

DATA-DRIVEN DECISION MAKING RELATED TO FUTURE SERVICE ROBOTICS¹

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Abstract

The future of service robotics is changing rapidly and there are signs of service robotic operators who may want to sell a variety of robot-enabled services for companies on industrial sites and real estate. This paper studies data-driven decision making related to future service robotics. We explore the theme by presenting findings from 13 recent interviews from seven robotics, software, and service companies and three common company workshops. As a result, the paper presents the actors involved in the future service robotics ecosystem from decision making perspectives as well as illustrations and tools for data-driven decision making related to future service robotics.

Keywords: data; decision making; service robot; data-driven decisions; multi-purpose service robot; robotics

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1. Purpose

There is growing interest in the business world and academia in topics related to developing business with constantly growing data, automatization, and service robotics. Digital technologies have developed rapidly and companies are transforming from a traditional, product-centred logic to a service-centred logic (cf. Vargo and Lusch, 2016). Data-based solutions are becoming ever more complex and solutions such as multi-purpose service robots are being developed. These transformations and new solutions involve a range of services and actors in value networks. These complex data-based solutions pose challenges for decision makers.

Service robotics has been studied from various perspectives, for example technical, customer interaction, service outcomes and value creation perspectives (e.g. Fragapane et al., 2021, Belanche et al., 2020). However, the decision-making perspective remains scarce. There are some papers focusing on the robot's internal decision making based on data (e.g. Wojtak et al., 2021). However, managerial decisions related to robots have not been widely studied (e.g. Polyakova et al., 2019). There are some papers focusing on data-related themes, such as data to wisdom (Hussain et al., 2021), data to business opportunities (Rantala et al., 2020), and big data-driven value creation (Elia et al., 2020). This paper will focus on the data related strategic decisions of future service robotics by presenting empirical findings from qualitative interviews. The paper will widen the literature of service robots, data utilization and decision making by presenting a framework combining all these previous aspects.

1.1 Future service robotics

Professional service robots are becoming more popular as their sales are continuously growing annually by about 20% (IFR, 2021). The service literature has paid attention to robots since 2016 (Čaić et al. 2019), and later studies have been focused on certain types of service robots, such as home, healthcare and traffic robots (Royakkers and Est, 2015; Čaić et al., 2019; Vandemeulebroucke et al., 2021).

Service robots are usually either professional or consumer service robots. According to the World Robotics 202 Service Robots Report presented by the International Federation of Robotics (IFR), the global market for service robots in 2020 reached a turnover of 11.1 billion U.S. dollars. From this turnover, around 60% came from the professional service robots and around 40% from consumer service robots. The turnover for both professional and consumer service robots grew up 12–16 % compared to 2019. According to one estimation, around half of work activities could be automated by 2055 (McKinsey Global Institute, 2017).

Professional service robots perform different tasks in the manufacturing industry, e.g. in intra-logistics, maintenance, professional cleaning, inspection. There is huge potential for developing new professional service robot enabled services especially by utilising data that the robots collect and/use in their operations. So called "basic services" (transporting, cleaning etc.) can then be complemented with innovative data-intensive services. It is estimated that in the future there will be service robotic operators selling a variety of robot-enabled services to companies for industrial sites and real estate property (Hakanen, et al., 2022). This will enable customers to make inexpensive investments in robotic infrastructure as they will not need to invest in expensive robots, but rather they will be able to invest in robot-enabled services with the flexibility offered by the service robotic operator. This operator model is not in use yet, but there could be fast changes in the markets. Network and value chain management is the core of the operator model as various service robots, technical support, and service providers as well as the outcome and value to the customer need to be managed (Hakanen et al., 2022). Moving

towards future service robotics requires understanding of decision-making related to all the data related to this network and value chains. This paper studies future service robotics and, therefore, focuses on professional multi-purpose service robots navigating autonomously in their working environment and performing several tasks. These tasks may include security surveillance, material handling, cleaning, guidance, and more.

1.2 Data-driven decision making

Nowadays, data is an integral part of our society. Today's data-driven environment is characterised by the presence of large amounts of data, "big data", which can be described by data sets with a certain data structure, volume, velocity, variety, and variability. This data includes traditional data, for example accounting system data, customer relationship management or IoT/measurement data from production process or machines, and so on. Newly available and often unstructured data sources on the other hand can include social media data, Internet of Things data, document collections (invoices, emails), video, audio & image files, and artificial intelligence (AI) data. Additionally, professional service robots are equipped with a wide set of sensors, lasers scanners and cameras to ensure their capabilities for safe autonomous navigation and interaction with the surroundings and potentially also with humans. All these technological solutions gather vast amounts of data in various forms that can be utilized-not only for robot control and operations-but also in service innovation. Data collected or utilised by mobile robots and analysed further offers new business potential for robot firms and the companies utilizing robots. Organisations will need to modify their practices and acquire additional skills because of this data-driven evolution. New skills will focus on innovative data acquisition and analysis practices, which will provide a competitive advantage for organisations (Ballou et al., 2018).

Data has been described, for example, as a set of "discrete, structured symbols" (Sveiby, 2001), "both a physical, external substance and a resource" (Hey, 2004), or "computerized representations of models and attributes of real and simulated entities" (Chen et al., 2009). Information, on the other hand, can be defined as "a medium for explicit communication" (Sveiby, 2001), "something that can possess anything at all", "a manipulated object", "data with meaning" (Hey, 2004), or results of a computational process (or in some cases human beings) for assigning meanings to the data (Chen et al., 2009). Knowledge is "dynamic and personal" (Sveiby, 2001), "personal, subjective, inherently local within the heads of employees" (Hey, 2004), or as "results of computer-simulated cognitive processes with some knowledge acquired by human beings" (Chen et al., 2009). In this paper we use the term "data" regarding future service robotics in a wider sense, containing all the above-mentioned aspects related to data, information, and knowledge and their strategic relations.

Although data is an integral part of the lifecycle of products and services, studies related to data-driven managerial decisions remain scarce. There are some studies related to multi-criteria decision making applications (Jamwal et al., 2021), data-driven decision making for supply chain networks (Long, 2018), and the effects of data-driven decision making to firm productivity (Brynjolfsson, et al., 2011). However, these studies examine the subject very narrowly by presenting findings, frameworks, and illustrations on certain restricted perspectives. Data has become a customary part of a company's performance in the last years. Studies related to data-driven decision making are quite old (see e.g., Brynjolfsson, 2010) due to lesser data availability at that time. However, the amount of data has been growing constantly and managers need to struggle with large amounts of data from different sources, of differing types and amounts, and need to make decisions based on their own analyses and summaries. This is challenging already from a traditional product/service/company performance perspective, and extremely complex when considering complex ecosystems, where groups of companies are providing new kinds of services to new types of customers. However, the support

in the current literature is scarce for this. This paper studies data-driven decision making related to future service robotics by presenting a framework and practical viewpoints based on company interviews.

2. Methodology

In this paper, we focus on the data-driven decision making concerning future service robotics with the main research question (RQ1) of the study: Who are the actors involved in the future service robotics ecosystem from the decision making perspective? The second research question (RQ2) of the study is: How can the data-driven decision making related to future service robotics be categorised and illustrated?

The study employs a qualitative case study approach. A case study can be used as an empirical study, when the phenomenon, e.g. the service robot concept, is examined and volatile boundaries between the phenomenon and real-life contexts exist (Yin, 2014). The qualitative data was collected in June-August 2021 from 13 semi-structured interviews from seven robotics, software, and service companies and three collective company workshops. The workshops were held remotely during October–December 2021. We used two data collection methods, interviews and workshops, to ensure the validity of the research findings. Multiple data sources are seen also one of the key elements in solving the problem of generalisation and testing theories (Yin, 2014). To understand the business of the case companies in more detail, there were 1–3 interviews with each company using Microsoft Teams.

The case companies (n=7) all operate in B2B markets. They were selected because they are actively developing and adopting complex data-based solutions such as service robots that collect, utilize, and transfer versatile data. They also share the same interest in developing and offering future service robotics solutions to customers.

The concept for selling future service robots is based on the findings from the interviews and workshops, and the findings were discussed with the researchers and company representatives. The study was conducted within the EU.

3. Results

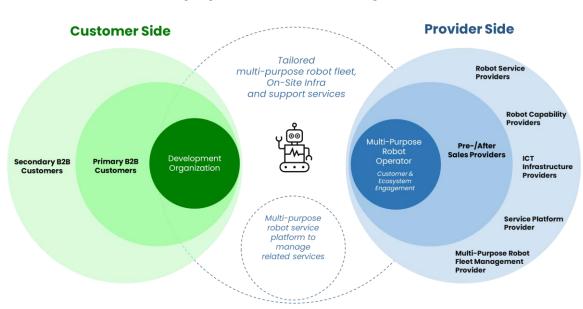
In this study, complex data-based solutions related to future service robotics was studied from a multi-purpose service robot perspective. Multi-purpose service robots can be described as autonomous, mobile service robots that are used indoors or outdoors, e.g. in last mile deliveries, maintenance, surveillance, and customer service. The main research question (RQ1) of the study was, "Who are the actors involved in the future service robotics ecosystem from the decision making perspectives?" Based on the interviews and workshops, these kinds of robots include a large ecosystem of actors around them to enable the service and use of robots or a robot fleet (Figure 1). The multi-purpose robot ecosystem actors include for example:

- robot service providers providing service robots and related robotics infrastructure,
 e.g. charging stations, and so on,
- robot capability providers providing the required capabilities for robots, e.g. autonomous driving, navigation, applications, etc.,
- ICT infrastructure providers providing required ICT infrastructure, e.g. connectivity, cloud services etc.,
- service platform provider providing digital service platforms to track and manage the use of multi-purpose robot related services,
- multi-purpose fleet management providers providing a fleet management platform to define and dynamically optimise each robot task and time slot.

To make this happen, there is a need for multi-purpose robot operator for engaging with the customers and ecosystem as well as pre- and after sales providers for solution planning and deployment, training, technical support, repairs, and maintenance. So far, the list of ecosystem actors is already large. However, the list needs to be extended on the customer side. If there are several companies, e.g. in industrial park settings, there is a need to a development an organisation which would collect the key needs of the companies in the industrial park and agree on the infrastructure-related aspects. It will be necessary for primary business-to-business (B2B) customers to take part in the assessment and decision making of multi-purpose robot solution suitability to fulfil their needs. Secondary B2B customers will need to give their input on their needs related to the solution.

Figure 1 shows that there are several decisions to be made to initiate the collaboration and make it happen during the usage. For example, if a robot is helping in warehousing at one time and then detecting indoor environment anomalies (e.g. air quality, people flow), there are several people involved in the decision process. The robotic tasks will need to be agreed upon and the data from robot warehousing procedures and environment detection will need to be monitored and used for compensatory actions. Other multi-purpose robotic tasks can consist of combinations of aspects such as on-demand delivery, warehouse inventory, indoor logistics, indoor cleaning, infra condition monitoring, and other industry-specific tasks.

Figure 1. Multi-purpose service robot ecosystem actors.



Multi-purpose Service Robot Ecosystem Actors

The second research question (RQ2) of the study was "How can the data-driven decision making related to future service robotics be illustrated?" Based on the interviews and workshops, future service robotics is also challenging to sell as the list of different actors is long. There might be difficulties to find the right person or even a company to sell the robotic solution. Figure 2 shows that parties vary in each case of industrial park setting. In an industrial park, there may be development organisations, large industrial companies, maintenance and cleaning companies, cargo, logistics and delivery companies, and other service providers.

The complexity of the ecosystem and agreements will make the data utilisation and databased decision making more complex as well. There is need to understand the data, company and task in question related to each data set. The data can be related to several purposes, e.g. improving robotic solution and services, selling to the customers, finding new customers, improving customers' processes, improving safety and security, and improving the customers' business. There are a large variety of data sets related to each robotic use case. The utilisation of data sets in decision making is dependable on aspects such as the form and quality of the data, data reliability, and useful implications based on the data. The data needs to be turned into knowledge or wisdom to utilise it best (see e.g. Ackoff, 1999).

Long-term contract with multi-purpose robot operator										
Service Robotics Examples of Use Cases	Development Organization	Large Industrial Companies	Maintenance and Cleaning Companies	Cargo, Logistics, and Delivery	Other service providers					
Cargo Handling and warehousing		х 🗸		×	×					
On-Demand Delivery		х 🔶		¥	×					
Warehouse inventory and shelving		x		×	×					
Indoor logistics		x		×	×					
Outdoor sweeping, sand/salt, snow and waste management	x	×	x							
Indoor cleaning & disinfection, waste management, accessibility	x	×	x							
Indoor environment anomaly detection (air quality, people flow, pathways, etc)	x	X <	x							
Infra condition / anomaly monitoring (roads, waste mgmt., fire safety, property condition etc.)	x	x	x							
Process specific dull, dangerous, distance and dirty tasks		x								
Collaborative robotics for process specific tasks		x								

Figure 2. Service robotics uses cases and agreements between actors in industrial park.

When starting to create a big picture of different data sources from the decision making perspective, it could be valuable to collect them into a table, where the target and benefit of the dataset is described (Table 1). The tool consists of ten features or categories for each data item: category, the data's descriptive name, location, content, form, user, purpose of use, object, own benefit, and benefit to the customer. The tool is valuable in identifying the value of each data set and categorising data from different perspectives than traditionally (e.g. the object of the data).

Table 1. Tool for identifying data sets for decision making.

Category	Name of data	Location	Content	Form	User	Purpose of use	Object	Own benefit	Benefit to the customer
categorize the data?	By what name would you describe the data?	the data located? (eg database, distributed to different people	data handle? What kind of individual things does it describe?	(e.g. numeric / text, continuous	Who uses the data?	What is the purpose of the data used for?	Who or what does the data handle? (Internal, distribution network, customer, stakeholder / market / industry / trends)	How does data benefit us? What does data help?	What are the benefits of the data for the customer? What added value does the data bring to the customer?

4. Discussion and Conclusions

A service robot can be described as a robot that performs useful tasks for humans or as a piece of equipment excluding industrial automation applications (ISO 8373:2012). The aim of this paper is to study the actors involved in the future service robotics ecosystem from a decision making perspective and categorise and illustrate the required decision making. This paper provides an understanding on future service robotics and data-related decision making by presenting empirical findings from 13 interviews in seven robotics, software, and service companies and three workshops with attendees from these seven companies. In recent years, support from information systems for managerial decisions has become significantly more important (Polyakova et al., 2019). This is in the line with our study that data-based decision making is more and more important. The study shows that data-related decision making is challenging when thinking about future service robotics. For example, a service robot could be responsible for inventory shop shelves autonomously by night. This data is valuable for management as purchasing and sales volumes could be enhanced with the data. It is fairly straightforward to see the value of this kind of robot for decision making. In the future, there could be multi-purpose mobile robot fleets with data collected into one large databank that is utilized by many robots and stakeholders. However, the value for strategic decisions is challenging to identify when developing future service robot solutions. The value for strategic decisions also affects the sales perspectives. Based on the results, this paper presents the actors involved in the future service robotics ecosystem from the decision making perspective as well as illustrations and tools for data-driven decision making related to future service robotics. The ecosystem includes several actors from customer and provider side. There could be multiple actors who agree on and contract multi-purpose service robots with multiple needs and goals. The decision process needs data for verifying and highlighting different perspectives. The paper presents a tool for identifying different data sets for decision making, which can be valuable in creating a big picture.

The empirical findings on service robotics in the literature are mainly focused on technical perspectives, human interaction, or outcomes. There are only a few studies combining data utilization, decision making and service robotics. This paper contributes to the service robotics and data decision making literature. This paper provides a practical viewpoint om making managerial decisions based on data related to future service robots for the practitioners. This paper will contribute to the service robotics and decision-making literature by developing a framework for data-driven decision making for service robots.

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