring product-service performance is challenging if product value varies over time (Grönroos and Voima, 2013). This makes it difficult to detect the opportunities to deploy and redeploy the product in ways that create value (Wang et al., 2022). Conventional value retention models (Reike et al., 2018) assume the buying or leasing customer is responsible for using a product to create value and, when no longer needed, making it available for other users and uses (den Hollander et al., 2017). However, novel solutions are needed for situations where market mechanisms cannot be relied upon for effective deployment and redeployment of products (Spring and Araujo, 2017). In the robot dispenser PSS, decision-making shifts from the client and homecare organization towards the PSS operator, requiring the PSS operator to develop an actionable measurement of value and a new type of operation to respond to temporary value.

To determine the temporary value of the PSS, we examined the effect of deploying the robot dispenser on the productivity of the homecare ecosystem (Talmar et al., 2020). The addition of PSS and its operator to the existing ecosystem (clients, nurses, physicians, and pharmacies) created opportunities to modify operations and reduce nurse requirements, with operational value creation stemming not just from the dispenser's use, but from broader operational changes. Reduction of staffing requires the care organization to actively shift visits from the morning peak (Groop et al., 2017). Making these changes requires a prompt, actionable measurement of deployment opportunity and operational value creation. Detection of reduced medicine adherence signals opportunity for dispensing robot deployment, while regular nurse presence during morning peak indicates need for redeployment.

The PSS operator can implement actionable measurements in the PSS design by using smart, connected technology for the robotic dispenser and including a smart, connected conventional dispenser as a precursor solution. We propose these as general principles to be used in PSS design, enabling the PSS operator to continuously ***re-servitize,*** i.e. actively guide the user organization in where and when to deploy the PSS. This is a novel smart solution-based practice (Huikkola et al., 2022), which relies on the deployment sequence of increasingly sophisticated products as the means for achieving the service objectives.

However, a limitation of our research is that we have not yet implemented and tested the proposed smart and connected solution designs for detecting the opportunity to redeploy precursor solutions and the robotic dispensers. This is a task that we leave for further research. Furthermore, we have only investigated re-servitization for one specific PSS. Further research is needed to identify and study other settings where value creation is temporary, and explore the possible solution designs for re-servitization.

To conclude, the design and operation of PSS in dynamic settings has received limited attention in research, despite its relevance to digitalization and servitization (Kohtamäki et al., 2021, 2022). Our study on the use of robot dispensers for prescription medication in the homecare ecosystem address value creation opportunity and actionable measurement, contributing re-servitization of PSS as a value retention option and available solution design to theory.

CRediT authorship contribution statement

Vesa Tiitola: Writing – review & editing, Writing – original draft, Visualization, Software, Resources, Project administration, Investigation, Formal analysis, Data curation, Conceptualization. **Jouni Lyly-Yrjänäinen:** Writing – review & editing, Writing – original draft, Supervision, Resources, Project administration, Investigation, Funding acquisition. **Mika Apell:** Writing – review & editing, Validation, Resources, Funding acquisition, Conceptualization. **Mikko Rönkkö:**

Writing – review & editing, Visualization, Methodology, Formal analysis. **Jan Holmström:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization.

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APPENDIX A. The robot dispenser the enabling innovation ecosystem

A care robot is a machine that autonomously or semi-autonomously performs tasks related to physical or emotional care (Goeldner et al., 2015). Care robots allow patients to continue living at home longer, increasing their autonomy, and assist nurses in providing efficient and effective care in both home and institutional settings (Baer et al., 2014; Decker et al., 2011). Our case company provides robots that dispense prescription medications for memory-impaired homecare clients (Rantanen et al., 2017). The robot is deployed at a homecare client's home, helping the client administer her medication independently, hence improving medication safety and adherence.

The medicine dispensing robot relies on a combination of solutions provided by a different actors in the associated innovation ecosystem (Talmar et al., 2020). In addition to the robot, three complementary solutions are needed for the medicine dispensing service to work: (1) automated dose dispensing technology, (2) artificial intelligence and machine vision, (3) electronic prescriptions and centralized information systems for prescriptions. Each technology is a required component for a functioning medicine dispensing service because the homecare operation needs to both reliably dispense the prescribed medicine and adjust the care process according to the changes in the medical condition of the clients. Each technological component is provided by a different actor of the innovation ecosystem.

Regarding the functionality of the PSS, the most important component is the automated dose dispensing technology (Sinnemäki et al., 2013, 2014, 2017), also called multi-dose dispensing (Johnell and Fastbom, 2008) or prepacked multidose sachets service (Lyly-Yrjänäinen et al., 2017). The sachets service is provided by pharmacies. All the medicines of one client are dispensed in a roll of unit-dose bags known as sachets (Sinnemäki et al., 2013) with the client's name and administration time printed on each sachet (Larsen and Haugbølle, 2007). This technology makes the manual process of preparing the pill dispenser faster and more reliable, while also providing the basis for the robotic dispensing of medications.

For the robot to dispense the doses correctly, it needs artificial intelligence and machine vision (Wuest et al., 2016) for reading the text on the multi-dose sachets. The robot dispenser reads the information printed on the sachet and dispenses it autonomously based on this information (Lyly-Yrjänäinen et al., 2017), hence enabling distributed and interactive control of the dispensing robot (e.g., Lyly-Yrjänäinen et al., 2016).

Electronic prescriptions (Kierkegaard, 2013) and centralized information systems for prescriptions (Kivekäs et al., 2016) provide easy yet reliable information flow from the physician to the preparation of the multi-dose sachets, and all the way to robotic dispensing. The main purpose for introducing e-prescriptions is to reduce medication errors arising from, for example, medication-to-medication interactions and wrong dosage (Ammenwerth et al., 2008). However, when all the prescriptions of one client are in one place (Kivekäs et al., 2016), it not only enables more reliable cross-checks of medications (Kierkegaard, 2013), but the automated dose dispensing, too.

How it works

The medicine dispensing robot is placed in a client's home. The robot reminds the client when it is time to take the medicine first with a flashing green light, and when the planned time is reached, with human voice (Fig. 1). To access the sachet, the client must press the only button on the front panel. The volume of the reminder will increase until there is a risk that the safe time window between two medicine intakes becomes too short, in which case the sachet is stored in a locked compartment. When that happens, the robot notifies the homecare organization team who will then decide on the action to take.

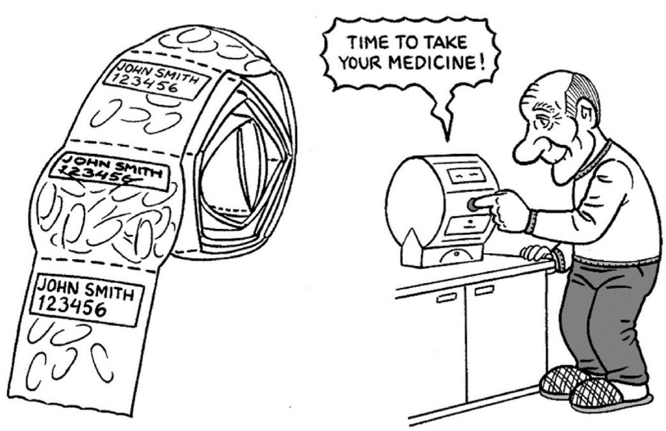

Fig. 1. The medicine dispensing robots of the PSS operator.

When a new automated dose dispensing roll is inserted in the robot, the robot visually checks that the roll belongs to the right patient and the time the first sachet is to be consumed, hence providing the dispensing settings for the robot; if the medication schedule is changed, the texts in the next automatic dose dispensing roll will automatically implement the new schedule. The robot has two tracks for the dispensing rolls, hence enabling flexibility with the replenishment visits (similar to KanBan). Both the machine vision and the feed system were built to handle sachets with a few pills (flat and square) as well as sachets full of medicine (almost like a ball with wrinkles) to achieve the reliability needed for a medical device.

The robot is not a stand-alone device sold to the homecare clients, but part of a PSS fleet provided with a monthly fee to homecare organizations. The homecare organization is responsible for the client's medical care and takes care of the activities needed for robot deployment and the replenishment of the dispensing rolls. They also take care of the automatic alarms in case the medicine is not taken, or if someone tries to break into the robot. However, the PSS operator provides the back-office processes needed to ensure reliable 24/7 performance of the service, monitoring and troubleshooting the robots remotely. They also provide 24/7 customer support to ensure that the nurses will be able to resolve anything related to the robots at any time.

APPENDIX B. The Regression Discontinuity Design (RDD) and Latent Profile Analysis (LPA)

Our quantitative analysis consists of two steps. First, we made a baseline RDD analysis to investigate if there was statistically significant discontinuity indicating that the dispensing robots have potential for operational value. Second, we ran an LPA to identify latent profiles among the clients, since our discussions with homecare representatives suggested varying operational value between clients.

In RDD, a statistically significant discontinuity at the cutoff point between control and treatment periods indicates causal relation to the treatment activity (Imbens and Lemieux, 2008). In our setup, we use RDD to identify potential discontinuities in the outcome variable (morning peak hour workload) around a certain cutoff point (robot deployment date) on the running variable (weeks in relation to the deployment date). We set the deployment of the robots as the treatment activity, splitting datapoints 'before deployment' in control and 'after deployment' in treatment. Thus, week 0 represents the week starting from the deployment date. We utilized 'plm' package (Croissant et al., 2008) in R for the RDD analyses. We modelled our regression model for the discontinuity using third degree polynomial to capture the dynamic changes but not to introduce too much noise to the model. We had reason to believe that there are more longitudinal changes in how the workload develops, which is why we used different slopes model to estimate the changes in the slope after the deployment. The variance in the intensity of workload and the number of visits among clients is taken into consideration by using a 'within' estimator for client-specific fixed effects. This normalizes the variance in workload among clients (i.e., sets the client-level workload right before the deployment to zero) providing a better estimate of the discontinuity.

RDD does not require randomized treatment and control groups but differentiates the data of each individual to control and treatment groups based on a clear cutoff point (i.e., deployment of the dispensing robot) (Lonati et al., 2018). RDD focuses on the discontinuity at this cutoff point (immediate value), but it also provides an estimate of how the slopes (i.e., the weekly care workload before and after the deployment) change after the cutoff point.

We then ran our LPA using the tidyLPA package (Rosenberg et al., 2019) in R studio. LPA identifies distinct latent profiles among the clients based on two parameters: number of profiles and the LPA model. Since our work with the homecare organizations suggested that the value varied between clients, we introduced LPA to identify if there are any latent profiles among the clients based on the evolution of their care workload. More specifically, we wanted to determine if the perception of nurses is correct, in that there is a subgroup of clients with a more significant value. Unlike the model in RDD where the within effect "normalizes" the data by giving a fixed effect variable for each client, in the LPA analysis we wanted to see the changes in visits in absolute values, typically varying between 0 and 7 visits per week. We investigated visits instead of workload in minutes as it gave a better representation of the changes in care plans (workload changes could be the result of longer or shorter visits). We chose a sample of 6 weeks before deployment and 6 weeks after to minimize the need for imputing and to focus on the care developments close to deployment. This dataset had 44 missing values (1,04% out of the total 4224 values) each representing the number of visits per week per client.[7] These missing values were filled with the mean value of each week by using single imputation package as part of the tidyLPA package, since tidyLPA package could not handle missing data and removing missing client rows was not a suitable option as we wanted a profile for each client (Rosenberg et al., 2019).

To choose appropriate number of profiles, we compared the models using Akaike Information Criterion (AIC), Bayesian Information Criteria (BIC), and sample-adjusted BIC (SABIC) and compared the best fit using bootstrap likelihood ratio test (BLRT). In a study by Tein et al. (2013), these selection methods were found most accurate in identifying an appropriate number of profiles. In Table 1, we show the Log-likelihood, AIC and BIC for having 1 to 6 profiles around the three models[8] (of tidyLPA). However, as typical for LPA analyses, both criteria did become smaller when more profiles were added (Masyn, 2013). However, the tidyLPA package could not fit Model 2 with 6 profiles, most likely due that the model did not converge.

Table 1
Log-likelihood, AIC, and BIC with one to seven profiles for model.

No. of profiles	AIC			BIC			SABIC		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
1	21464	21464	15587	21557	21557	15935	21481	21481	15649
2	17989	16298	15285	18131	16488	15683	18014	16332	15356
3	16055	14787	14830	16248	15073	15278	16089	14838	14910
4	15669	13770	14717	15913	14153	15215	15713	13839	14806
5	15372	**13038**	14726	15666	**13517**	15274	15425	**13124**	14824
6	15398		14751	15742		15350	15460		14859

As visible in Table 1, Model 2 seemed to provide best results among all criteria with five profiles having the lowest value in each criterion. The BLRT analysis on this five-profile model compared to four-profile model provided a p-value of 0.0099, indicating that the model provides a

[7] The missing values are explained by the turnover of clients as some clients are either deployed the dispensing robot before they have been a homecare client for 10 weeks, and vice versa, the dispensing robot might be redeployed with some clients before they have 10 weeks of use. Each client had data from at least 4 weeks before and after deployment.

[8] In Model 1 (class-invariant parametrization), the variances of weekly visits were set as equal and its covariances fixed to zero. In Model 2 (class-varying diagonal parametrization), the variances were set as varying, but the covariances fixed to zero. In Model 3 (class-invariant unrestricted parametrization), both variances and covariances were set as equal (Rosenberg et al., 2019). The entropy of all estimates in Model 2 were higher than 0.990.

significantly better fit than the four-profile model (Tein et al., 2013). We also reviewed the mean plots of each fit and the five-profile Model 2 plot seemed to best fit our empirical insights from the respondents. At the same time, we ensured that the increase in profiles did not radically change the findings of the LPA by running the analysis, by comparing the plots with lower and higher profile count models. Thus, we chose the five-profile model with varying variances and covariances fixed to zero (i.e., class-varying diagonal parameterization) for our analysis.

Data availability

The data that has been used is confidential.

References

Adeogun, O., Tiwari, A., Alcock, J.R., 2010. Informatics-based product-service systems for point-of-care devices. CIRP J. Manuf. Sci. Technol. 3 (2), 107–115. https://doi.org/10.1016/j.cirpj.2010.04.006.

Ammenwerth, E., Schnell-Inderst, P., Machan, C., Siebert, U., 2008. The effect of electronic prescribing on medication errors and adverse drug events: a systematic review. J. Am. Med. Inf. Assoc. 15 (5), 585–600. https://doi.org/10.1197/JAMIA.M2667/2/JAMIAM2667.F07.JPEG.

Anderson, W., 2007. Elderly migrants, primordial affinities, and ethnic identity. Cimexus 2 (2), 15–38.

Baer, M., Tilliette, M.-A., Jeleff, A., Ozguler, A., Loeb, T., 2014. Assisting older people: from robots to drones. Gerontechnology 13 (1). https://doi.org/10.4017/GT.2014.13.1.012.00.

Baines, Tim S., Lightfoot, H.W., Evans, S., Neely, A., Greenough, R., Peppard, J., Roy, R., Shehab, E., Braganza, A., Tiwari, A., Alcock, J.R., Angus, J.P., Basti, M., Cousens, A., Irving, P., Johnson, M., Kingston, J., Lockett, H., Martinez, V., et al., 2007. State-of-the-art in product-service systems. Proc. IME B J. Eng. Manufact. 221 (10), 1543–1552. https://doi.org/10.1243/09544054JEM858.

Baines, Tim S., Ziaee Bigdeli, A., Bustinza, O.F., Shi, V.G., Baldwin, J., Ridgway, K., 2017. Servitization: revisiting the state-of-the-art and research priorities. Int. J. Oper. Prod. Manag. 37 (2), 256–278. https://doi.org/10.1108/IJOPM-06-2015-0312.

Basak, S., Baumers, M., Holweg, M., Hague, R., Tuck, C., 2022. Reducing production losses in additive manufacturing using overall equipment effectiveness. Addit. Manuf. 56, 102904. https://doi.org/10.1016/j.addma.2022.102904.

Croissant, Y., Millo, G., Croissant, Y., Millo, G., 2008. Panel data econometrics in R: the plm package. J. Stat. Software 27 (i02), 1–43. https://doi.org/10.18637/JSS.V027.I02.

Damha, L.G., Trevisan, A.H., Costa, D.G., Costa, J.M.H., 2019. How are end-of-life strategies adopted in product-service systems? A systematic review of general cases and cases of medical devices industry. In: Proceedings of the Design Society: International Conference on Engineering Design, vol. 1, pp. 3061–3070. https://doi.org/10.1017/dsi.2019.313, 1.

Decker, M., Dillmann, R., Dreier, T., Fischer, M., Gutmann, M., Ott, I., Spiecker genannt Döhmann, I., 2011. Service robotics: do you know your new companion? Framing an interdisciplinary technology assessment. Poiesis Praxis 8 (1), 25–44. https://doi.org/10.1007/S10202-011-0098-6/TABLES/1.

Dimov, D., Maula, M., Romme, A.G.L., 2023. Crafting and assessing design science research for entrepreneurship. Entrep. Theory Pract. 47 (5), 1543–1567. https://doi.org/10.1177/10422587221128271. https://repository.tudelft.nl/islandora/object/uuid/3Ae0ce994d-e402-44ef-8bed-10c922542d77.

den Hollander, M.C., Bakker, C.A., Hultink, E.J., 2017. Product design in a circular economy: development of a typology of key concepts and terms. J. Ind. Ecol. 21 (3), 517–525. https://doi.org/10.1111/JIEC.12610.

Eftekhar, M., Van Wassenhove, L.N., 2016. Fleet management policies for humanitarian organizations: beyond the utilization–residual value trade-off. J. Oper. Manag. 44 (1), 1–12. https://doi.org/10.1016/J.JOM.2016.03.008.

Epstein, L.H., 1984. The direct effects of compliance on health outcome. Health Psychol. 3 (4), 385–393. https://doi.org/10.1037/0278-6133.3.4.385.

Epstein, L.H., Cluss, P.A., 1982. A behavioral medicine perspective on adherence to long-term medical regimens. J. Consult. Clin. Psychol. 50 (6), 950–971. https://doi.org/10.1037//0022-006x.50.6.950.

Eurostat, 2022. Population structure and ageing. https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Population_structure_and_ageing.

Goeldner, M., Herstatt, C., Tietze, F., 2015. The emergence of care robotics—a patent and publication analysis. Technol. Forecast. Soc. Change 92, 115–131. https://doi.org/10.1016/J.TECHFORE.2014.09.005.

Grönroos, C., 2008. Service logic revisited: who creates value? And who co-creates? Eur. Bus. Rev. 20 (4), 298–314. https://doi.org/10.1108/09555340810886585.

Grönroos, C., 2011. Value co-creation in service logic: a critical analysis. Market. Theor. 11 (3), 279–301. https://doi.org/10.1177/1470593111408177.

Grönroos, C., Helle, P., 2010. Adopting a service logic in manufacturing: conceptual foundation and metrics for mutual value creation. J. Serv. Manag. 21 (5), 564–590. https://doi.org/10.1108/09564231011079057.

Grönroos, C., Voima, P., 2013. Critical service logic: making sense of value creation and co-creation. J. Acad. Market. Sci. 41 (2), 133–150. https://doi.org/10.1007/s11747-012-0308-3.

Groop, J., Ketokivi, M., Gupta, M., Holmström, J., 2017. Improving home care: knowledge creation through engagement and design. J. Oper. Manag. 53–56 (1), 9–22. https://doi.org/10.1016/j.jom.2017.11.001.

Holmström, J., Ketokivi, M., Hameri, A.-P., 2009. Bridging practice and theory: a design science approach. Decis. Sci. J. 40 (1), 65–87. https://doi.org/10.1111/j.1540-5915.2008.00221.x.

Huikkola, T., Kohtamäki, M., Rabetino, R., Makkonen, H., Holtkamp, P., 2022. Overcoming the challenges of smart solution development: Co-alignment of processes, routines, and practices to manage product, service, and software integration. Technovation 118, 102382.

Imbens, G.W., Lemieux, T., 2008. The regression discontinuity design—theory and applications. J. Econom. 142 (2), 611–614.

Johnell, K., Fastbom, J., 2008. Multi-dose drug dispensing and inappropriate drug use: a nationwide register-based study of over 700 000 elderly. Scand. J. Prim. Health Care 26 (2), 86–91. https://doi.org/10.1080/02813430802022196.

Kapoor, K., Bigdeli, A.Z., Schroeder, A., Baines, T., 2022. A platform ecosystem view of servitization in manufacturing. Technovation 118, 102248.

Kierkegaard, P., 2013. E-prescription across europe. Health Technol. 3 (3), 205–219. https://doi.org/10.1007/S12553-012-0037-0/TABLES/2.

Kivekäs, E., Enlund, H., Borycki, E., Saranto, K., 2016. General practitioners' attitudes towards electronic prescribing and the use of the national prescription centre. J. Eval. Clin. Pract. 22 (5), 816–825. https://doi.org/10.1111/JEP.12548.

Kleinaltenkamp, M., Plewa, C., Gudergan, S., Karpen, I.O., Chen, T., 2017. Usage center – value cocreation in multi-actor usage processes. J. Serv. Theor. Pract. 27 (4), 721–737. https://doi.org/10.1108/JSTP-04-2016-0074.

Kohtamäki, M., Rabetino, R., Einola, S., Parida, V., Patel, P., 2021. Unfolding the digital servitization path from products to product-service-software systems: practicing change through intentional narratives. J. Bus. Res. 137, 379–392. https://doi.org/10.1016/J.JBUSRES.2021.08.027.

Kohtamäki, M., Rabetino, R., Parida, V., Sjödin, D., Henneberg, S., 2022. Managing digital servitization toward smart solutions: framing the connections between technologies, business models, and ecosystems. Ind. Market. Manag. 105, 253–267. https://doi.org/10.1016/J.INDMARMAN.2022.06.010.

Lafuente, E., Vaillant, Y., Vendrell-Herrero, F., 2023. Product-service innovation Systems—opening-up servitization-based innovation to manufacturing industry. Technovation 120, 102665.

Larsen, A.B., Haugbølle, L.S., 2007. The impact of an automated dose-dispensing scheme on user compliance, medication understanding, and medication stockpiles. Res. Soc. Adm. Pharm. 3 (3), 265–284. https://doi.org/10.1016/J.SAPHARM.2006.10.002.

Lee, S., Geum, Y., Lee, S., Park, Y., 2015. Evaluating new concepts of PSS based on the customer value: application of ANP and niche theory. Expert Syst. Appl. 42 (9), 4556–4566. https://doi.org/10.1016/j.eswa.2015.01.006.

Lonati, S., Quiroga, B.F., Zehnder, C., Antonakis, J., 2018. On doing relevant and rigorous experiments: review and recommendations. J. Oper. Manag. 64, 19–40. https://doi.org/10.1016/J.JOM.2018.10.003.

Lyly-Yrjänäinen, J., Holmström, J., Johansson, M.I., Suomala, P., 2016. Effects of combining product-centric control and direct digital manufacturing: the case of preparing customized hose assembly kits. Comput. Ind. 82, 82–94. https://doi.org/10.1016/j.compind.2016.05.009.

Lyly-Yrjänäinen, J., Suomala, P., Laine, T., Mitchell, F., 2017. Interventionist management accounting research: theory contributions with societal impact. Intervent. Manag. Account. Res. https://doi.org/10.4324/9781315316161.

Masyn, K.E., 2013. Latent class analysis and finite mixture modeling. In: Little, T.D. (Ed.), The Oxford Handbook of Quantitative Methods. Oxford University Press.

Mellal, M.A., 2020. Obsolescence – a review of the literature. Technol. Soc. 63, 101347. https://doi.org/10.1016/j.techsoc.2020.101347.

Mielikäinen, L., Kuronen, R., 2019. Säännöllisen Kotihoidon Asiakkaat Marraskuussa 2018. Terveyden ja Hyvinvoinnin Laitos (THL).

Pedraza Martinez, A.J., Stapleton, O., Van Wassenhove, L.N., 2011. Field vehicle fleet management in humanitarian operations: a case-based approach. J. Oper. Manag. 29 (5), 404–421. https://doi.org/10.1016/J.JOM.2010.11.013.

Pialot, O., Millet, D., Bisiaux, J., 2017. "Upgradable PSS": clarifying a new concept of sustainable consumption/production based on upgradablility. J. Clean. Prod. 141, 538–550. https://doi.org/10.1016/j.jclepro.2016.08.161.

Porter, M.E., Heppelmann, J.E., 2014. How smart, connected products are transforming competition. Harv. Bus. Rev. 92 (11), 64–88.

Rantanen, P., Parkkari, T., Leikola, S., Airaksinen, M., Lyles, A., 2017. An in-home advanced robotic system to manage elderly home-care patients' medications: a pilot safety and usability study. Clin. Therapeut. 39 (5), 1054–1061. https://doi.org/10.1016/j.clinthera.2017.03.020.

Reike, D., Vermeulen, W.J.V., Witjes, S., 2018. The circular economy: new or refurbished as CE 3.0? — Exploring controversies in the conceptualization of the circular economy through a focus on history and resource value retention options. Resour. Conserv. Recycl. 135, 246–264. https://doi.org/10.1016/j.resconrec.2017.08.027.

Reim, W., Parida, V., Örtqvist, D., 2015. Product–Service Systems (PSS) business models and tactics – a systematic literature review. J. Clean. Prod. 97, 61–75. https://doi.org/10.1016/J.JCLEPRO.2014.07.003.

Romme, A.G.L., Holmström, J., 2023. From theories to tools: calling for research on technological innovation informed by design science. Technovation 121, 102692. https://doi.org/10.1016/j.technovation.2023.102692.

Rosenberg, J.M., Beymer, P.N., Anderson, D.J., Lissa, C. j. van, Schmidt, J.A., 2019. tidyLPA: an R package to easily carry out latent profile analysis (LPA) using open-source or commercial software. J. Open Source Softw. 3 (30), 978. https://doi.org/10.21105/JOSS.00978.

Sinnemäki, J., Airaksinen, M., Valaste, M., Saastamoinen, L.K., 2017. Impact of the automated dose dispensing with medication review on geriatric primary care patients drug use in Finland: a nationwide cohort study with matched controls. Scand. J. Prim. Health Care 35 (4), 379–386. https://doi.org/10.1080/02813432.2017.1398933.

Sinnemäki, J., Saastamoinen, L.K., Hannula, S., Peura, S., Airaksinen, M., 2014. Starting an automated dose dispensing service provided by community pharmacies in Finland. Int. J. Clin. Pharm. 36 (2), 345–351. https://doi.org/10.1007/S11096-013-9899-0/TABLES/4.

Sinnemäki, J., Sihvo, S., Isojärvi, J., Blom, M., Airaksinen, M., Mäntylä, A., 2013. Automated dose dispensing service for primary healthcare patients: a systematic review. Syst. Rev. 2 (1), 1. https://doi.org/10.1186/2046-4053-2-1.

Sjödin, D.R., Parida, V., Lindström, J., 2017. Barriers and conditions of open operation: a customer perspective on value co-creation for integrated product-service solutions. Int. J. Technol. Market. 12 (1), 90–111. https://doi.org/10.1504/IJTMKT.2017.081505.

Spring, M., Araujo, L., 2017. Product biographies in servitization and the circular economy. Ind. Market. Manag. 60, 126–137. https://doi.org/10.1016/J.INDMARMAN.2016.07.001.

Talmar, M., Walrave, B., Podoynitsyna, K.S., Holmström, J., Romme, A.G.L., 2020. Mapping, analyzing and designing innovation ecosystems: the Ecosystem Pie Model. Long. Range Plan. 53 (4), 101850.

Tashakkori, A., 1998. Mixed Methodology: Combining Qualitative and Quantitative Approaches. Sage.

Tein, J.-Y., Coxe, S., Cham, H., 2013. Statistical power to detect the correct number of classes in latent profile analysis. Struct. Equ. Model.: A Multidiscip. J. 20 (4), 640–657. https://doi.org/10.1080/10705511.2013.824781.

van Aken, J., Chandrasekaran, A., Halman, J., 2016. Conducting and publishing design science research. J. Oper. Manag. 47–48 (1), 1–8. https://doi.org/10.1016/J.JOM.2016.06.004.

Wang, Y., Gao, J., Wei, Z., 2022. The double-edged sword of servitization in radical product innovation: the role of latent needs identification. Technovation 118, 102284.

Wu, P., Hartman, J.C., Wilson, G.R., 2005. An integrated model and solution approach for fleet sizing with heterogeneous assets. Transport. Sci. 39 (1), 87–103. https://doi.org/10.1287/TRSC.1030.0050.

Wu, X., Ryan, S.M., 2014. Joint optimization of asset and inventory management in a product–service system. Eng. Econ. 59 (2), 91–115. https://doi.org/10.1080/0013791X.2013.873844.

Wuest, T., Weimer, D., Irgens, C., Thoben, K.D., 2016. Machine learning in manufacturing: advantages, challenges, and applications. Product. Manuf. Res. 4 (1), 23–45. https://doi.org/10.1080/21693277.2016.1192517.

Xing, K., Rapaccini, M., Visintin, F., 2017. PSS in healthcare: an under-explored field. Procedia CIRP 64, 241–246. https://doi.org/10.1016/j.procir.2017.03.068.