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Developing data analytics capabilities of circular economy SMEs

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Tiivistelmä

Kestävyyskriisi vaatii toimia, joilla kulutus ja tuotanto sovitetaan luonnon kantokykyyn. Kiertotalouden odotetaan ratkaisevan kestävyyshaasteen, jossa kierrätys- ja jätehuoltoteollisuudella on suuri rooli materiaalien kierrossa ja neitseellisen materiaalitarpeen vähentämisessä. Digitalisaatio ja datan kasvava määrä tarjoavat avaimet tehokkaiden materiaalikiertojen kehittämiseen. Siksi on olennaista kysyä, miten kiertotaloudessa toimivat yritykset, erityisesti pk-yritykset, pystyvät hyödyntämään dataa.

Tämä väitöskirja yhdistää kiertotalouden, dataan pohjautuvan päätöksenteon ja data-analytiikan kyvykkyydet hakien vastausta tutkimuskysymykseen: *Millaisia kyvykkyyksiä, tarpeita ja haasteita kiertotalouden pk-yrityksillä on datan hyödyntämiseen ja miten kyvykkyyksiä voitaisiin parantaa yhteistyössä korkeakoulujen kanssa?* Tämä kysymys on jaettu neljään alakysymykseen, joita käsitellään neljässä tutkimusartikkelissa. Tutkimus toteutettiin laadullisena tapaustutkimuksena keräämällä empiiristä dataa seitsemästä pk-yrityksestä, jotka toimivat kiertotalouden alalla, tarkemmin kierrätyksen ja jätehuollon parissa. Tutkimus toteutettiin vuosina 2018–2022 Suomessa.

Tämän tutkimuksen tulokset lisäävät ymmärrystä siitä, miten kiertotalouden pk-yritykset hyödyntävät dataa päätöksenteossa, mitkä ovat niiden käytännön haasteet datan hyödyntämisessä ja miten pk-yritykset voisivat parantaa kykyään hyödyntää dataa. Tulokset paljastavat, että kiertotalouden pk-yritysten datan hyödyntämistarpeet liittyvät toiminnan suunnitteluun ja tulevaisuuteen varautumiseen kilpailun lisääntyessä, muuttuviin trendeihin, kasvaviin ympäristövaatimuksiin, investointeihin sekä hiilidioksidipäästöjen vähentämiseen. Haasteena on yhdistää relevanttia dataa useista sisäisistä ja ulkoisista lähteistä sekä käyttää analytiikkaa. Nämä haasteet liittyvät tiedonhallintaan, resurssien ja kyvykkyyksien puutteeseen sekä sääntelyyn. Lisäksi kiertotalouden pk-yrityksiä näyttää ohjaavan enemmän sääntely kuin data.

Asiasanat: tietoon pohjautuva päätöksenteko, data-analytiikan kyvykkyydet, kiertotalous, pk-yritys, korkeakoulu-yritysyhteistyö.

Abstract

The sustainability crisis demands action to match consumption and production to the limits of the nature. The circular economy is expected to solve the sustainability challenge, in which the recycling and waste management industry are envisioned to play a major role maintaining materials in a cycle to reduce the need for virgin materials. There are high expectations that digitalization and increasing amounts of data will provide the keys to develop efficient circular material cycles. Thus, it is relevant to ask how companies operating in the circular economy, especially SMEs, are able to utilize this data.

This dissertation integrates the circular economy, data-driven decision-making and data analytics capabilities, and seeks answers to the research question: *What kinds of capabilities, needs and challenges do SMEs in the circular economy have for data utilization, and how these capabilities could be improved by means of collaboration with universities*? This question is divided into four sub-questions, which are addressed in four research articles. The research was conducted as a qualitative case study by collecting empirical data from seven case companies that operate in the field of the circular economy—namely in recycling and waste management. This research was conducted during 2018–2022 in Finland.

The results of this study increase the understanding of how circular economy SMEs utilize data in decision-making, what their practical challenges are regarding data utilization, and how SMEs in the circular economy could improve their data utilization capabilities. The results reveal that the data utilization needs for SMEs in the circular economy relate to planning operations and preparing for the future in terms of increasing competition, changing trends, high environmental standards, investing in facilities and capabilities and reducing carbon emissions. The challenge is to combine relevant data from several internal and external sources and use analytics. These challenges relate to data management, lack of resources and capabilities, as well as to regulation. Moreover, circular economy SMEs are more driven by regulation than by data.

Keywords: data-driven decision making, data analytics capabilities, circular economy, SME, university-industry collaboration.

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To my wonderful children, thank you for letting mommy do her "school stuff”.

September 2022
Anne-Mari Järvenpää

"If we knew what it was we were doing, it would not be called research, would it?"

– Albert Einstein

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Publications

Article 1. Järvenpää, A.-M., Kunttu, I., & Mäntyneva, M. (2020). Using foresight to shape future expectations in circular economy SMEs. Technology Innovation Management Review, 10(7), 41–50. https://doi.org/10.22215/timreview/1374

Article 2. Järvenpää, A.-M., Kunttu, I., Jussila, J., & Mäntyneva, M. (2021). Data-Driven Decision-Making in Circular Economy SMEs in Finland. Springer Proceedings in Complexity, 371–382. https://doi.org/10.1007/978-3-030-84311-3_34

Article 3. Järvenpää, A.M, Jussila, J., Kunttu, I. (2023) "Barriers and practical challenges for data-driven decision-making in circular economy SMEs", in: Visvizi, A., Troisi, O., Grimaldi, M. (eds) (2023) Big Data and Decision-Making: Applications and Uses in the Public and Private Sector, Bingley, UK: Emerald Publishing, ISBN: 978–1803825526

Article 4. Järvenpää, A.-M., Jussila, J., & Kunttu, I. (2022). Developing data analytics capabilities for circular economy SMEs by Design Factory student projects. The XXXIII ISPIM Innovation Conference "Innovating in a Digital World," June.

1 INTRODUCTION

Circular economy companies face increasing targets to reduce, reuse and recycle. This is affected by strict legislation and growing environmental requirements, e.g. concerning the reduction of carbon emissions. Increasing demands caused by the European Commission, national governments as well as customers are also bringing changes to the business environment. The circular economy is expected to solve the sustainability crisis with help of digitalization and increasing amounts of data. This in turn requires education and continuous learning to build the needed capabilities in companies. To achieve the targets of the circular economy in society, it is important to understand the challenges of companies to be able to support them in the development as well as to provide education on the skills needed in industry.

This dissertation aims to increase the understanding of how small and medium-sized enterprises (SMEs) operating in the circular economy business utilize data in decision-making, what the challenges are in utilizing the data and how the SMEs could be supported to develop their capabilities.

1.1 Background

Today, we are facing a sustainability crisis as production exceeds the limits of nature (Prieto-Sandoval et al., 2019). The circular economy aims to provide a solution by fitting material consumption within nature's boundaries according to the 3R principle, aiming to reduce material consumption, increase reuse of materials and recycling (Kirchherr et al., 2017; Prieto-Sandoval et al., 2018). This transition requires promoting high-quality material cycles, digitally exploitable information, research, experimentation, and legislation that enables innovations.

The European Commission's new action plan for the circular economy (European Commission, 2020) expects that the global consumption of materials will increase 100% by 2060, while annual waste generation will increase 70% by 2050. The European Union aims to double the use of circular materials by 2030 and closed-loop material cycles could increase the profitability of manufacturing companies and protect them from price fluctuations. To achieve this, the European Union should increase recycling by 100 megatons per year (Tisserant et al., 2017).

The transition towards a circular economy and circular material flows requires data to enable efficient recycling, component harvesting, material value assessment (Charnley et al., 2019) and the creation of closed-loop production-consumption systems (Auh et al., 2022). The best time to transform a traditional linear material flow into a circular process is the decision-making phase in product and service development, as well as raw material production and procurement (Kauppila et al., 2022). Breakthroughs in the circular economy can be found in ecosystems, for example, in industrial symbioses between companies, where side stream or waste are exploited to save resources, and to reduce costs and environmental impacts (Järvenpää et al., 2021).

There is need for a data-driven circular economy and digital solutions to manage and utilize resources efficiently. This in turn requires skills, education, continuous learning, and innovation. Data can help the efficient use of resources in the whole value chain by optimizing material flows, and minimizing the used materials and environmental effects. Technology is available to develop digital solutions in the circular economy (Niska & Serkkola, 2018), however, the challenge lies in linear supply chains where information is not shared (Salmenperä et al., 2021), and where demand and supply do not meet (Charnley et al., 2019; Cramer, 2018). Furthermore, the increased utilization of data increases energy and material consumption as well, which is the opposite of the aim of the circular economy (Bressanelli et al., 2022). As the circular economy is expected to provide a solution to the sustainability challenge at least partly through the use of digitalization and data, it is relevant to ask, how industry, especially SMEs, can utilize data to achieve the goal.

1.2 Research gap

In the transition towards a circular economy and fulfilling the aims of strategies set by the EU (European Commission, 2020; Tisserant et al., 2017) and governments, there are opportunities and threats for SMEs. Empirical foresight research in Europe is focused on large companies (Jannek & Burmeister, 2007) while SMEs have received less attention (Stonehouse & Pemberton, 2002). Many SMEs work in an environment that does not require foresight activities (Jun et al., 2013), but SMEs operating in rapidly changing environments do need foresight capabilities (Uotila et al., 2012) to ensure success and survival (Rohrbeck, 2011). The circular economy is rapidly changing the business environment, providing both threats and opportunities that require foresight activities. Thus, there is a need to develop a greater understanding on how circular economy SMEs collect data for foresight activities and what they expect from the future.

Prediction and forecasting require data from the business environment. Utilizing data requires competence and resources, but despite the benefits of data based decision-making, many SMEs face challenges understanding how to use analytics and they may face difficulties such as the lack of understanding of data, as well as lack of in-house experts and tools to analyze data (Iqbal et al., 2018; Kim et al., 2003; Ormazabal et al., 2018; Parra et al., 2019; Ransbotham et al., 2016; Rizos et al., 2016). Previous research has concentrated mainly on large-scale companies and somewhat on SMEs, but circular economy SMEs remain unexplored. This research aims to generate practical understanding at the grassroots level.

The transition towards the circular economy is driven by digitalization, thus utilizing digital tools and data are considered as one of the key capabilities facilitating the circular economy (Parida & Wincent, 2019). However, circular economy SMEs face challenges utilizing digitalization and the increasing amount of data (Iqbal et al., 2018), despite the fact that data enables companies to develop material flows, logistics and customer behavior (Lacam, 2020). Thus, there is a need to develop more understanding on the development needs concerning the data analytics capabilities of SMEs as well as how these capabilities could be improved.

To fill the aforementioned gaps in the existing literature, this dissertation integrates the literature on the circular economy, data-driven decision-making and data analytics capabilities (Figure 1) to extend the research by studying how circular economy SMEs collect data for decision-making, how they utilize data, what practical challenges they face, and what opportunities exist to develop data analytics capabilities.

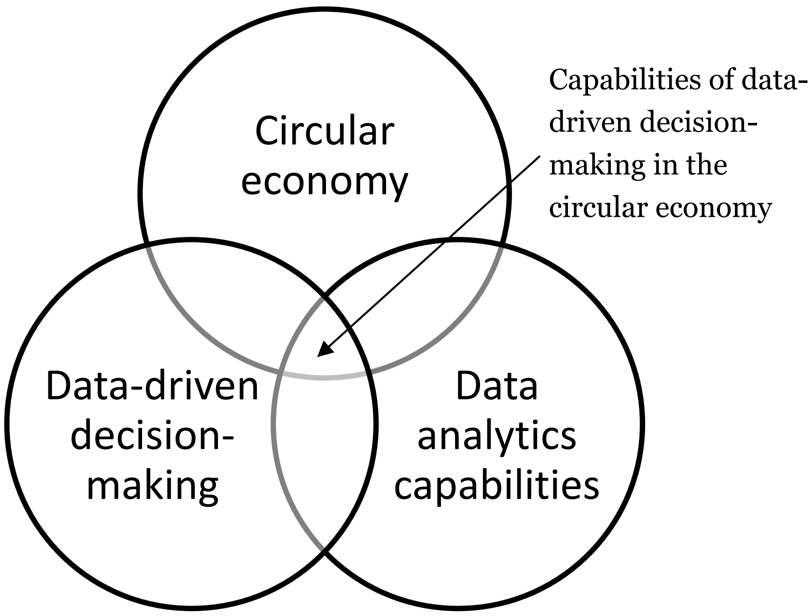

Figure 1 Data analytics capabilities for data-driven decision-making in the circular economy.

1.3 Research questions

The primary objective of this dissertation is to address the following research question: *What kinds of capabilities, needs and challenges do circular economy SMEs have for data utilization, and how could these capabilities be improved by means of collaboration with universities?* This research question is divided into four sub-questions:

RQ1: How do industrial actors and service providers operating in the circular economy foresee future changes in their operational environment?

RQ2: How can SMEs operating in a circular economy utilize data to support their decision-making?

RQ3: What are the practical challenges to data-driven decision-making in circular economy SMEs?

RQ4: How are the data analysis capabilities in SMEs developing in joint action between university and companies?

By seeking answers to the abovementioned research questions, this dissertation aims to increase the understanding on how circular economy SMEs collect and utilize data, what challenges they face, and how they could develop their capabilities to utilize data in collaboration with educational institutions. For academia, this study aims to provide an understanding of how to develop joint activities with SMEs to support collaborative learning. For public administration and regional development organizations, this work provides an understanding of what it takes from circular economy companies to utilize data to boost circular economy targets and environmental benefits.

Each research question is covered in one article. The first research question (RQ1) in article 1 aims to identify the data collection practices and activities to predict the future as well as expectations for the future. The second research (RQ2) question in article 2 aims to identify the types of data and analytical methods that circular economy SMEs typically utilize. The third research question (RQ3) aims to seek barriers and practical challenges to utilizing data in circular economy SMEs. The fourth research question (RQ4) explores how circular economy SMEs' capabilities may increase during the collaboration with universities. A summary of the articles is presented in Table 1.

Table 1 Summary of articles.

	Article 1	**Article 2**	**Article 3**	**Article 4**
Focus area	Data collection practices for organizational foresight activities	Data sources and methods used in decision-making	Barriers and challenges to utilizing data in decision-making	Development of data analytics capabilities
Theory	Organizational foresight	Data-driven decision-making	Data-driven decision-making	Dynamic capabilities, relationship learning
Research Strategy	Comparative multiple case study	Comparative multiple case study	Comparative multiple case study	Comparative multiple case study
Research Context	Foresight activities and future expectations in circular economy SMEs	Data-driven decision-making and management practices in circular economy SMEs	Barriers and practical challenges for data-driven decision-making in circular economy SMEs	Opportunities to develop data analytics capabilities of circular economy SMEs
Data Collection Methods	Interviews	Interviews	Interviews, group interview	Interviews, group interview

	Article 1	Article 2	Article 3	Article 4
Main Findings	1. Activities to predict the future 2. Expectations for the future	1. The most used types of data 2. The most used analytical methods	1. The barriers to utilizing data 2. Practical challenges to utilizing data	SMEs capabilities increased during collaboration with university students

1.4 Research context

This research involves the Finnish circular economy industry, namely SMEs providing recycling services, recovery of sorted materials, waste management and biogas production. Companies in this field often lack digitalization and data utilization, but they have increasing pressure to do gain these capabilities, as the environmental, operational, and business requirements are increasing all the time. As digitalization and data are expected to boost the circular economy and bring environmental benefits, it is important to study the situation from the point of view of SMEs operating in the circular economy. As SMEs represent a major part of companies in Europe, their development is important (Coleman et al., 2016).

1.5 Key concepts

This subchapter explains the key concepts related to the research questions.

- The circular economy refers to minimizing the demand for resources and recovering value from waste.
- Data refers to the objective facts that can be used to produce information.
- Data-driven decision-making uses data to guide the decision-making process.
- Data analytics capabilities refers to the skills, abilities and knowledge to create value from data.
- Small and medium-size (SME) enterprise refer to the size of a company in terms of the number of staff and turnover.

1.6 Structure of the dissertation

This dissertation is structured in two parts. The first part consists of five chapters that provide both a theoretical and practical background to the dissertation. The first chapter of part one introduces the background and objectives of this dissertation. The starting point is the sustainability crisis and strategies that expect that the circular economy will be able to help solve the sustainability challenge. It is expected that digitalization and ever-increasing amounts of data will drive the development of the circular economy, and it is important to research and explore the reality in the context of circular economy SMEs.

The second chapter introduces the theoretical framework of the study, relating to data, data-driven decision-making, business intelligence, knowledge management, the circular economy, data analytics and capability development. This constructs a theoretical base for empirical exploration and reflection.

The third chapter introduces the research design and methodology. This study is conducted as a comparative qualitative case study. Data was collected by interviewing SMEs operating in circular economy businesses in Finland. Each interview round sought a cross-sectional snapshot for one research question.

The fourth chapter provides a summary of the articles, each article covering one research question. The article summaries provide an overview of the related literature, explain the research methods used, and present the main results.

The fifth chapter answers the research questions and discusses the contribution and limitations of the study, and provides some suggestions for future research.

Part two contains the four dissertation articles. In all the articles, the author of this dissertation is the primary author, who had the main responsibility for the data collection, analysis, composing, and writing the articles, and also for managing the review processes.

2 THEORETICAL BACKGROUND

This chapter introduces the theoretical background for this study, relating to data, data-driven decision-making, business intelligence, knowledge management, the circular economy, data analytics and capability development. These concepts form a theoretical base for the study to empirically explore circular economy SMEs and to answer the research question.

The circular economy is a developing business area, and the operational environment provides both, threats, and opportunities. For this reason, data-driven decision-making is important for companies in this business field. Predicting future changes enables businesses to anticipate threats and opportunities (Korreck, 2018; Rohrbeck & Gemünden, 2011; Uotila et al., 2012) and to get prepared for the future or even shape it (Cuhls, 2003). As SMEs have fewer resources and shorter planning horizons than large companies, their foresight goals relate to planning operations and managing innovations (Jannek & Burmeister, 2007). Activities often occur when SMEs are forced into the product development (Bidaurratzaga & Dell, 2012; Jannek & Burmeister, 2007). However, SMEs are typically focused on certain markets, and they might overlook new opportunities (Coleman et al., 2016).

2.1 Data-driven decision-making in SMEs

> *"Where a firm can go is a function of its current position and the paths ahead. Its current position is often shaped by the path it has travelled."* (Teece et al., 1997, p. 522)

Data-driven decision-making enables cost reduction, increased operational efficiency, customer loyalty and communication (Pulkkinen et al., 2019; Troisi et al., 2020). It requires managing data to make decisions to prescribe actions, predict development, and drive change (Troisi et al., 2020), as well as the capability to harness data into value, innovations, or competitive advantages (Troisi et al., 2021; Watson, 2016). In the case of SMEs, there is lack of understanding of data, data analytics infrastructure, and the necessary expertise to select appropriate solutions (Iqbal et al., 2018; Parra et al., 2019; Ransbotham et al., 2016).

Companies can utilize data from several internal or external sources, and data can be generated by machines, humans or business (Olshannikova et al., 2017; Saggi & Jain, 2018). As data can be utilized in many ways, the company must understand the feasibility of available analytic methods (descriptive, predictive, or prescriptive) that can provide answers to business questions.

For circular economy companies, data analytics provides opportunities to optimize the material flow and manage the supply chain, that can enable a leap to the operational efficiency and improved sustainability (Kristoffersen et al., 2019). However, even there are simple tools available, SMEs may not be capable to utilize them (Parra et al., 2019).

2.1.1 Data

A huge volume of real-time data is generated by digital platforms every day. For this reason, many organizations cannot use all of the generated data effectively (Lavalle et al., 2011). The data does not contain any meaning itself, it just consists of objective facts that can be used to produce information by contextualization (Nykänen et al., 2016) for economic benefit. Data is defined as a carrier to store and transfer information and knowledge, but data becomes information or knowledge only through interpretation (Kock et al., 1997). Information quality plays an important role in the data environment in terms of achieving business value, customer satisfaction and company performance (Fosso Wamba et al., 2019). The quality of data reflects the completeness, currency, format and accuracy of information. However, the quality of data is affected by processes where the data is handled and analyzed (Ferraris et al., 2019).

Data comes from different sources either inside or outside the organization, and it exists in structured, semi-structured or unstructured forms, thus, the organization must identify important data and utilize it (Nykänen et al., 2016). Structured data can be stored in databases and therefore can be computed. For this reason, data analysis tools mainly focus on numerical business data (Baars & Kemper, 2008). Semi-structured data is becoming important for companies, but there are difficulties applying analytics to it (Nykänen et al., 2016). In recent years the amount of data has increased due to the Internet, mobile devices and integrated databases generating big data (Olszak & Zurada, 2020). Big data is often described in terms of high-volume, high-velocity and high-variety (Hartmann et al., 2016), veracity, value (Ferraris et al., 2019), high complexity (Coleman et al., 2016), valence, and variability (Saggi & Jain, 2018). Data can be generated by machines, humans or business information systems (Saggi & Jain, 2018). Despite the definitions, big data needs to be processed to gain information and insight.

Data is only a set of facts (Nykänen et al., 2016) or a set of signs. Information refers to empirical knowledge, whereas knowledge refers to the meaning in a context

(Zins, 2007). Information describes the past and the present, while knowledge enables predictions of the future (Kock et al., 1997).

A prerequisite to fully benefit from data is to make it understandable for all employees, so they can be committed to utilizing it in decision-making (Ferraris et al., 2019). The steps (Figure 2) to generate knowledge from data include: the selection of the data set, pre-processing, transformation, data mining, and interpretation (Fayyad et al., 1996). The pre-processing step includes cleaning the data, while the transformation step involves reducing the number of variables, whereas data mining identifies patterns that the final step of interpretation visualizes (Fayyad et al., 1996; Hartmann et al., 2016).

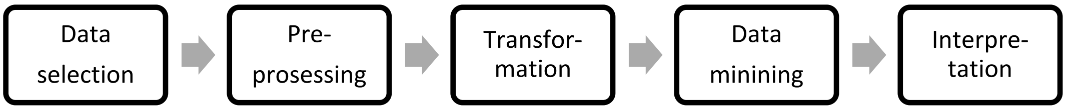

Figure 2 Generating knowledge from data (Fayyad et al., 1996; Hartmann et al., 2016).

Large companies are making advances in utilizing data, while SMEs appear to be rather slow adopters (Coleman et al., 2016). Data related challenges for SMEs include heterogeneity, scale, timeliness, privacy, and human collaboration (Wang & Wang, 2020), as well as "extremely low understanding of data analytics by SME representatives", shortage of qualified data analysts, difficulty to choose the suitable solution and to understand the European General Data Protection regulation (Coleman et al., 2016). As SMEs form a great part of the economy in Europe, their development requires attention (Coleman et al., 2016).

Evaluation of a company's maturity for the strategic use of data is the starting point for development. Maturity model asses data adoption by business strategy, data management, analytical skills, technological infrastructure, engagement in data-driven management, leadership and culture, and data governance (Coleman et al., 2016).

2.1.2 Data-driven decision-making

Data provides a strategic asset for companies by improving data-driven decision-making (Qaffas et al., 2022). Top management requires scenarios and simulations to be able to quickly determine optimal solution based on complex business data (Lavalle et al., 2011).

Data-driven culture refers to the ways that companies deal with data in data creation, collection, consolidation, analysis, and sharing, as well as in decision-making and managerial support (Medeiros & Maçada, 2022). A data-driven culture is required to realize the potential of data, where organization members make "decisions based on the insights extracted from data" (M. Gupta & George, 2016, p. 1053). Decision-making is supported by knowledge sharing, and includes actions to disseminate knowledge enabling access to relevant information as well as data analytics tools that provide a source for sharing knowledge (Ghasemaghaei, 2019). Dissemination is important, as reporting has a strong effect on performance (Bianchini & Michalkova, 2019).

Data-driven decision-making can increase performance through data-driven development, processes, marketing and organization management, as well as data products and data-intensive products (Bianchini & Michalkova, 2019). LaValle et al. (2011) reported that organizations that use business information and analytics differentiate themselves in their markets, and they utilize analytics for small and large decisions, as well as for future strategies and daily operations.

SMEs need different approaches in decision-making than large companies as there are several differences between them (Salles, 2006): e.g. decision-making processes might be poorly formalized in SMEs and their decision-makers are required to make decisions at different levels. Small companies often have a flat organization, and they are informal and non-bureaucratic, while their management style encourages innovation and owner-managers are often in the central position. For these reasons, the decision-making might be limited to one person (Durst & Edvardsson, 2012; Valkokari & Helander, 2007).

Companies must move from experience-based decision-making toward data-driven decision-making. This can be disruptive and cause discomfort in the organization (Auh et al., 2022) because the analytical information derived from big data will reduce the value of the experiential knowledge of central decision-makers as big data tends to improve decisions and performance with analytics capabilities and a knowledge management orientation (Ferraris et al., 2019). Even though the technology is available, challenges may arise in managerial issues, as achieving real gains requires the willingness of employees to utilize facts based on analytics (Auh et al., 2022). Analytics are currently used more to validate actions afterwards, not used in proactive decision-making and a major barrier is the lack of understanding on how to use analytics in decision-making (Auh et al., 2022).

Strategic decisions are non-repetitive decisions, where the decision makers have insufficient information (Salles, 2006). The analytical readiness to utilize data in strategic decision-making can be evaluated by cultural readiness to integrate people towards the same goal, leadership commitment, strategic alignment, structures and systems, and talent capacity (Auh et al., 2022). For example, existing technology can hamper an SME's ability to meet their customers' needs. When managers are making decision to adopt new information technology solutions, they need to understand how it would improve productivity and whether it would be compatible with existing processes. The challenge is to predict the advancement and the value that new solution provides (Eze et al., 2018).

2.1.3 Business intelligence

Decision-making process are facilitated by business intelligence, providing quality, timely and accurate data, considering past events, present and future (Gauzelin & Bentz, 2017). There are two approaches to defining business intelligence, that emphasize either the technology that makes data available, or that emphasize processes to transform data into information (Nykänen et al., 2016). From the technology point of view, business intelligence creates information from data and refers to processes and software used to collect, analyze, and disseminate data aiming at better decision-making (Davenport, 2005). Intelligence refers to finding unseen contexts from data (Herschel & Jones, 2005). Business intelligence encompasses an organization's large-scale decision support system and is the most important information technology application for an organization to support decision-making (Arnott et al., 2017). The whole business can be built by collecting and analyzing data (Davenport, 2005). The benefits provided by business intelligence lead to the opportunity to reduce costs, and increase revenues and profits (Gauzelin & Bentz, 2017). Gaining a competitive advantage requires understanding the data generated in the business, e.g. SMEs can improve their understanding of business processes by analyzing historical data to search for unknown patterns (Guarda et al., 2013).

Competing in the dynamic business environment can be hard. Competitive intelligence is a part of business intelligence providing understanding of the competition in the market (Pirttimäki, 2007). Competitive intelligence collects information and develops insights into the external environment including competitors, customers, suppliers, and technology (Calof, 2020, p. 565; Gauzelin & Bentz, 2017). Market analyses identify changing and emerging trends.

In Finland, business intelligence is common among large-scale companies that invest in sophisticated business intelligence tools to improve their decision-making and enhance their competitiveness (Hannula & Pirttimaki, 2003). The most common reasons for large Finnish companies to use business intelligence are to increase their business knowledge, improve operational efficiency and improve their decision-making (Nykänen et al., 2016). SMEs have been slower to adopt business intelligent systems than large companies, and they tend to believe that business intelligence systems are effective only for large-scale companies that are able to invest in technology and have skilled staff to work with it (Gauzelin & Bentz, 2017). Nykänen et al. (2016) noted, that it is not easy for companies to get data out of its repositories for use as an analysis tool, as business intelligence systems do not provide adequate integration with data sources and other applications. In addition to that, business intelligence systems were not perceived to be user friendly.

The adoption of business intelligence in SMEs might require adaptation of processes, as information must be available at the right time for the right people (Guarda et al., 2013). Utilizing large amounts of data is a challenge to SMEs and there are no promises that business intelligence itself will bring success (Gauzelin & Bentz, 2017). Challenges that SME might face with business intelligence relate to the high cost of the systems and availability of skilled employees (e.g. with mathematical and IT skills). SMEs can adopt business intelligence in four steps (Figure 3), including defining the needed data, choosing suitable technology and tools, defining the critical success factors, metrics and alerts, and lastly, interpreting and sharing the results (Guarda et al., 2013).

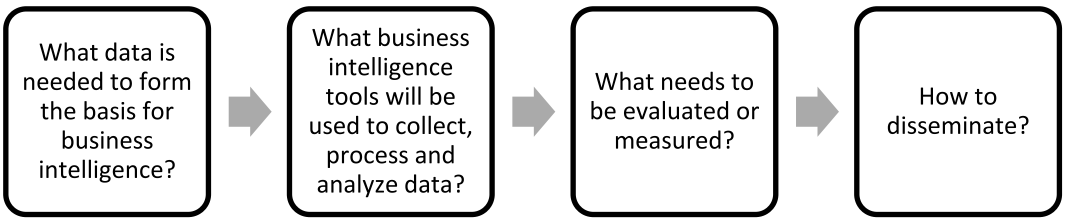

Figure 3 Steps to adopt business intelligence in SMEs (adapted from Guarda et al., 2013, p. 189).

2.1.4 Knowledge management

As business intelligence concentrates on explicit knowledge, knowledge management covers both, tacit and explicit knowledge (Herschel & Jones, 2005). Knowledge management enables the creation of “big knowledge”, where human knowledge defines how the generated information will be utilized at the operational, tactical, and strategical level (Wang & Wang, 2020).

Knowledge management provides the opportunity to increase the understanding from the organization's own experience and it is "a systematic process of finding, selecting, organizing, distilling and presenting information in a way that improves employees' comprehension in a specific area of interest" (Herschel & Jones, 2005). Quintas et al. (Quintas et al., 1997, p. 387) defined knowledge management as "the process of continually managing knowledge of all kinds to meet existing and emerging needs, to identify and exploit existing and acquired knowledge assets and to develop new opportunities". Demarest (1997, p. 379) suggest that knowledge management "is the systematic underpinning, observation, instrumentation, and optimization of the firm's knowledge economies". Jennex et al. (2009, p. 183) defined knowledge management as a multidimensional concept of "capturing the right knowledge, getting the right knowledge to the right user, and using this knowledge to improve organizational and/or individual performance".

SMEs manage knowledge differently than large organizations—it is not about scaling down practices, as SMEs have their own uniqueness. SMEs have a lack of explicit knowledge repositories and they utilize external sources of knowledge. Their domain specific knowledge is deep and wide, and they are capable of avoiding knowledge losses in the case of an employee leaving the organization (Desouza & Awazu, 2006). The key elements in knowledge management are knowledge construction, knowledge embodiment, knowledge dissemination and knowledge use (Mcadam & Reid, 2001). The critical success factors for adopting knowledge management in SMEs in prioritized order are management leadership and support; culture; strategy and purpose; resources; processes and activities; training and education; human resource management; information technology; motivational aids; organizational infrastructure; and measurement (Wong & Aspinwall, 2005).

Knowledge management challenges are different in large and small companies and researchers tend to apply approaches to SMEs that were created for large companies, which can reduce SMEs' capacity to act (Durst & Edvardsson, 2012). Compared to large companies, many SMEs do not have a policy for strategic knowledge management, and they conduct knowledge management at the operational level (Durst & Edvardsson, 2012). SMEs are found to be weaker in knowledge construction due to the lack of systematic and formal social interaction as they tend to have an unstructured and short-term approach to organizational learning, and managers might try to block knowledge sharing to prevent knowledge leakage from the company (Durst & Edvardsson, 2012). Knowledge sharing takes time and requires trust. SMEs may have a limited terminology for knowledge, and they may define knowledge as "useful information or a list of scientific facts" (Mcadam & Reid, 2001).

A knowledge management model of data for SMEs emphasizes knowledge management over sophisticated information technology and the volume of data. This knowledge management model includes the strategic use of data and long-term planning, a knowledge-guided definition of data requirements, information technology solutions suitable for SMEs, and new outcomes as knowledge, new product or decision-making rules (Wang & Wang, 2020). Companies must integrate the processes of data and knowledge management and to understand the managerial reason for doing so.

2.2 Data analytics in circular economy SMEs

Despite the benefits of data-driven decision-making, many companies face challenges understanding how to use data analytics (Iqbal et al., 2018; Lavalle et al., 2011). The managerial and cultural barriers to adopting analytics are larger than the technological obstacles (Lavalle et al., 2011). To take advantage of data, LaValle et al. (2011) reported that better performing organizations utilize analytics at a five-fold rate compared to others. The literature reports numerous challenges for SMEs in terms of utilizing data (Iqbal et al., 2018; Kim et al., 2003; Parra et al., 2019; Ransbotham et al., 2016), such as the lack of capabilities and resources, including lack of financial or technological resources (Ormazabal et al., 2018; Rizos et al., 2016).

2.2.1 Circular economy

The expanding global needs, including population, urbanization and climate change mean that social prosperity and the resilience of nature require new management strategies toward the implementation of circular economy (Prieto-Sandoval et al., 2019). The circular economy concept is created by different disciplines such as ecology, economy, engineering, design and business (Prieto-Sandoval et al., 2018). This might be one reason the circular economy has several definitions and concepts which cause challenges for research (Kirchherr et al., 2017) and dissemination (Kalmykova et al., 2018). Until 2012, the circular economy research was focused mainly on China, as China had adopted this concept in its national strategy. Subsequently, Europe started to develop the concept, especially the European Commission, and governments or non-governmental organizations in European countries (Kalmykova et al., 2018).

The circular economy is often explained by the 3R principle of reduce, reuse and recycle, that can be applied in the cycle of production, consumption and return of resources (Kirchherr et al., 2017; Prieto-Sandoval et al., 2018). 3R refers to the recirculation of resources, minimizing the demand for resources, and recovering value from waste (Prieto-Sandoval et al., 2018). In addition, the literature explains the 4R framework including dimensions of reduce, reuse, recycle and recover (e.g. Directive 2008/98/EC) and 9R including refuse, rethink, reduce, reuse, repair, refurbish, remanufacture, repurpose, recycle and recover (Kirchherr et al., 2017).

The circular economic model obtains supplies from waste and other side streams, makes better use of resources, and is able to reduce the negative impact of industries (Prieto-Sandoval et al., 2019). For doing this, companies must have sufficient information about waste streams. The circular economy aims to be restorative, meaning not only to prevent environmental impacts, but to also repair damage (Murray et al., 2017). However, there are criticisms that the circular economy is weakly linked to sustainable development (Kirchherr et al., 2017), it has overly simplistic aims (Murray et al., 2017), and that there is a lack of economic theory to guide the transition towards a sustainable circular economy (Velenturf & Purnell, 2021). For example, logistics causes environmental impacts from CO2 emissions, which raises the need for optimized collection system, and these require data. The circular economy aims to close the loop of resource flows between production and consumption and to reduce the need of virgin materials and the generation of waste. It is generally viewed as a cycle to extract, transform, distribute, use, and recover materials (Prieto-Sandoval et al., 2018). Customers are increasingly aware of environmental issues, and they require sustainability. This causes the need for companies to verify and report their sustainability and reduced environmental impacts. This can only be done with sufficient data and analyses.

Recycling is a fundamental part of the circular economy (Murray et al., 2017), namely recycling is the most common component in circular economy definitions, the second is reuse (Kirchherr et al., 2017). To achieve the targets of the Action Plan for Circular Economy by 2030, the European Union should increase recycling by 100 megatons per year and reduce landfilling by approximately 35 megatons per year (Tisserant et al., 2017).

Circular economy strategies contain risks for industry that relates e.g. to the uncertainty of fluctuating demand and supply (Charnley et al., 2019). Cost-efficient waste management requires monitoring data and novel analytic approaches. Containers can be monitored by sensors and transportation control systems, and combining this data with other data sources helps to create data-driven insight into waste flows (Niska & Serkkola, 2018). This insight is important in the circular economy, where uncertainties relating to the volume, quality, time and location of returned end-of-use products may reduce profitability (Bressanelli et al., 2022). The four key conditions in recycling material flows are a sufficient collection system, sufficient volumes, market demand, and the quality of the recycled material, while important drivers involve collaboration in the circular material chain and information exchange (Cramer, 2018).

The waste management industry could promote the maintenance of material value in the cycle by providing services for manufacturers and demonstrating the economic value of recycled materials and by sharing waste data (Salmenperä et al., 2021). Regardless of the development and strategies of the circular economy, regulation, taxation and policy systems have been criticized not fully supporting the aims of the circular economy (Bressanelli et al., 2022).

Salmenperä et al. (2021) reported that barriers to the circular economy were viewed differently by different actor groups and there is a lack of systemic thinking and barriers exist in the material supply chain. Kirchherr et al. (2018) found that technological barriers were not ranked as a top barrier for the circular economy, but the most mentioned barriers were cultural e.g. lack of consumer interest, a hesitant company culture, operating in a linear system, and limited willingness to collaborate in the value chain. These are serious challenges for the exploitation of external data, which prevents the development of an efficient circular economy system.

2.2.2 Digitalization and the smart circular economy

Digitalization offers new opportunities for SMEs to innovate, grow and go to the global markets (Bianchini & Michalkova, 2019). This transition involves large amount of data, which challenges SMEs to access and analyze relevant data, as they might face internal and external barriers. Data-driven circular economy relates to the Industry 4.0 technologies, the term refers to the digitalization that 4th Industrial Revolution enables. It is about smart factories and real-time information for decision-making, where data flows are used in recycling, harvesting components, value assessment of materials and the value of supply chain as well as to inform end-of-life behavior (Charnley et al., 2019).

In the smart circular economy waste data forms a resource to be exploited, the focus is in the ecosystem instead of single organization and integrated digital technologies are assessed by their environmental impact (Bressanelli et al., 2022).

Manufacturing companies are forced to develop circular economy practices due to the increasing scarcity or resources, digitalization could help to create closed-loop production-consumption systems (Awan et al., 2021). By data analytics, productivity, and resource efficiency as well as waste to resource process can be improved.

Identified categories for data utilization in the circular economy include behavior of customers, lifetime of products and services, performance of systems and value chain network and flow of materials (Kauppila et al., 2022). In Finland, there are several publicly available data sources for the circular economy such as registers, statistics and databases containing data about raw materials, products, side streams and production capacity for food, carbon, batteries, textiles, plastics, mining, and industrial production. These data sources can be utilized to design solutions for the circular economy. However, one challenge is that there are no centralized data standards or governance for data collection as the data has several owners from the private and the public sector and there is no systematic data collection or automatic update (Kauppila et al., 2022). These issues lead to challenges in information quality (Fosso Wamba et al., 2019), and thus affect business value and company performance.

The smart circular economy is defined as “an industrial system that uses digital technologies during the product life-cycle phases to implement circular strategies and practices, aiming at value creation through increased environmental, social, and economic performance” (Bressanelli et al., 2022, p. 9). The smart circular economy is supported by digital technologies such as the Internet of Things (IoT), data, and analytics. Digitalization enhances sustainability by replacing physical flows with information flows to avoid over-transportation or over-production, both causing costs and environmental impact. Operational efficiency and sustainability can be increased if relevant information is available for the right actor at the right time. One solution to demonstrate material and information flows are digital twins, that is a virtual and real-time illustration of physical objects (Rocca et al., 2020) that can provide relevant information to the right actor at the right time, presenting relevant information to manage and control product life-cycles (Preut et al., 2021) or material flows. In the circular economy, digital twins can provide information for recyclers about materials and instructions for disassembly. For logistics partners it can provide information needed for transportation such as condition and location.

2.2.3 Data analytics in circular economy SMEs

In the circular economy, the drivers to implement analytics include the visibility of material flows, operational efficiency, and collaboration between supply chain partners (Kazancoglu et al., 2021). Data analytics refers to the business intelligence, while analytics refers typically to data mining and statistical analysis (Chen et al., 2012). Raw data from various sources do not generate value automatically, but data analytics can make sense from data, for example by identifying hidden patterns and relations. Before conducting analytics, raw data must be cleaned, standardized, consolidated, and organized (Bianchini & Michalkova, 2019).

SME often underutilize data as they suffer a lack of information technology resources for data collection and analyses (Wang & Wang, 2020). SMEs face challenges because of their limited resources to utilize data for competition by analyzing costs and profits, customer's purchases, marketing campaigns and long-term risks (Wang & Wang, 2020). Even if the technology is available, challenges might arise due to managerial issues (Auh et al., 2022). For instance, achieving real gains may require the willingness of employees to utilize facts that are produced by analytics (as discussed earlier).

The key internal barriers preventing SMEs from adopting data analytics are the lack of managerial awareness and skills to utilize analytics for improving the business, lack of specialists to conduct analyses at an advanced level, inability to assess and prevent digital risks, and limited data sources or amounts of data (Bianchini & Michalkova, 2019). The key external barriers are financial constraints, accessing complementary external data, complex regulation of personal data, and lack of solutions suitable for SMEs.

The transition to utilizing analytics requires leadership from executives with quantitative desire; it is known that this is a hard job for business unit leaders as they lack perspective and cross-functional scope to change the company culture (Davenport, 2005). A leader needs to understand quantitative methods and their limitations to apply analytics to business. LaValle et al. (2011) recommended for organizations that are developing analytics, to focus on the highest value opportunity and to start with questions instead of gathering all the available data, and by doing so, wasting resources on cleaning and converting data. Starting with questions means first defining the needed insight to meet business targets, and only after this, is the needed data identified.

Companies may act reactively or pro-actively. Reactive companies conduct analyses due to negative situations, while pro-active companies conduct analyses regarding positive situations (Guarda et al., 2013). Companies can use analytics for describing, predicting, and improving operations. For example, in the waste management sector, analytics allows players to predict forthcoming waste volumes from certain customers and recognize exceptions in waste generation, while advanced analytics relates to machine learning and complex behavior prediction (Niska & Serkkola, 2018). Analytics can be used to simulate and optimize material flows in the supply chain, identify the most profitable customers, detect quality issues, and to recognize financial performance drivers (Davenport, 2005). Companies should integrate their internal and external data to entirely utilize the potential of data analytics (Qaffas et al., 2022). For example, waste monitoring data may include the waste quantity, time stamp and location. By combining this data with external data, such as socio-economic data, it may be possible to create predictive models for waste generation (Niska & Serkkola, 2018). With descriptive analytics, each waste producer can be grouped with similar producers and required operations can be planned for them (Niska & Serkkola, 2018).

Descriptive statistics shows aspects such as the size of an average order, while predictive modelling enables users to recognize the most profitable potential customers by pooling internal and external data sources (Davenport, 2005). Description aims to achieve human-interpretable patterns, while prediction uses variables to predict future values. These aims can be achieved by data-mining methods such as classification (data to predefined classes), regression (to predict e.g. the volume), clustering (identification of categories), summarization (compact description e.g. by tabulation), dependency modelling (describing dependencies between variables), and change and deviation detection (discovering changes) (Fayyad et al., 1996; Saggi & Jain, 2018). Descriptive analytics helps to understand what is happening at the current moment using dashboards and scorecards (Ghasemaghaei, 2019; Ghasemaghaei & Calic, 2019). Descriptive analytics summarizes data to provide easy access and understanding using graphics and statistical metrics (Coleman et al., 2016).

Figure 4 summarizes the explanations for descriptive, predictive, and prescriptive analytics. Predictive analytics helps to determine what is likely to happen in the future and offers forecasts (Ghasemaghaei, 2019; Ghasemaghaei & Calic, 2019). Predictive analytics allows forecasts that are based on historical data (Coleman et al., 2016). Prescriptive analytics helps to identify needed actions for the optimal result, including optimization and simulation (Ghasemaghaei, 2019; Ghasemaghaei & Calic, 2019). Prescriptive analytics uses results of descriptive and predictive analytics and converts them into decision-making (Coleman et al., 2016).

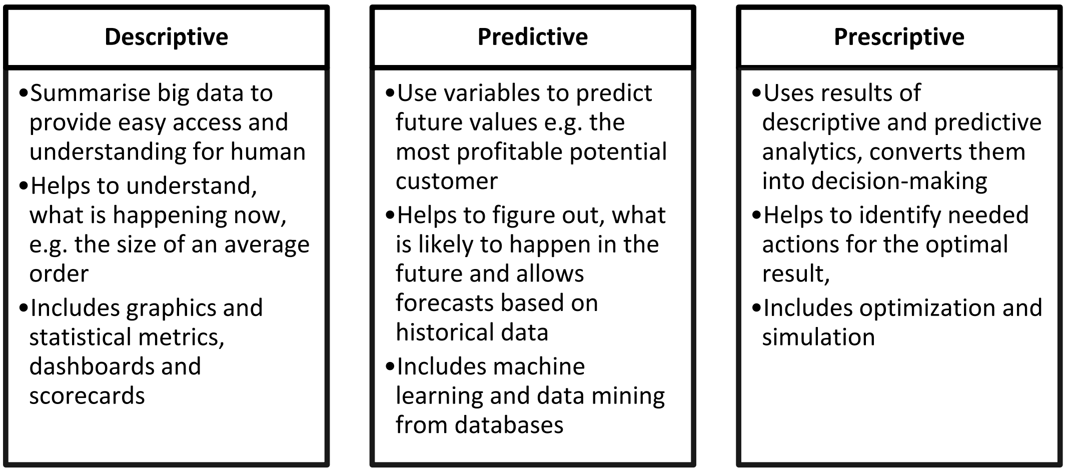

Figure 4 Descriptive, predictive and prescriptive analytics.

As an example of the circular economy, a waste management company can utilize external data such as maps, orthophotos, road data, property data, civil data, traffic data and weather data to generate insight for managers, transportation planners and drivers (Strand & Syberfeldt, 2020). The analytic value of external data provides predictive opportunities such as avoiding overloaded trucks and estimating the duration of collection routes. Prescriptive opportunities include optimized routes for waste container collections, in addition to optimal fleet usage and configuration.

2.3 Developing the data analytics capabilities of circular economy SMEs

Dynamic capabilities refer to a company's "ability to integrate, build, and reconfigure internal and external competences to address rapidly changing environment" reflecting the ability to gain a competitive advantage—companies cannot buy capabilities, they must build them (Teece et al., 1997). Dynamic means "the capacity to renew competences" in the changing business environment, while capabilities refer to strategic management choices to adapt, integrate and reconfigure skills, resources and competencies (Teece et al., 1997). The strength of dynamic capabilities affects the speed at which the customer's needs can be met (Teece, 2018).

Dynamic capabilities are one of the most studied topics in the intersection of innovation and the circular economy (Sehnem et al., 2022). Digital tools and data are key capabilities in the circular economy, as it is driven by digitalization (Parida

& Wincent, 2019). Nevertheless, utilizing data and digitalization poses challenges to circular economy SMEs, who would benefit from data enabled development in material flows and customer behavior (Lacam, 2020).

Educational organizations can act as development partners for SMEs to enhance the dynamic capabilities of SME. This can take place in co-operation with students, who can facilitate shared knowledge creation, learning and innovation (Kunttu & Neuvo, 2019; Perkmann et al., 2013).

2.3.1 Opportunities data provides

In the growing digital environment, a data analytics capability offers opportunities for performance improvement, quality of decision-making and opportunities for innovation. It is difficult to sustain a competitive advantage without analytical capabilities, as they are needed to guide decisions and operations. Analytical capabilities are required to gain insight into processes, customers, supply and demand—to understand changes and take action (Medeiros & Maçada, 2022). The understanding provided by data analytics can transform the means of competition (Ferraris et al., 2019).

Performance and data analytics capabilities are related (Ferraris et al., 2019; M. Gupta & George, 2016) as SMEs with higher technological and managerial data analytics capabilities have been found to increase their performance, while knowledge management increases the effect of data analytics capabilities (Ferraris et al., 2019).

Data analytics capabilities affect decision-making. Data analytics tools increase knowledge sharing in company, but knowledge sharing does not increase the quality of decision-making without adequate data analytics competency (Ghasemaghaei, 2019). The quality of decision-making is also affected by the quality of the data and sophistication of the analytics tools. Data analytics capabilities must be considered not only from the technological perspective, but as a strategic skill to develop an open innovation process to increase company's performance, to promote the development of innovations, and to improve customer satisfaction (Arias-Pérez et al., 2022). Data analytics capabilities require skills, abilities and knowledge to enable creating value from data (Visvizi et al., 2021).

Circular economy needs collaborators and requires systems thinking - otherwise the supply chain with several actors suffers lack of coordination and conflicting interests as different actors aims to optimize their own activities and they are not viewing the big picture of the whole chain which leads to inefficiency and decreased profitability. All stakeholders should be viewed as a system with a shared goal, that in turn requires trust between actors. Once there is trust, information sharing takes place and data analytics can support coordination with common stakeholder view of shared sustainability goals for circular economy system. (S. Gupta et al., 2019). Circular economy ecosystem with many actors increase the complexity, and the complex interaction with different objectives can be analyzed by game theory (Palafox-Alcantar et al., 2020).

Data analytics capabilities do not directly bring sustainable performance, but can lead to circular economy practices and supply chain flexibility (Edwin Cheng et al., 2021). Analytics capabilities need to be connected to data-driven circular economy strategies to achieve sustainable supply chain flexibility that in turn leads to sustainable supply chain performance.

2.3.2 Capabilities needed in data utilization

A data analytics capability is an important organizational capability to achieve a sustainable competitive advantage and to enable company performance. It is challenging for companies to recruit employees with high analytic capabilities (Davenport et al., 2001). Data analytics capabilities are positively related to circular economy performance (Awan et al., 2021). The quality of decision-making is driven by data analytics capabilities that enable companies to transfer insight to recyclable and reusable products.

LaValle et al. (2011) explain the three level of analytics capability: aspirational, experienced, and transformed. By aspirational, they refer to companies that pay attention to automating processes to gain cost savings—these companies are short of resources that are needed for analytics. Experienced organizations develop analytics to optimize the organization, while transformed organizations aim to improve customer profitability.

Investing in data analytics is not enough on its own, the capability must be developed as well, as companies need capabilities that competitors find hard to match (M. Gupta & George, 2016), and the data analytics talent capability is “a significant enabler for firm performance” (Qaffas et al., 2022). A competitive advantage can be gained by developing organizational capabilities for the targeted use of analytics including the expertise to organize data analytics resources, separating data analytics capabilities from data-enabled capabilities, the rationality of data analytics in relation to the quantity and quality of data, utilizing analytics insight in practice, and building managerial trust towards analytics insight (Mikalef et al., 2018).

Data analytics competency describes the capability to utilize data analytics, which is a requirement for using analytics tools (Ghasemaghaei, 2019). A data analytics capability refers to the skills required to collect, store, process, analyze and visualize data to create information, including dimensions of data integration and interpretation (Medeiros & Maçada, 2022; Sabharwal & Miah, 2021, p. 9). A data analytics capability includes technical knowledge (as operational systems, programming, statistics), technology management knowledge (such as data resource management), business knowledge (such as business functions and environment), and relational knowledge (such as collaboration) (Qaffas et al., 2022).

Visualization is a way to communicate insight extracted from data in a graphical form (Saggi & Jain, 2018). When creating visualizations, the first step is to identify the main questions that need to be answered and the relevant analysis unit (Figure 5). Then, different data types need to be integrated in analysis and visualization. Visualization should be linked during ongoing data collection and it should provide interactions for dynamic visualization (Tay et al., 2018, pp. 664–665). As discussed earlier, it is important to provide information for employees so it is understandable and applicable for their needs.

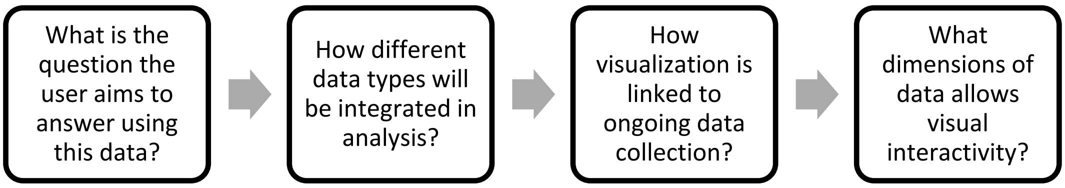

Figure 5 Questions to guide data visualization (adapted from Tay et al., 2018, p. 664).

Davenport et al. (2001) identified key competencies and key roles for developing analytics capabilities. The key roles working together are a database administrator, business analyst and data modeler, decision maker and outcome manager. Key competencies relate to the technology skills, statistical modelling and analytic skills, knowledge of the data, knowledge of the business, and communication and partnering skills. De Mauro et al. (2018) identified data related work roles such as business analysts, data scientists, developers, and data engineers. Business analysts transform insight into business impact, data scientists transform data using analytical methods into insight, data developers design data solutions, while data engineers build infrastructure to store and process big data. Developers and engineers are technology experts who focus on systems and applications, while business analysts and data scientists are business experts connecting data analyses to value creation. These roles and required skills need to be understood in companies.

SMEs have a lack of understanding of data and analytics, as they are dominated by field specialists, the general management functions might be poorly covered, and the domain specific culture and conservatism are not interested in management trends (Coleman et al., 2016). For this reason, SMEs could benefit from case study examples and appropriate consulting and analytics services.

Ghasemaghaei (2019) found that companies rarely mentioned success in data analytics investments—the explanation was given that companies did not know what was required to apply data analytics tools. Another explanation for the lack of success in data investments is that companies are not ready or do not utilize the gained insight in decision-making (M. Gupta & George, 2016, p. 1049). SMEs find challenges in data projects as long-term data storage, integration of internal and external data, and the fact that SMEs are "more worried about the unstructured nature of the data rather than the volume of data" (M. Gupta & George, 2016).

Data analytics readiness in industry can be measured in terms of resources, information systems, culture, and organization (Gürdür et al., 2019). Resource readiness is measured by data analytics tools and human resources working on data analytics. Information systems readiness is measured by data-related policies linked to the definition, collection and utilization of data as well as by easy access to data. Cultural readiness measures the importance of data analytics for employees and the organization. Organizational readiness examines the roadmap towards data analytics and the business impact. Even though the readiness in terms of resources, information systems and culture may be high, the organizational structures enabling the adaption of data analytics can be low (Gürdür et al., 2019). For this reason, companies are recommended to focus actions on the business impact of data analytics by educating managers and employees to utilize analytics on a daily basis.

2.3.3 Developing capabilities

There is increasing demand for experts in the field of descriptive, predictive and prescriptive analytics to serve the needs of decision-making and to communicate knowledge to business experts (Qaffas et al., 2022). As SMEs might not be able to recruit data analytics experts, they should build the skills internally (Coleman et al., 2016).

As digitalization accelerates the transition towards the circular economy, companies need to develop business analytics resources (Kristoffersen et al., 2021). The development of data analytics capabilities is complex and requires a combination of tangible, intangible and human resources (M. Gupta & George, 2016; Kristoffersen et al., 2021). Tangible resources relate to data, technology, time and finance (M. Gupta & George, 2016; Kristoffersen et al., 2021). Human resources include managerial and technical skills (M. Gupta & George, 2016), systems thinking and data science skills (Kristoffersen et al., 2021). Intangible resources refer to a data-driven culture, organizational learning (M. Gupta & George, 2016), a circular-oriented innovation culture, and openness and co-creation (Kristoffersen et al., 2021). As companies can buy tangible resources, the importance of intangible and human resources are highlighted (M. Gupta & George, 2016).

Figure 6 Resources needed to develop data analytics capabilities (M. Gupta & George, 2016; Kristoffersen et al., 2021).

Education for analytics and business intelligence needs to be interdisciplinary. Information technology and analytics skills are not enough, analytics specialists need a general understanding of management, logistics, operations management, accounting, finance, and marketing (Chen et al., 2012) to be able to communicate and interact with others. SMEs can use open-source tools and Massive Open Online Courses (MOOC) to develop analytics capabilities or to increase business knowledge among IT personnel, but the challenge is the lack of time allocated to learning and the need for intuitive software with short learning curve (Coleman et al., 2016).

Successful business intelligence and analytics education implements the “learning by doing” principle in hands-on projects carried out by student, internships, and industry-guided practicum, as data analytics requires experimentation, meaning trial and error (Chen et al., 2012, p. 1183; Teece et al., 1997). Thus, education needs a strong relationship with industry to promote experiential learning in practice.

> *"Learning is often a process of trial, feedback, and evaluation. If too many parameters are changed simultaneously, the ability of firms to conduct meaningful natural quasi experiments is attenuated. If many aspects of a firm's learning environment change simultaneously, the ability to ascertain cause-effect relationship is confounded because cognitive structures will not be formed and rates of learning diminish as a result."* (Teece et al., 1997, p. 523)

Organizational learning happens by processing information to develop insight and association between actions in the past and the future (Selnes & Sallis, 2003). Organizations try to make sense of information, but they reject some information as they do not have the capability to make sense of it. Organizational learning can happen in a relationship between organizations, where the relationship can be a source and a target for learning that are dependent of the organizations' willingness to collaborate. Selnes & Sallis (2003) reported findings that relationship learning increases the relationship performance and commitment in collaboration. Interestingly, even though relational trust is a prerequisite for collaboration, a high level of trust can decrease the outcomes of learning for several reasons, such as avoiding negative information and not risking the relationship, not seeking critical information to question the current situation, as well as falling into group thinking. Mutual trust can be created by close and personal-level interactions between key stakeholders that in addition increases commitment towards the collaboration (Kunttu & Neuvo, 2019). Data analytics capabilities can be developed in relationships between industry and universities by applying co-creation pedagogy to apply knowledge in practice (Lahdenperä et al., 2022).

2.4 Summary

Data-driven decision-making provides opportunities to reduce costs and increase efficiency but it requires managing and harnessing data into value. In the case of SMEs there is still a lack of understanding, technological infrastructure and expertise in this area. As SMEs form a great part of the economy in Europe, their development in the area of data-driven decision-making needs attention. As the circular economy aims to achieve the efficient use of resources and minimize environmental emissions, data provides valuable opportunities to optimize the material flows. Hence, the key internal barriers in SMEs are a lack of managerial awareness and the lack of skills to utilize analytics.

Today there are increasing amounts of data available, but the data itself does not contain any meaning. Data typically originates from different sources inside and outside an organization in many forms, and the most important data needs to be identified and utilized. However, without appropriate data processing there is no information and insight. To fully benefit from data it is necessary to make it understandable for companies, but SMEs face challenges such as the shortage of qualified data analysts, difficulty in choosing suitable solutions, and in understanding data protection regulations. However, investing in data analytics tools is not enough, SMEs must build their analytics capabilities as well. It must be highlighted that data analytics tools increase knowledge sharing, but they do not increase the quality of decision-making without data analytics competency.

Dynamic capabilities can be built and reconfigured rapidly to answer to the changing requirements in the business environment, which is an active topic in the intersection of innovation and the circular economy. Data analytics capabilities include the skills required to collect, store, process, analyze and visualize data. As SMEs have a lack of understanding of data and analytics, they could benefit from case study examples and analytics services.

As SMEs might not be able to recruit data analytics experts, they should build the skills internally. This requires a combination of tangible, intangible, and human resources. Education on analytics must be interdisciplinary, as there is a need to understand business, management, logistics, finance, and marketing aspects. Successful analytics education could implement “learning by doing” principles to carry out hands-on projects and experimentation.

3 METHODOLOGY

This chapter discusses the research design, shown below according to a research onion (Saunders et al., 2012) model, which explains the research philosophy and approach, methodological choices, research strategy, time-horizon, data collection and analysis, as well as research quality. The overview of approaches and choices are visualized in Figure 7.

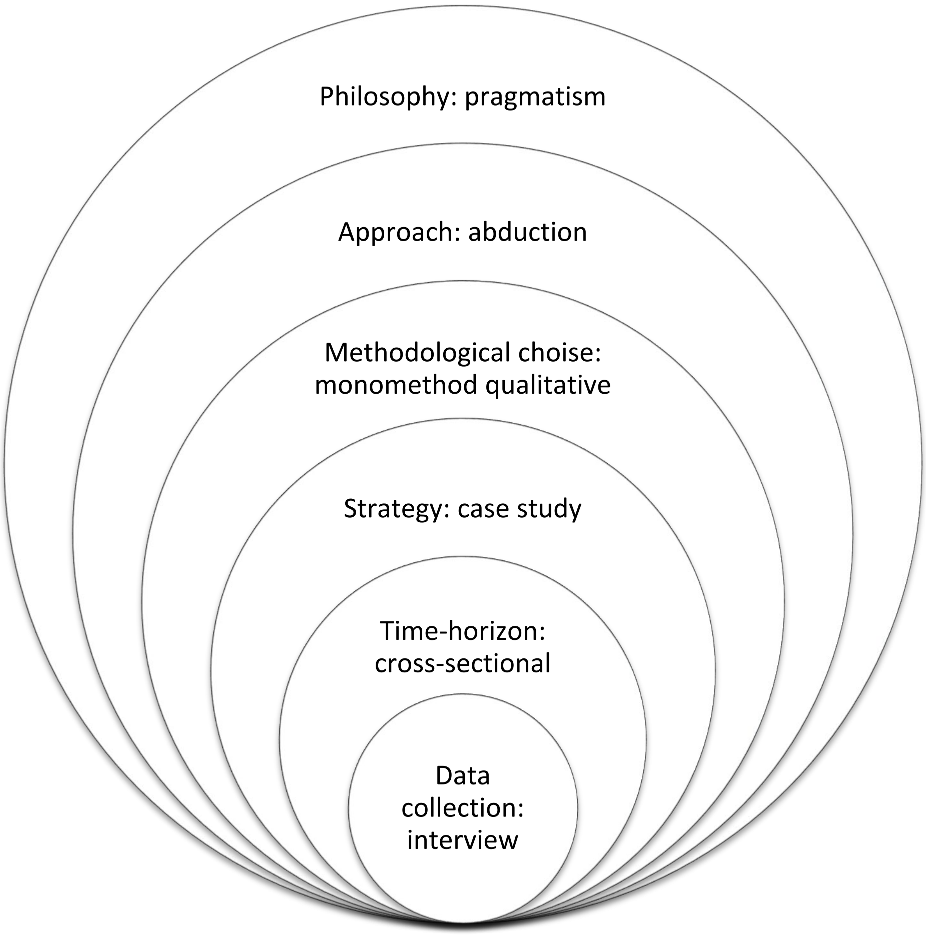

Figure 7 Research design according to a research onion model (adapted from Saunders et al., 2012).

This research seeks answers to questions of "what" and "how" that can be studied by qualitative research. It is pragmatic research seeking to contribute to practical phenomena from the grassroots level, by finding out how things work from companies.

3.1 Research philosophy and paradigm

Research philosophy relates to the development and the nature of knowledge, and it considers what knowledge is acceptable and how it should be developed. Ontology refers to the nature of reality with two aspects: objectivism and subjectivism. According to objectivism, "social entities exist in reality external to and independent of social actors" (Patton, 2015; Saunders et al., 2012, p. 131). Subjectivism refers to the concept "that social phenomena are created from the perceptions and consequent actions of social actors" (Patton, 2015; Saunders et al., 2012, p. 132). In the subjective meaning, individuals in an organization represent their own experience (Bell et al., 2019). The ontology of this dissertation is subjectivism, as the study focuses on SMEs by interviewing company representatives, obtaining their views, opinions and experiences.

Epistemology refers to what constitutes acceptable knowledge. Positivism requires observable reality to find regularities and causalities to produce generalizations. Realism refers to the concept "that objects have an existence independent of human mind" (Saunders et al., 2012, p. 136). Interpretivism contrasts with positivism (Bell et al., 2019) and refers to social phenomena and subjective meaning. It is focused on details and related reality. Interpretivisms uses small samples and aims to carry out an in-depth investigation using qualitative data. Pragmatism refers to practical applied research and to multiple ways of interpreting reality and conducting research, as from one single view it is impossible to see the entire picture (Patton, 2015; Saunders et al., 2012, p. 130). Pragmatists may adopt both subjective and objective views, while values are used in interpreting the results, and they collect data by methods that enables well founded and relevant data. The epistemology of this dissertation is pragmatism, as it represents practical applied research that aims to explore SMEs in depth using qualitative data. This study does not aim to observe causalities or produce wide generalizations.

A research paradigm "is a way of examining social phenomena from which particular understandings of these phenomena can be gained and explanations attempted" (Saunders et al., 2012, pp. 140–141). The four paradigms can be arranged by dimensions of subjectivist - objectivist and radical change - regulation. The functionalist paradigm is a combination of objectivism and regulatory dimensions. This paradigm is interested in rational explanations and developing recommendations. The interpretive paradigm is a combination of subjectivism and regulation. This paradigm is more interested in understanding and explaining things, than making changes. The interpretive paradigm focuses on building understanding from the experience of individuals (Bell et al., 2019). The radical humanist paradigm is a combination of subjectivism and radical change. The radical structuralist paradigm is a combination of objectivism and radical change. Radical paradigms are interested in achieving a fundamental change according to the analysis of phenomena. This dissertation follows the interpretive paradigm, as the study aims to understand and explain the situation in companies. The paradigm could be a functionalist paradigm, if the aim would be stronger in terms of rational explanation and the creation of recommendations. The paradigm is clearly not radical, as it does not aim to make fundamental changes.

3.2 Research approach

There are three research approaches: deductive, inductive and abductive (Bell et al., 2019; Patton, 2015; Saunders et al., 2012). The deductive research approach is used for testing a theory from a theory-based hypothesis, the inductive approach is used to generate theory as a result of data collection and data analysis, while an abductive approach combines both theory generation and theory testing to generate and to test new theories. Deductive research begins with a theory developed from the literature and the aim is to test the theory. When research aims to explore a phenomenon and generate theory, the approach is inductive, and the research starts with data collection. In an abductive approach, data is collected to explore the phenomenon, identifying categories to generate a theory that will be tested through supplementary data collection.

This dissertation uses an abductive approach as it combines theory and empirical findings to collect data, identify categories and generate theory. The research group involved in this study has previous experience and has researched the situation in SMEs.

3.3 Methodological choice and nature of research

Quantitative research refers to the numerical data collection and analysis methods, while qualitative research refers to the data and methods used with non-numerical data (Bell et al., 2019; Patton, 2015; Saunders et al., 2012). However, quantitative, and qualitative methods can be combined in mixed-methods research. Multi-method research uses more than one, either quantitative or qualitative, data collection and analysis technique. Quantitative research is typically associated with the research philosophy of positivism and a deductive research approach with experimental and survey research strategies (Saunders et al., 2012, pp. 162–163). Qualitative research is generally associated with the research philosophy of interpretivism and an abductive approach with a variety of research strategies, such as action research or case study research (Saunders et al., 2012, p. 163). Quantitative research examines the connection between variables with numerical measures and analyses by using statistical techniques (Bell et al., 2019; Saunders et al., 2012, p. 162). Qualitative research examines meanings and relationships between them, exploiting a variety of analytical procedures to generate a conceptual framework, where success in research relies on building trust to gain data (Saunders et al., 2012, p. 163). This dissertation represents qualitative research that collects and analyzes non-numerical data, with research questions starting with "what" or "how". A qualitative method suits interpretivism and abduction and can be used with case study research strategy.

The nature of research can be exploratory, descriptive, or explanatory (Saunders et al., 2012, pp. 171–172; Yin, 2018, p. 8). Exploratory research discovers what is happening by asking open questions and it aims to gain insight and understanding into a problem. Descriptive research aims to gain an accurate profile of what is being studied. Explanatory research aims to study causal relationships between variables. This dissertation represents exploratory research, as it discovers the situation of SMEs operating in the circular economy and it collects research data by interviewing respondents with open questions.

3.4 Research strategy

A research strategy is a plan of how the research questions aim to be answered, and it forms a methodological link between the research philosophy, data collection, and data analysis methods. Typical research strategies in qualitative research are experiment, survey, archival research, case study, ethnography, action research, grounded theory, and narrative inquiry (Saunders et al., 2012, p. 173).

According to Yin (2018, p. 15), a case study is an empirical method that "investigates a contemporary phenomenon in depth and within its real-world context, especially when the boundaries between phenomenon and context may not be clearly evident". Research design is a logic that connects empirical data to research questions and conclusions. Case study design includes five components: research questions, propositions, cases, logic links from the data to the propositions, and the criteria to interpret the findings (in statistical analyses) or to identify rival explanations for the findings (Yin, 2018, pp. 27, 33). However, exploratory research does not necessarily have any proposition, or the propositions may be a research outcome providing direction and determining what should be examined next (Yin, 2018, p. 28). The research questions show what information needs to be collected. The cases being studied could be a person, an organization, or organizational learning—if the study includes many cases, it is a multiple-case study (Yin, 2018, p. 29).

Eisenhardt (1989) described a process of building theory from case study research. Case study research aims to understand the dynamics present in a single setting. The definition of research questions is tentative and research questions can shift during the research. Random selection of cases is not required. Eisenhardt says that theory-building research should start with no theory under consideration, but specification of potentially important variables based on the literature is needed. When selecting cases, random selection is not necessary. Cases can be chosen to fill theoretical categories or to provide examples of polar types. There are no set numbers for the relevant number of cases, but Eisenhardt suggests that a number of cases between 4 to 10 works well. Case analyses should be done within-case and it is important to get familiar with each case before trying to generalize patterns across cases.

According to Dubois & Gadde (2002), case studies enable the development of theory by exploiting in-depth insight of phenomena and its context. Abduction-based case studies necessitate an integrated approach, and there is difficulty to manage several interrelated elements. For this reason, the researcher moving between research activities from theory to empirical observation can enlarge understanding. The authors further stated that "theory cannot be understood without empirical observation and vice versa" (Dubois & Gadde, 2002, p. 555).

The research strategy in this dissertation is a case study, as this research aims to investigate the in-depth situation in SMEs. As Eisenhardt suggests, cases in this study are not randomly selected. The cases are companies, and the study focuses on their practices, challenges, and development needs. As this research includes several companies, it is a multiple-case study.

3.5 Time-horizon

The time horizon in research can be either cross-sectional or longitudinal (Bell et al., 2019). The cross-sectional horizon provides a snapshot of events in a chosen time, while a longitudinal horizon provides "a representation of events over a given period" (Bell et al., 2019; Saunders et al., 2012, p. 190). The time-horizon in this dissertation is cross-sectional, as it studies the practices, challenges, and development needs of case companies at the moment.

3.6 Data collection and analysis

An interview is a method to collect research data. There are different ways of conducting interviews: structured, semi-structured and unstructured or in-depth interviews (Patton, 2015; Saunders et al., 2012, p. 374). Structured interviews are constructed by a predetermined set of questions. Structured interviews use questionnaires, and each question must be asked the same way in each interview. This type of interview collects quantifiable data. Semi-structured interviews contain a list of themes to be covered in an interview, where questions and their order may be different in each interview. Unstructured interviews are informal and in-depth interviews without a list of questions, and they are used for in-depth exploration. These types of interviews are often referred to in qualitative research.

The strength of interviews in case studies is the opportunity to target the focus on the study topic and the insight for explanations. Weaknesses stemming from interviews are possible bias if the questions are articulated poorly or if the interviewee tells the interviewer what they expect to hear (Yin, 2018, p. 114). Interviews in a case study are guided conversations with a list of themes to be covered. A case study interview typically takes about an hour (Yin, 2018, p. 119).

This dissertation uses semi-structured interviews and group interviews, including a list of themes and questions to be covered during the interview. The aim is to have a conversation with the interviewee, as they would provide the big picture to the topic discussed. It is impossible in exploratory research to give exact and strict questions as there is not yet enough information about the current situation in the cases—this is to be explored in the research being conducted. The research data was collected for each research question. The interviews were conducted during 2019-2021. In addition, secondary data was used from company websites and datasets that the companies provided.

There are four general analysis strategies: to follow the propositions, to work with data from the ground up, to develop case descriptions and to examine competing explanations (Yin, 2018, pp. 168–172). When working with data from the ground up, there are no propositions, and the aim is to find useful concepts from the data. Cases can be described according to a descriptive framework that comes from the literature. According to Yin (2018, pp. 175–195), there are five analytic techniques for case study research: pattern matching, explanation building, time-series analysis, logic models, and cross-case synthesis. Pattern matching is one of the most desirable techniques when analyzing cases as it compares empirically-based patterns with a predicted one. A pattern search serves generalizability in case study research, and it can be done by constructing an array to search for similarities or differences. Explanation building describes aspects such as how and why something happened. Cross-case synthesis is for multiple-case study research when the aim is to compare or synthesize cases (Patton, 2015; Yin, 2018, p. 196).

The analysis strategy in this dissertation is developing case descriptions and conducting pattern matching, which are then summarized (RQ1, RQ4) or compared (RQ2, RQ3) in the research question specific articles within a selected framework from the literature. The analysis method is a cross-case synthesis of multiple cases as the cases are summarized and compared.

3.7 Quality criteria

The quality of qualitative research should be evaluated by different terms that quantitative research. Measures for qualitative research are credibility instead of internal validity, transferability instead of external validity (generalizability), dependability instead of reliability, and confirmability instead of objectivity (Guba, 1981, cited in Shenton 2004, p. 64).

Triangulation is a combination of actions or methods to avoid bias or misinterpretations in research. Triangulation can be conducted in four ways: by using several data sources, mixed qualitative and quantitative methods, multiple researchers reviewing the results, and multiple theories for interpretation (Patton, 2015).

Credibility refers to the consistency of findings and reality. It depends on systematic fieldwork and data analysis, credibility of the researcher, and the readers' philosophical beliefs (Patton, 2015). Shenton (2004) explains ways to ensure trustworthiness as follows. Credibility includes familiarity with the culture of the participating organization, securing honesty of the informants, as well as triangulation in data collection, analysis, and interpretation. Transferability indicates the scope with which to apply the findings to other conditions. This requires a detailed description of the context of the study. Dependability means overlapping methods and reported processes of the study, allowing other researchers to repeat the research from the methodological description. Confirmability stands for ensuring that the findings are derived from the experience of the informants rather than the researcher's preferences. This can be achieved via investigator triangulation and recognition of the limitations of the study.

Consideration of the number of cases (7) being studied is relevant according to Eisenhartd (1989, p. 545). Dependability is realized by using individual interviews and group interview in data collection. Findings and interpretations from individual interviews can be verified with informants in group interviews. Confirmability can further be secured by investigator triangulation in data collection, analysis, and interpretation. If the researchers have different views, there will be discussion and interpretations can be verified with the informants.

This dissertation does not aim for wide generalizability of results. The results are applicable in waste management and recycling SMEs in Nordic countries. Triangulation was carried out by reviewing the results involving multiple researchers. The findings from the interviews were verified by informants in group interviews to ensure the findings are consistent with reality. In this dissertation, credibility was ensured by being familiar with the participating organizations and informants, securing trust, and by creating an open atmosphere in the interview situation. Information to evaluate the transferability of this study, is ensured by describing the context of this study in chapter 1.4 and providing case descriptions in each article of this research.

3.8 Summary

This chapter summarizes the methodological choices of this research, as summarized in Table 2.

Table 2 Research design.

Research Design	Approach in this Research	Explanation
Research Philosophy	Ontology: subjectivism Epistemology: pragmatism	This study focuses on SMEs by interviewing the company representative to gain their views, opinions and experiences.
Research Paradigm	Interpretive	This study aims to understand and explain the situation in companies.
Research Approach	Abduction	This dissertation combines theory and empirical findings to collect data, identify categories and generate theory.
Methodological Choice	Qualitative	This study collects and analyses non-numerical data
Research Strategy	Case Study	This research aims to investigate the situations in SMEs in depth. As this research includes several companies, it is a multiple-case study.

Research Design	Approach in this Research	Explanation
Time Horizon	Cross-sectional	This study is interested in practices, challenges, and development needs of case companies at the moment.
Data Collection Method	Interviews and group interviews, semi structured	The interviews include a list of themes and questions to be covered during the interviews.
Data Analysis Methods	Case descriptions, pattern matching, cross-case synthesis	Developing case descriptions and conducting pattern matching, that are then summarized (RQ1, RQ4) or compared (RQ2, RQ3) Cross-case synthesis of multiple cases, as the cases are summarized and compared.

Empirical data collection was conducted for each research question by interviewing the representatives of the case companies individually and by conducting a group interview (Table 3). In total, seven case companies were involved in interviews for research questions RQ1-RQ3, and three case companies for RQ4. Research data were collected by 35 separate interview session.

Table 3 The number of case companies.

Research question	Number of case companies	Individual interview was conducted in	Group interview was conducted in
RQ1	7	2019	-
RQ2	7	2019 and 2020	-
RQ3	7	2021	2021
RQ4	3	2020 and 2021	-

4 RESEARCH ARTICLES

This chapter reviews the research articles covering the research questions, research methods and results. Each article covers one research question.

4.1 Article 1 Using foresight to shape future expectations in circular economy SMEs

Predicting the future is important for organizations and they need to have tools to foresee threats and opportunities in the business environment (Korreck, 2018; Rohrbeck & Gemünden, 2011; Uotila et al., 2012). Organizational foresight is intelligence gathering from the future (Daheim & Uerz, 2008) and it depends on organizational capabilities (Rohrbeck, 2011). Because of SMEs' limited resources compared to large companies, their foresight activities are different and not all strategic tools are suitable for SMEs (Stonehouse & Pemberton, 2002). Foresight activities are conducted typically when the company is forced into product development (Bidaurratzaga & Dell, 2012; Jannek & Burmeister, 2007), which is emphasized in the case of SMEs. As the circular economy industry is in its early stages, and the operational environment is in rapid change, circular economy SMEs need foresight practices and strategic planning to cope in an environment of discontinuity and disruption that provides both threats and opportunities.

Article 1 examines forecasting in circular economy SMEs that are operating in a changing business environment, where changing legislation provides both opportunities and challenges. This paper seek answers to the research questions: "How do industrial actors and service providers operating in the circular economy foresee future changes in their operational environment?" In addition to, "How do foresight activities affect their business development expectations?" The research method was a qualitative case study with seven circular economy SMEs in Finland. Interviews were conducted in 2019. The PESTEL framework (Aguilar, 1967) was utilized in semi-structured interviews, where companies were asked to describe how they predict future from the political, economic, social, technological, environmental, and legal point of view.

The results show the companies' foresight activities and future expectations. Systematic information collection from the operational environment was seen as an important activity in the case companies. Table 4 shows that case companies' foresight activities include strategic analysis tools, internal key performance indicators (KPIs), named responsibilities to follow changing trends and legislation, investment in digital services for customers and tools for monitoring. The companies followed the media, held discussions with customers, followed and benchmarked their competitors, collected customer feedback in several ways, attended events, and conducted studies.

Table 4 Foresight activities of the case companies.

Political aspects - Strategic analysis tools, risk analyses - Following the media and the information distributed by the association	**Economic aspects** - Discussions and follow-up regarding the customers and competitors - Internal KPIs form a central tool for predicting the future	**Social aspects** - Customer and consumer feedback and expectations are collected through the customer service function - Face-to-face contacts with consumers in, e.g., interviews, surveys, and commercial fairs - Strong investments in digital services in consumer interfaces: e.g., online-tools and chat services developed to better serve the end users
Technological aspects - Benchmarking competitors - Attending fairs, seminars, workshops, and events - Making studies in the areas of the company’s interest	**Legal aspects** - Clear organizational responsibilities defined for following the changes and trends in legislation	**Ecological aspects** - New tools and resources are needed to process controlling and monitoring

Table 5 shows the companies’ future expectations. The case companies highlighted the importance of forecasting changes in environmental policies and legislation. The economic aspect shows that the competitive environment is becoming more challenging due to new competitors, consumer trends, and environmental policies. Interestingly, in the circular economy, competitors can be seen to also be collaborators. From the social point of view, “green thinking” favors high environmental standards that require understanding the expectations of both consumers and B2B-customers. There is demand to develop digital services that would provide a way to collect valuable feedback from consumers and customers for further development of services. As technological development is rapid in the area of recycling, companies need to invest resources to develop both facilities and capabilities. There is a lot of pressure to reduce carbon emissions by optimizing logistics and waste collection. The legal aspect affects the whole value chain in the circular economy as quite often changing environmental laws mean new investments for companies. The ecological aspect is dominant in the field of the circular economy, preferring recycling over incineration of waste, and expecting to reduce carbon emissions, while recycling is dependent on transportation.

Table 5 Future expectations of the case companies.

Political aspects	Economic aspects	Social aspects
- Environmental aspects are a hot topic in political decision-making, partly because the audience pays lot of attention to environmental issues; the circular economy is one essential part of this political debate - The follow-up and prediction of the changes in political decision-making are included in the companies' strategy work - The role of the industrial association is central: the association transmits information on the political climate to the companies, and on the other hand, the association tries to influence on the political decision-making by promoting the industry viewpoints	- Competition is increasing all the time since the number of service providers is increasing, leading to a decrease of prices - To maintain a position as a remarkable actor in the business area requires investments in production	- Customer and user expectations follow consumption trends - Consumers are nowadays aware of the environmental issues, and they require products and services to fulfill high environmental standards - A key issue is to understand the behavior and expectations of single consumers in their waste management - Private consumers in particular expect digital services
Technological aspects	**Legal aspects**	**Ecological aspects**
- Strong demand for low carbon emissions in all activities—transportation is a remarkable challenge - Burning waste is often an efficient way of using it, but material recycling is more sustainable - Developing efficient methods for waste collection and logistics - There are increasing needs for digital services in consumer interfaces and in, e.g., the planning and optimization of logistics	- Legislation has a strong impact on all parts of the circular economy value chains and business development - Policies and decision-making processes related to, e.g., companies' environmental licenses are getting tighter - Predicting changes in legislation clearly steers the strategic planning in the companies	- Carbon-neutral waste management is expected - Nowadays recycling is preferred to the previously desired energy usage of waste - There are growing demands for responsibility, transparency, and sustainability in all the processes

4.2 Article 2 Data-driven decision-making in circular economy SMEs in Finland

Data-driven decision-making can provide development opportunities for organizations to reduce costs, increase operational efficiency, customer loyalty and communication (Pulkkinen et al., 2019; Troisi et al., 2020). Data-driven decision-making means managing data to make decisions to prescribe actions, predict development, and drive change (Troisi et al., 2020). Turning data into value, requires the capability to harness data (Troisi et al., 2021; Watson, 2016). In the case of SMEs, there is a lack of understanding of data, data analytics infrastructure, and expertise to select appropriate solutions (Iqbal et al., 2018; Parra et al., 2019; Ransbotham et al., 2016).

Article 2 examines the data-driven decision-making and management practices of circular economy companies. This paper seeks answer to the research question: “How can SMEs operating in a circular economy utilize data to support their decision-making?” The interview results were analyzed with three sub-questions: 1) “What data is utilized in strategic decision-making?”; 2) “How is data utilized in decision-making?”; 3) “How much has Covid-19 affected data utilization in decision-making?” The research method was a qualitative case study with seven circular economy SMEs in Finland. Interviews were conducted in 2019 and a second round in 2020.

The results show that the case companies most typically use business-generated data. The companies utilized data on finances, production, transportation routes, materials, and customers. They followed their competitors’ development in different ways as well as the price trends of materials. A partnering company can be an important data source to estimate the volume of forthcoming material flows. Circular economy SMEs could benefit from external data sources such as maps, roads, traffic, and weather (Strand & Syberfeldt, 2020). However, the case companies did not mention these kinds of external data sources. All seven case companies in this study conducted descriptive analytics that showed the current state of the business (Sivarajah et al., 2017), while only two of them mentioned predictive analytics that would allow forecasting. This might relate to the type of customer, as circular economy companies serving consumers might face limited competition, meaning the consumer may not have opportunity to select the service provider. In the circular economy, descriptive analytics could be used to show the annual waste volume, while predictive analytics could optimize the number and configuration of transport equipment (Strand & Syberfeldt, 2020). The results indicated that 1) internal business-generated data was the most utilized in the case companies, and 2) descriptive analysis was the typical way to utilize data (see Table

6). The case companies reported that Covid-19 had only a small or no impact at all on data-driven decision-making conducted in company.

Table 6 Data utilized in decision-making in the case companies.

	A	B	C	D	E	F	G
1.What data is utilized in strategic decision-making?							
Machine-generated	x	x	x	x			
Human-generated	x		x		x		x
Business-generated	x		x	x	x	x	x
2.How data is utilized in decision-making?							
Descriptive	x	x	x	x	x	x	x
Predictive				x		x	
Prescriptive							
3. How much Covid-19 is affected to data utilization in decision-making?							
Not at all		x	x		x	x	x
Only a little	x			x			
To some extent							
Rather much							
Very much							

4.3 Article 3 Barriers and practical challenges for data-driven decision-making in circular economy SMEs

Many SMEs face challenges understanding how to utilize analytics, due to lack of competence and resources for data-driven decision-making (Iqbal et al., 2018), which is an approach to managing data throughout the entire decision-making cycle of an organization (Troisi et al., 2020). Circular economy SMEs have industry related challenges linked to the material quality issues, and information exchange in the supply chain. As a resource based barrier circular economy SMEs may lack financial or technological resources (Ormazabal et al., 2018; Rizos et al., 2016), meaning the need to invest in information management systems. Regulation brings challenges as well for circular economy SMEs, meaning complex administrative procedures and the cost of meeting regulations (*Flash Eurobarometer 441. European SMEs and the Circular Economy*, 2016). Other regulative barriers are the lack of a consistent regulatory framework and obstructive regulation (Hart et al., 2019).

Article 3 examines the barriers and practical challenges to data-driven decision-making in circular economy SMEs. This paper seeks answer the research question: “What are the practical challenges in data-driven decision-making in circular economy SMEs?” The research method was a qualitative case study with seven circular economy SMEs in Finland. The research data was collected in semi-structured interviews in May 2021 and in a semi-structured group interview in November 2021. The results are divided into four categories that were identified from the literature: data utilization, lack of resources, lack of capabilities, and regulation.

The results shown in Table 7 indicate that challenges can be caused by various information systems, lack of platforms and time, lack of expertise and infrastructure, as well as legislation. Companies may have large amounts of data in several information systems that do not communicate with each other, the data collection and entering might be manual, and they may have no resources to process data into relevant information. The platforms that many case companies used was for reporting purposes without visualization options. Legislation plays a major role in the circular economy, and it prescribes what is allowed and what must be done as well as determines how operations and materials must be reported. This paper interpreted that circular economy SMEs are more driven by legislation than data, as they pay attention to what they “must have”, while less attention is given to “what they could have” because resources are reserved for the core business activities and there are no dedicated resources to process and utilize data for the needs of data-driven decision-making. The circular economy, as other industries, would benefit from open data. This paper suggests for policymaking to support business development with open data. This could be done by combining resources to develop information for the needs of circular economy SMEs. An interesting highlight for educational institutions is that the case companies identified co-operation with students as valuable for companies, as the interviewees stated that the students have better skills than the people in companies. The paper noted that circular economy companies would benefit from design thinking to increase customers’ recycling activity.

Table 7 Data utilization challenges in the case companies.

Challenge category	**Challenge in cases**
Utilization of data	Data is scattered in various information systems Combining data from various sources is challenging and time-consuming Pre-processing and cleaning of data is challenging and time-consuming Manually inputting data is needed because the data is not automatically transferred between information systems

Challenge category	Challenge in cases
Lack of resources	Inadequate information management systems Current in-house information systems do not support ad hoc reporting and drilling of essential data
Lack of capabilities	Insufficient competence in using existing information systems Lack of capability in using and refining collected data No in-house competence in developing reporting, automated queries
Regulation	The legislation must be followed, the data must be collected in the form required by legislation

4.4 Article 4 Developing data analytics capabilities for circular economy SMEs by Design Factory student projects

Dynamic capabilities refer to the capacity to quickly develop competences to match changing requirements in the operational environment (Teece et al., 1997). Digital tools and data are considered as one of the key capabilities facilitating the circular economy, but many circular economy SMEs face challenges utilizing it. Data enables companies to develop material flows, logistics, and customer behavior (Lacam, 2020). Because university students can transfer knowledge to industry, companies could utilize collaboration with students to facilitate shared knowledge creation, learning and innovation (Kunttu & Neuvo, 2019; Perkmann et al., 2013) and enhance company's dynamic capabilities.

Article 4 examines how SMEs' data analytics capabilities can be developed in co-operation with a university. The research data was analyzed using the relationship learning framework by Selnes & Sallis (2003). This paper seeks answers to the research question: "How the data analysis capabilities in the SMEs are developing in the joint action between university and companies?" The sub-questions are: 1) "How does the university-industry collaboration correspond to the data analytics capability needs of the CE SMEs?" 2) "How did the capabilities of the CE SMEs develop during the collaboration?" The research method was a comparative multiple case study of three circular economy SMEs in Finland. The case companies collaborated with students as challenge owners and data providers in data analytics student projects that were conducted in spring 2020 and 2021. The companies were interviewed after the collaborating project.

The results show that data visualizations created by students helped the companies understand business and data analytics tools as well as new ideas. However, in

2020, the companies found it challenging to apply the results the students provided. For this reason, the project course was developed by paying attention to sharing the results with the companies. It was noticed that when the companies collaborated for the second or third time, they managed to define the problem better and received more useful results at the end of the project. Table 8 shows the collaboration in a relationship learning framework. The means of collaboration with SMEs and students included the student's project course, a tailored course for companies, students' training periods in companies, and a number of theses. In the project course, knowledge sharing included data analysis methods. Joint sensemaking refers to the shared understanding of the problem to be solved, including regular communication and interaction between the students and the company. Knowledge integration included an instruction manual created by students for the company to adopt the results. The article suggests the university should pay attention to how the methods and results of the student's projects are transferred to the companies.

Table 8 Developing data analytics capability in university-industry collaboration.

	Knowledge sharing	**Joint sensemaking**	**Knowledge integration**
Co-created student project course	Methods for data analysis are shared between university and companies, university learns about company needs	Weekly or biweekly meetings between students and company create shared understanding on problem and solution space	Student created data analytics solution instruction manual help companies to adopt the results
Tailored course for companies	Company learns about university data analytics methods and tools, while the university learns about industry needs and problems	Discussions in tailored data analytics course for the company increase understanding of the match between needs and tools used	Companies' data analytics capability is enhanced by tailored course
Student trainees for companies	University gains knowledge about company information systems and problem space and the company gains information about data analytics tools and methods	Trainee interaction with company and university increase domain specific understanding on data analytics problem and solution space	Student trainee contributes to development of data analytics solution and absorptive capacity of the company

	Knowledge sharing	**Joint sensemaking**	**Knowledge integration**
Thesis projects for companies	Data analytics focused thesis disseminates learnings to company and future student projects	Thesis meetings and work increase domain specific understanding on data analytics problem and solution space	Thesis project provides extended opportunity to integrate knowledge with the company knowledge base

5 DISCUSSION

The results of this dissertation are presented in its articles. The purpose of this section is to briefly summarize the results of the articles and present their individual contribution to this dissertation.

This dissertation aims to increase the understanding on how circular economy SMEs collect and utilize data, the challenges they face, and how they could develop their capabilities to better utilize data.

Circular economy SMEs operate in a rapidly changing operational environment that requires continuous foresight activities. The empirical data in this research shows that circular economy companies understand that it is important to systematically collect information from their operational environment, as regulations and legislation change quite often, environmental demands are growing, customers expect digital services, technological development provides new business opportunities for recycling, and new competitors are entering the market. Legislation, regulation, customer behavior and environmental consciousness will have strong impacts on the future of the circular economy SMEs, where the challenge is to achieve profitable business, and the opportunity exists to grow the business.

The empirical data in this research shows that business-generated data, that mostly origins from companies' internal processes, is the most utilized data type in circular economy SMEs. Hence, external data holds increasing value for companies including information about competitors and material flows. Descriptive analyses are the mainstream in companies, and this might relate to the limited competition and steady material flows or conservative companies with low use of technology. Those companies that use predictive analytics clearly understand the value of data in their strategic planning, but there is significant room to develop more efficient use of predictive analytics.

In the empirically collected research data, the barriers to utilizing data included various information systems, challenges in data processing, and manual data input. The case companies mentioned the lack of resources, such as the lack of time and tools to process data with. There was a lack of capabilities, such as the expertise and experience necessary to understand analytics, while the company culture focused more on technology at the operational level. The information system that most of the case companies currently use, fell short of discovering and visualizing relevant information. As regulation and legislation enforce what companies can and must do, circular economy SMEs in many cases may be seen to be more legislatively driven than data driven.

The results of this dissertation show that SMEs can develop their capabilities with educational institutions through knowledge sharing, joint sensemaking and knowledge integration with student project courses, tailored course for companies, student training periods in company, and student written theses. These activities can form a continuum, where capabilities are developed step by step. Moreover, when students work in a company as a trainee, it promotes the effective transfer of knowledge and competence between the educational institution and industry.

5.1 Answers to the research questions

RQ1: How do industrial actors and service providers operating in the circular economy foresee future changes in their operational environment? And how do foresight activities affect their business development expectations?

> The results in article 1 can be considered in two dimensions, activities for predicting the future and expectations for the future.
>
> Activities for predicting the future include using strategic analysis tools, key performance indicators (KPIs), creating organizational responsibilities to follow changing trends and legislation, making investments in digital services and tools, media monitoring, holding discussions with customers and collecting feedback, observing and benchmarking competitors, attending events, and conducting studies.
>
> Expectations for the future include the highlighted importance of environmental policies and legislation, increasing competition, changing consumer trends, "green thinking" with high environmental standards, the demand to develop digital services, the need to invest in facilities and capabilities, pressure to reduce carbon emissions by optimizing logistics and waste collection.

RQ2: How can SMEs operating in a circular economy utilize data to support their decision-making?

> The empirical data in article 2 reveals that companies most typically use business-generated data that includes data on finances, production, transportation routes, materials, and customers. In addition, many companies utilize both business-generated data and machine-generated or human generated-data.

All the case companies conduct descriptive analytics showing the current state of the business. Only a small number of cases conducted predictive analytics that allowed forecasting.

RQ3: What are the practical challenges in data-driven decision-making in circular economy SMEs?

The empirical data in article 3 reveals that the challenges relate to data utilization, lack of resources and capabilities, as well as regulation. The practical challenges are caused by the fact that data is scattered in several information systems, and that combining and pre-processing data is challenging and time-consuming. In addition, there is a need to manually enter some data in the systems. There are insufficient information management systems that allow ad hoc reporting and visualization. There is a lack of competence in the use of existing information systems, refining collected data and developing reporting. Legislation requires certain kinds of reporting and that causes difficulties as well.

RQ4: How the data analysis capabilities in the SMEs are developing in the joint action between university and companies?

The results in article 4 show that the SMEs capabilities increased during the student project course according to the outcomes of the student groups. This gave an understanding for companies about the business, opportunities of data analytics tools and methods as well as new ideas. Another finding was that companies collaborating a second or third time, managed to define their development needs better, which led to better results from the student project.

In the project course, knowledge was shared about data analysis methods and tools. Joint sensemaking included the shared understanding of the problem to be solved via regular interaction between the students and the company. Knowledge integration consisted of an instruction manual created by students for the company, so as to adopt the results of the project and modify the solution. The results suggest that the university should pay attention to how the methods and results are transferred efficiently to companies.

Finally, an answer is presented to the main research question: *"What kinds of capabilities, needs and challenges do circular economy SMEs have for data utilization, and how can the capabilities be improved by means of collaboration with universities?"*

Data utilization needs relate to planning operations as well as preparing for the future in terms of increasing competition, changing trends, high environmental standards, investing in facilities and capabilities as well as reducing carbon emissions.

To utilize the potential of data, there is a need to combine relevant data from several internal and external sources and to use advanced analytics methods to make predictions.

Challenges to overcome in data utilization relate to data handling, lack of resources and capabilities, as well as regulation.

Overcoming capability-related challenges can be helped by collaboration with educational institutions in joint learning activities with students including knowledge sharing, joint sensemaking and knowledge integration.

5.2 Theoretical contribution

The results of this dissertation as a whole provide insights into the literature concerning data analytics capabilities in the SME field, particularly in the circular economy sector. The theoretical contribution of the dissertation comes from the four articles, each answering their own research question as described in the previous section.

The results of article 1 contribute to the literature on organizational foresight (Cuhls, 2003; Jannek & Burmeister, 2007; Stonehouse & Pemberton, 2002) concerning circular economy SMEs, describing how they collect data for their foresight activities, as well as what their expectations are for the future from political, economic, social, technological, environmental and legal perspectives.

Article 2 contributes to the previous research the field of knowledge management in the SME sector concerning data utilization (Parra et al., 2019; Troisi et al., 2020; Watson, 2016) in decision making by empirically identifying data utilization practices in circular economy SMEs. The outcomes of the article provide new understanding on the types of data or analysis methods used in the companies.

The outcomes of article 3 contribute to the previous literature concerning the challenges and barriers of data utilization in companies (Iqbal et al., 2018; Ransbotham et al., 2016; Susha et al., 2017; Troisi et al., 2020), by presenting new and practical information from the grassroots level, explaining the current situation and challenges in circular economy SMEs regarding data collection, data analytics and data utilization, as well as how the studied companies' data analytics capabilities could be improved. The results also indicate that circular economy SMEs are driven more by legislation than data.

Article 4 contributes to the literature on relationship learning in university-industry collaboration (Bruneel et al., 2010; Perkmann et al., 2013), particularly in the area of the data analytics capability development in SMEs. The results reveal specific practices that support knowledge transfer from educational institutions to the SME field.

5.3 Managerial recommendations

The results of this dissertation suggest that the circular economy SMEs need to pay attention to foresight activities via systematic information gathering from their operational environment. The PESTEL framework (Aguilar, 1967) provides a feasible tool to carry out this kind of information gathering, and to use the collected information to plan for the future and for processing this information as a strategic key activity.

Advanced data utilization can increase the resilience of business as well as sustainability, as data utilization can enable a leap toward operational efficiency, and in this manner to improve sustainability (Kristoffersen et al., 2019), as well as enable the development of material flows, logistics and customer behavior (Lacam, 2020).

The transition to utilizing data analytics requires leadership with quantitative desire, perspective and cross-functional scope to change the company culture (Davenport, 2005). SMEs should integrate external data with internal data to fully utilize the potential (Qaffas et al., 2022), e.g. by combining socio-economic data with waste data to create predictive models (Niska & Serkkola, 2018).

Collaboration with educational institutions is one possible way to develop capabilities (Chen et al., 2012;), e.g. via student project courses, courses tailored for companies, student training periods in companies, and from student written theses. Recruiting students and graduates is one way to transfer new knowledge from academia to industry. It should be highlighted that the companies that collaborated in a student project course a second or third time, were able to define the problem to be solved better and gained more useful results. This indicates the benefits of long-term collaboration.

Educational organizations need to pay more attention to how results and approaches are transferred to companies to increase their performance and commitment in collaboration (Selnes & Sallis, 2003). Collaboration requires mutual trust between industry and academia, so for this reason close interaction at the personal level is required (Bruneel et al., 2010; Kunttu & Neuvo, 2019).

It was noted that circular economy SMEs are often more legislatively driven than data driven. However, regulation and legislation were found to cause challenges for the case companies. Some of these challenges can be overcome by increasing knowledge. For example, the case companies were not familiar enough with the European General Data Protection Law (Coleman et al., 2016), which caused challenges for data utilization, as the companies did not know exactly what the law actually prevents, and the development was stopped just in case.

5.4 Practical implications

The case companies found it challenging to apply student project course results. For this reason, the project course was developed by paying attention to sharing the results with the companies by providing instructions and guidance written by the students. It was noted that when the companies collaborated for the second or third time on the project course, they managed to define the problem better and received more useful results at the end of the project.

However, data analytics skills are not enough, some SMEs need to consider knowledge management at a strategy level and invest in business intelligence tools. as well. For example, the data adoption maturity of SMEs (Coleman et al., 2016) can be evaluated according to how a business strategy supports the development of data analytics infrastructure, how efficient the process of data collection and storage is, and the level of data analytics skills. The results of this dissertation are much in line with this by highlighting the importance of the data analytics capabilities in SMEs. On the other hand, the steps SMEs needs to take when adopting business intelligence (Guarda et al., 2013) include the definition of the needed data, choosing the tools to collect, process and analyze data, defining the critical success factors to be measured and evaluated, and how the results will be interpreted and shared. In all these steps, SMEs have development needs in terms of capabilities and infrastructure. Moreover, analytical readiness is required to utilize data in decision-making, involving the integration of people towards the same goal, leadership commitment and strategic alignment (Auh et al., 2022). In this manner, the development of data analytics capabilities is both a strategic and organizational investment for SMEs. In this, the critical success factors include management leadership, resources, processes, education, motivation, and measurement (Wong & Aspinwall, 2005), and knowledge management is emphasized over sophisticated information technology and the volume of data (Wang & Wang, 2020).

As the education of analytics should be interdisciplinary, student activities should integrate general understanding of management, logistics, operations management, accounting, finance and marketing (Chen et al., 2012). The literature shows that the education of analytics should be conducted as hands-on projects, as analytics requires experimentation, trial and error (Chen et al., 2012; Teece et al., 1997). This can be provided by pedagogical approaches that implement learning by doing.

The literature shows that SMEs could benefit from case study examples and appropriate consulting and analytics services (Coleman et al., 2016). This is not surprising, as the major barrier is a lack of understanding on how to use analytics in decision-making (Auh et al., 2022). This could be helped by publishing a description of analytics projects conducted for companies, for example relating to the development of material flows and supply chain management as it could provide a leap toward operational efficiency and increase sustainability (Kristoffersen et al., 2019). Such a description could include the question or the problem to be solved, description of the data and analytical methods, as well as the results in visual form. It is known that academia prefer to publish their development activities, while SMEs do not, but they are able to negotiate a consensus on a matter of publicity (Kunttu & Neuvo, 2019). As companies are recommended to focus on the business impact of analytics on a daily basis (Gürdür et al., 2019), the description should include this point of view as well—it would be helpful for students as well to better identify the users for their analytics solution. This is because achieving real gains requires the willingness of the employees to utilize facts that are based on analytics (Auh et al., 2022). It would be beneficial to involve all employees (the users) who would use the analytic solution—this means that student projects should involve several persons from the SME, which might be a challenge due to their limited resources.

Coleman et al. (2016) suggest that SMEs could develop their data analytics capabilities via Massive Open Online Courses (MOOCs), but the challenge is lack of time to learn and a need for intuitive software with a short learning curve. These kinds of courses might not be effective alone, but they could be utilized during or after student projects for SMEs to gain similar capabilities to the students.

5.5 Limitations and future research

The result of this dissertation cannot be generalized widely but are applicable in similar kinds of SMEs operating in waste management and recycling in Nordic countries, with the following considerations. This study was limited to seven Finnish circular economy SMEs, and most of them were in the early stages of adopting data-driven decision-making. The case companies were located in the same region and most of them operated in the recycling and waste management business. The research method used was qualitative and interviews included only one interviewee from each case company. Due to these limitations, this research should be extended to cover more SMEs from other regions of Finland and other countries. The circular economy could be widened with companies that recycle different materials. The research method could be extended to include mixed methods, to collect research data from interviews and questionnaires, and to cover several relevant respondents in each case company. By including more interviewees from a company, it would be possible to achieve broader view of a particular company's situation in different departments or at different organizational levels.

Future research could investigate those circular economy SMEs that are more advanced in data-driven decision-making and to gain insight into the steps and actions needed to increase an SME's maturity in data-driven decision-making (cf. Lavalle et al., 2011; cf. Nykänen et al., 2016).

As managerial awareness is one of the key internal barriers of SMEs to adopting data analytics (Bianchini & Michalkova, 2019), it would be interesting to study the situation more closely in case companies of how managers focus on the business impact of data analytics (Gürdür et al., 2019).

The answers to the research questions of this dissertation provide opportunities for further investigation in several areas. Some key examples include the following: 1) an analysis of the data utilization opportunities and challenges focused on the reduction of carbon emissions, 2) investigation of the potential to combine internal and external data, 3) a study on the practical challenges that legislation causes to data utilization, and 4) a longitudinal study of the annual joint data analytics projects between a university and company focusing on the performance of collaboration and how the capabilities of the company develop.

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Using Foresight to Shape Future Expectations in Circular Economy SMEs

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> *"The best way to keep something bad from happening is to see it ahead of time ... and you can't see it if you refuse to face the possibility."*
>
> William S. Burroughs
> Author of Naked Lunch

Future foresight in business plays a central role in companies' strategic planning, innovation, and product development activities. This is particularly true for firms operating in rapidly changing business environments, in which they may obtain significant competitive advantages by coming up with new innovations and customer solutions. This article studies future foresight mechanisms and practices in innovative SMEs operating in circular economy-related industries. The future demands set by legislation and regulation, consumer buying behaviour, and environmental consciousness, all have a strong impact on an SME's future horizon, in which there may be prosperous business opportunities as well as several challenges. This paper presents a qualitative case study conducted on seven Finnish circular economy-oriented SMEs. The case study reveals that the SMEs in this industrial sector are quite active in foresight activities, and that they have developed a variety of practices for effectively utilizing foresight information in their product development and strategic planning activities.

Introduction

The future of business and industry includes both opportunities and threats. For this reason, industrial actors need to have effective and usable methods and tools to predict possible future changes, both in their own operations and in their business environments (Korreck, 2018). Organizational foresight assumes that even if the future is uncertain, some developments can be foreseen, and thus related options for the business can be considered. This makes it possible to prepare for the future or even to more actively shape it (Cuhls, 2003).

During the last few decades, future foresight in business has become a central part of companies' strategic planning, with clear implications for the development of innovation capabilities (Rohrbeck & Gemünden, 2011; Uotila et al., 2012). However, as indicated by, for example, Jannek and Burmeister (2007), so far, the empirical research on corporate foresight in Europe has mainly focused on large companies. During the last decade, some further research has been made on foresight in small and medium-sized enterprises (SMEs), but the mainstream is still focused on foresight in larger firms. Consequently, the foresight activities and processes for large firms have been well covered in the related academic literature, whereas foresight at the level of SMEs has received less attention (Stonehouse & Pemberton, 2002).

Based on existing research, a common denominator is formed between large firms and SMEs when it comes to implementing foresight objectives. Both SMEs and large firms use forecasting to help anticipate future developments, prepare for potential changes in the business environment, and identify relevant risks. Due to the limited resources of SMEs, their planning horizon is typically shorter, and the foresight planning more focused, for example, on short-term research and development (R&D) targets, or on specific innovation needs (Jannek & Burmeister, 2007; Bidaurratzaga & Dell, 2012). In this manner, SMEs often focus their foresight aims in order to support their short-term strategic and operational planning, as well as innovation management (Jannek & Burmeister, 2007), which often takes place in close interaction with the external environment and stakeholders (Vishnevskiy et al., 2015). Also, strategic foresight can be linked with design-based innovation (Gordon et al., 2019), which involves understanding customers' current and future needs.

The paper focuses on examining the forecasting practices of SMEs operating circular economy businesses. The notion of a "circular economy" is a rather new area of business that has strong development needs involving sustainability, new consumer expectations, and environmental targets. The current rapid changes in business environments and competition, as well as ongoing legislation, cause not only challenges but also new business opportunities for circular economic actors. To prepare for the changes so as to take advantage of them, SMEs operating in this rapidly changing business area need to continuously explore future challenges and opportunities in their business environment. For this reason, developing and utilizing effective foresight practices is essential for circular economy SMEs. Due to their relatively small size, SMEs are often rather streamlined organisations that follow the entrepreneurial intuition of their founders or management, rather than possessing highly sophisticated strategic planning tools and instruments for future foresight (Vishnevskiy et al., 2015). There is therefore an obvious need to investigate and describe the practical approaches that these companies employ in their future foresight activities, both in terms of strategic planning and innovation management.

This paper investigates the future foresight activities of SMEs operating in industries related to the circular economy by seeking answers to the research questions: How do industrial actors and service providers operating in the circular economy foresee future changes in their operational environment? And how do foresight activities affect their business development expectations? The future development of potential market demand may be difficult to evaluate for early-stage industries, which adds risk to the expansion and scaling-up of business operations. To improve understanding of how circular economy-focused SMEs foresee upcoming changes, challenges, and opportunities for their businesses, our study employs the widely applied PESTEL framework that originates from Aguilar's (1967) work, now been tweaked by different perspectives. The detailed questions related to the PESTEL framework deal with political and societal decision-making, economical changes, social issues, technological development, ecological and environmental issues, legislation, and regulatory issues. These are expected to cover the changes, challenges, and opportunities for SMEs operating in circular economy-related industries. Seeking answers to the research questions in terms of the PESTEL-based framework, this paper contributes empirical research focusing on foresight in SMEs that are operating in relatively early-stage industries related to the circular economy.

Organizational Foresight in Circular Economy-Oriented SMEs

Organizational foresight activities are used in companies to foresee possible future developments. In this manner, business leaders may consider and prepare for the future in order to act accordingly in a timely manner. As firms gain an understanding of trends, weak signals, and other developments that may impact on their business, they can build preparedness for the future (Korreck, 2018). In this process, the modeling and sensemaking of environmental uncertainty play key roles (Vecchiato, 2015). Moreover, for future-oriented innovative actors, foresight methods may provide a means to actively shape the future, and in this manner, obtain a competitive advantage in the market (Rohrbeck & Gemünden, 2011; Uotila et al., 2012). Daheim and Uerz (2008) defined organizational foresight as a process related to future intelligence gathering. Rohrbeck (2011) asserted that effective organizational foresight is dependent on organizational capabilities, such as culture and organization (for example, integrating foresight activities within a processes of foresight method sophistication, information usage, people, and networks). However, the literature provides insight into foresight activities conducted in large firms and SMEs, which both seem to have numerous common features. (Bidaurratzaga & Dell, 2012; Jun et al., 2013).

Stonehouse and Pemberton (2002) argued that not all strategic planning tools and methodologies are suitable for application by SMEs. This is because both the complexity and the time horizons differ between corporate foresight and foresight applied by SMEs. Since SMEs have more limited resources in their activities than larger firms, they are likely to implement foresight case by case. The most important trigger for foresight thinking seems to be when firms are forced to create new products (Jannek & Burmeister, 2007; Bidaurratzaga

& Dell, 2012). Foresight activities for product and service innovation are then emphasized in the SME context.

Also, the planning horizon of SMEs is relatively short compared to that of large corporations, which can even reach up to 15-20 years (Vishnevskiy et al., 2015). However, SMEs themselves are often quite heterogeneous, since the majority of SMEs operate in conditions that require little foresight implementation (Jun et al., 2013). On the other hand, SMEs operating in areas with rapidly changing business environments or knowledge-intensive innovation networks definitely require sophisticated foresight and visionary capabilities (Uotila et al., 2012). The specific choice for SME foresight implementation should be guided be the objectives of the foresight-related activity, the available resources, and the actual readiness of SMEs to implement such approaches (Vishnevskiy et al., 2015). Thus, the greater willingness an SME has to change itself, the more it is dependent on knowledge that foresight and planning may provide. This can also support the necessary changes and R&D-related investments.

Another benefit of foresight studies is that they expand the absorptive capacity of SMEs while they interact with the company's environment (Igartua et al., 2010). Vishnevskiy et al. (2015) emphasized that even if some corporate foresight methods have reasonable potential outcomes, they still cannot be applied by SMEs due to the need for allocating significant resources, which usually are not available. The practical relevance for organizational foresight comes from a SME's inability to cope with discontinuous change. Discontinuity within the business environment emphasizes the need to constantly adapt to the environment in order to ensure economic success and long-term survival (Rohrbeck, 2011). When it comes to a firm's ability to foresee long-term future threats and new promising technologies, this is more the objective of long term-oriented corporate foresight.

The concept of a "circular economy" was first used in the literature by Pearce and Turner (1990), who emphasized a circulating flow of value and resources that has restorative effects on the environment. Current academic discussion focuses more on the circular economy as a paradigm notable for its relationship with sustainable development (Prieto-Sandoval et al., 2018). According to Prieto-Sandoval et al. (2018), the circular economy is related to the circulation and recirculation of resources. It derives from a cycle of taking, transforming, using and returning. On the other hand, some firms in circular economy-related industries take resources available from the environment and transform them into products or services. After the transformation, these outcomes can be returned as materials or energy to other value chains (Park et al., 2010; Ellen MacArthur Foundation, 2013).

The technical or biological conversion of waste into a resource is crucial. After conversion from waste, the resource can be utilized in an industrial process or, alternatively, returned to the biosphere (McDonough & Braungart, 2010). These two outcomes generate new business opportunities for SMEs. As SMEs operating in circular economy and related industries are in the early stages of industry and product life cycles, their need for foresight practices and their links to strategic planning and business development are essential. Moreover, a rapidly changing operational environment, competition, and regulation can all cause potential future challenges and opportunities that should be handled by means of foresight and planning in these firms.

The actual need for and relevance of foresight are due to a SME's ability to cope with discontinuous change. In an early-stage industrial environment, which is typical of circular economy-related industries, it is probable that there will be both discontinuity and disruption. In some cases, these can be considered threats, but for some adaptive SMEs, these can be characterized as opportunities.

Research Methodology and Data Collection

This paper is based on qualitative case study research on seven Finnish SMEs operating in the circular economy. These companies provide waste management, recycling services, and make products out of waste materials, as well as designing, building, and operating biogas plants. The data was collected by interviewing company executives, mainly CEOs, in autumn 2019. All the interviews were recorded, transcribed, and then analyzed. The interview questions sought insight on how companies are preparing for changes in their operational environment, and which changes they are expecting.

Table 1 shows an overview of the interviewed companies. The interview questions were constructed by using the PESTEL framework and related to how companies predict future changes, challenges, and opportunities in their operational environment considering the political, economic, social, technological, environmental, and legal aspects.

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Table 1. Case Descriptions.

Case	Interviewed person	Number of employees	Industry	Core business area
Case A	CEO	50	Combined facilities support activities	Waste management, recycling services and solutions for households and companies
Case B	CEO	60	The treatment and disposal of non-hazardous waste	Waste management and recycling services for households and companies
Case C	CEO	80	The treatment and disposal of non-hazardous waste	Waste management and recycling services for households and companies
Case D	Marketing and sales coordinator	20	Town and city planning	Environmental engineering design and delivering biowaste treatment solutions.
Case E	CEO	40	The recovery of sorted materials	Recovering sorted materials
Case F	CEO	10	The dismantling of wrecks	Recycling services for wrecks
Case G	CEO	10	The manufacture of other food products	Recycling and processing of oil-based material into fuel and animal feed

Results

The analysis of interview data, as well as secondary data collected from the case companies, revealed several practices for predicting changes in business and operational environments. In this section, we review these practices in PESTEL's six areas, following the interview themes of political, economic, social, technological, ecological, and legal changes in business environments. The obtained results are summarized in Table 2. Following the research questions, the table summarizes both the firms' foresight activities and the interviewed managers' business development expectations in all six areas of PESTEL.

Political aspects
The interviewed managers agreed that the environmental aspects of their business are nowadays a "hot topic" in public discourse and debate, which also reflects the impact of political decision-making. Recycling and the related themes of the circular economy play a central role in this. For companies operating in the circular economy, predicting future trends in political decision-making is thus essential, and therefore a central part of companies' strategy work:

> *We actively follow the preparation processes of new legislation because they affect our business a lot.* (Case A)
>
> *Legislation concerning waste management has been changing recently. Different governments have implemented the norms set by the European Union in different manners, and this has a somewhat varying impact on the local (municipal) level. This all requires us to constantly follow legislation.* (Case B)

The interview data clearly shows that the expected changes in the policies regarding environmental issues and waste management are crucial factors for firms Therefore, firms follow relevant policy-making very closely on the management level:

> *We discuss the expected political changes frequently in our board meetings, and also involve our key stakeholders in this discussion.* (Case C)

The interviewees also emphasized the role of the industrial associations that provide their companies with valuable information on trends involving the climate of political decision-making, which helps them to prepare for future changes, for example, legislation and policies concerning their business. In a similar manner, the industrial associations act as influencers, aiming to promote the industry's viewpoints in political decision-making:

> *Our inputs regarding the environmental legislation processes are usually collected and transferred through our industrial association.* (Case A)

Economic aspects
When asked about the economic factors affecting a firm's current operating environment, most of the interviewed managers mentioned competition in the field of circular economy businesses. This may often lead to price decreases in company products. As this field is increasing due to changes both in terms of consumer trends and environmental policies, new commercial actors are entering the field:

> *The competitive environment is getting more challenging. The prices of our products have decreased during recent years, mainly because of the increased competition.* (Case A)

> *New actors are coming in on this business, but as initial investments in the production facilities are quite expensive, the newcomers are typically big players who are already operating in some industrial area.* (Case C)

However, the circular economy business area is networked in such a way that companies competing with each other also often have areas of collaboration:

> *The big industrial players in the circular economy sector are our competitors, but still we also collaborate with them in several areas.* (Case C)

Social aspects
Our interview data clearly showed that the expectations of the consumers and business-to-business (B2B) customers were dominated by consumer trends. As "green thinking" has become a major feature in almost all areas of consumer markets, products and services are favoured that fulfill high environmental standards. This, in turn, means that circular economy firms operating in both B2B and consumer markets have to understand the importance of consumer expectations regarding issues related to waste management and the use of circular economy products and services:

> *Face-to-face contacts with our customers are very important.* (Case E)

> *Despite the fact that our company is owned by the municipalities of this region, we feel that we have to focus on end users in our services. Serving private consumers is a top priority to us, and we do it in a multichannel manner by using face-to-face contacts, phone, and also increasingly, by digital communication channels such as chat.* (Case C)

The interview data also clearly suggested that consumers are increasingly expecting service providers to develop various digital services and online tools to serve their end users:

> *Private consumers expect us to provide them with digital services.* (Case A)

> *It seems that private consumers favour more and more digital services instead of the traditional communication channels such as phone or email. We have recently launched a chat service and an online store to serve our private customers in certain services.* (Case C)

The interviewed managers also pointed out that both face-to-face customer service and newly established online tools serve for collecting valuable consumer and customer feedback that can be used in further developing a company's services.

Technological aspects
When discussing the technological challenges facing companies operating in the circular economy, our interviewees emphasized the relatively rapid pace of technological development in the field of material recycling. The companies we spoke with invest a relatively large amount of resources into developing their capabilities and facilities in order to answer to this challenge:

> *The majority of the waste is nowadays burned. It is an efficient way of processing it, but material recycling is more sustainable. Therefore, all the technological development facilitating material recycling is important for our business.* (Case C)

> *Our engineering staff is very active in exploring new technological solutions by benchmarking competitors and following the latest developments in our area.* (Case D)

> *We participate in development projects in which new technologies are being developed for our business.* (Case A)

Another key technological aspect that arose in the interviews was the strong need to lower carbon emissions in all activities. This puts pressure on to continuously develop methods for logistics and waste collection:

> *Logistics and the emissions caused by them will be a big issue in the future.* (Case C)

Legal Aspects
As already discussed at the beginning of this section, legislation has made a remarkable impact on all aspects of circular economy value chains. This means that predicting future changes related to decision-making processes and legislation in this area are increasingly

Table 2. A summary of results obtained from the case interviews.

Political aspects	**Economic aspects**	**Social aspects**
Foresight activities: - Strategic analysis tools, risk analyses - Following the media and information distributed by the association *Future expectations:* - Environmental aspects are a hot topic in political decision-making, partly because the audience pays lot of attention to environmental issues; the circular economy is one essential part of this political debate - The follow-up and prediction of the changes in political decision-making are included in the companies' strategy work - The role of the industrial association is central: the association transmits political climate information to the companies, and tries to influence on political decision-making by promoting industry viewpoints	*Foresight activities:* - Discussions and follow-up regarding customers and competitors - Internal KPIs form a central tool for predicting the future *Future expectations:* - Competition is increasing all the time since the number of service providers is increasing, leading to a decrease in prices - To maintain a position as a remarkable actor in the business area requires investments in production	*Foresight activities:* - Customer and consumer feedback and expectations are collected through the customer service function - Face-to-face contacts with consumers in interviews, surveys, and commercial fairs - Strong investments in digital services in consumer interfaces: online-tools and chat services developed to better serve end users *Future expectations:* - Customer and user expectations follow consumption trends - Consumers are nowadays aware of environmental issues, and demand products and services meet high environmental standards - A key issue is to understand the behavior and expectations of single consumers in their waste management - Private consumers in particular expect digital services

Table 2 (cont'd). A summary of results obtained from the case interviews.

Technological aspects	**Legal aspects**	**Ecological aspects**
Foresight activities: - Benchmarking competitors - Attending fairs, seminars, workshops, and events - Making studies on the company's areas of interest *Future expectations:* - Strong demand for low carbon emissions in all activities makes transportation into a remarkable challenge - Burning waste is often an efficient way of using it, but material recycling is more sustainable - Developing efficient methods for waste collection and logistics - There are increasing needs for digital services in consumer interfaces, planning and optimization of logistics	*Foresight activities:* - Clear organizational responsibilities defined for following the changes and trends in legislation *Future expectations:* - Legislation has a strong impact on all parts of circular economy value chains and business development - Policies and decision-making processes related to companies' environmental licenses are getting tighter - Predicting changes in legislation clearly steers companies' strategic planning	*Foresight activities:* - New tools and resources are needed to process controlling and monitoring *Future expectations:* - Carbon-neutral waste management is expected - Nowadays recycling is preferred to the previously desired waste energy usage - There are growing demands for responsibility, transparency, and sustainability in all enterprise processes

important for business development and strategic planning. The interviewees indicated that the current trend is towards tighter policies and decision-making:

Environmental laws are renewed quite frequently, and they almost always mean new investments for us due to the tighter demands. For this reason, it is very important for us to be able to predict these changes and react to them in advance. (Case C)

Ecological aspects
As indicated in the previous discussion, the ecological aspects significantly dominate the business environment of the circular economy. The economic aspects in the interview data can be summarized in three main areas. Firstly, nowadays material recycling is preferred to energy usage (waste burning). This is a change compared with previous decades, during which waste was seen as both a good and cost-efficient source for energy production. However, the current target according to government policy to re-use over 50% of waste material means that energy production based on waste burning should be significantly reduced. Secondly, consumers and societies now expect the minimization of carbon emissions in waste management. This is nevertheless a real test since waste management and recycling are very much dependent on the logistics that cause these emissions. Consequently, one central challenge is to develop solutions for a combination of both logistics and transportation. Finally, companies operating in the circular economy face growing demands in regard to responsibility,

transparency, and sustainability in all their processes. These demands are set by consumers and customers, as well as by the government.

Conclusion

In this paper, we considered the foresight activities of SMEs operating in the circular economy. As indicated in the introduction by Jannek and Burmeister (2007), SMEs typically have narrower capabilities for future forecasting and strategic planning than larger companies. For this reason, foresight activities in SMEs often focus on more practical areas, such as collecting inputs for product development and innovation. Foresight is particularly relevant for SMEs operating in areas with rapidly changing operational environments, customer expectations, or competition (Vecchiato, 2015; Gordon et al., 2019;). In the circular economy sector, all of these areas are experiencing rapid change, which requires firms to undertake continuous foresight and monitoring activities.

In this study, we conducted a comparative case study of seven Finnish circular economy SMEs with a primary goal of understanding how companies foresee the future, and how foresight activities affect their business development. To do this, we employed the well-known PESTEL-analysis tool as a framework. The results of the study, summarized in Table 2, reveal that companies clearly understand the importance of systematic information gathering from their operational environment. As the circular economy is strongly regulated and legislation changes quite frequently, the importance of foreseeing future changes in environmental policies and decision-making was highlighted. Another central area of interest was that our interviewees emphasized the importance of interaction with consumers. As environmental issues, recycling, and resource consumption are all hot topics among consumers, they clearly expect that circular economy-oriented firms answer to the growing environmental demands in this area. We found it is also particularly important to be able to serve customers and consumers digitally. For this, there are clear expectations to provide on-line tools for customer interaction.

Based on the results, we conclude that the future demands set by changing legislation and regulation, consumer buying behavior, and environmental consciousness all will have a strong impact on SMEs' future horizons, upon which there may be prosperous business opportunities as well as several challenges. Among the challenges when an actual window of opportunity for doing profitable business is opening, are the kinds of immaterial rights that are required, when and how to scale-up a firm's capacity, when to expect pay-off for investments, the level of demand and supply, and so on. Future opportunities for business growth include the exploration of new innovative technological solutions, deployment of user innovations, and inputs for new service innovations that can be implemented in digital environments.

As a managerial recommendation, the paper suggests that SMEs operating in circular economy areas should pay attention to future foresight activities. In practice, this would mean gathering systematic information from the operational environment in all relevant areas of PESTEL. To utilize this information in future business development and planning, firms should include the processing and sensemaking of foresight information as one of their key strategic activities.

Using Foresight to Shape Future Expectations in Circular Economy SMEs

Anne-Mari Järvenpää, Iivari Kunttu and Mikko Mäntyneva

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Using Foresight to Shape Future Expectations in Circular Economy SMEs

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Data-Driven Decision-Making in Circular Economy SMEs in Finland

Anne-Mari Järvenpää, Iivari Kunttu, Jari Jussila, and Mikko Mäntyneva

Abstract This paper studies the data-driven decision-making and management mechanisms and practices in innovative SMEs operating in evolving circular-economy-related industries. Being a rather new area of business with strong development needs from the view of sustainable development, new consumer expectations and environmental targets, rapid changes in business environments and competition, and frequent changes in legislation bring not only challenges but also new business opportunities to circular economy SMEs. To prepare for operational changes, to optimize their operations, and to develop their competitive advantage, circular economy SMEs need to continuously develop dynamic capabilities related to the utilization of the data collected from various sources to explore future challenges and opportunities in their business environment.

In this paper, we present a case study consisting of seven industrial cases, all representing SMEs operating in the field of circular economy in Finland. In the case study, we investigate how SMEs utilize data in supporting their decision-making at both the strategic and operational level. The first round of interviews was conducted from October through December 2019. To understand the impact of the Covid-19 pandemic on data-driven decision-making, we conducted the second interview round from October through December 2020. The results predict that descriptive analysis is the mainstream in data utilization in circular economy SMEs, whereas there is still much room for improvement in the utilization of predictive analysis methods.

Keywords Data-driven decision-making · Circular economy · SMEs

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1 Introduction

The exploratory utilization of data collected from business processes, customers, competitors, and other sources enables data-driven approaches for various decision-making functions in companies. This is particularly true for firms operating in rapidly changing business environments in which a firm may obtain significant competitive advantages by coming up with new innovations and customer solutions. Organizations adopting a data-driven approach may have opportunities to improve their business and outperform other organizations [1]. Data-driven decision-making can reduce costs, improve operations efficiency, increase stakeholder loyalty, and increase communication flows within the organization and ecosystem [2, 3]. However, due to their relatively small organizations, SMEs are often rather streamlined and limited in their financial resources and capabilities. For this reason, developing capabilities to utilize data in their business analytics and operations is particularly important for SMEs.

A circular economy is based on closed-loop production systems and material flows. It aims to reuse materials and decrease the need for virgin materials, which requires the implementation of a reverse supply chain and cooperation between actors [4]. The principal logic of the circular economy is to convert waste into resources by applying technical or biological conversion. The outcome of the conversion can be re-used in an industrial process or returned to the biosphere [5]. The business concepts related to the area of circular economy aim at addressing sustainable development needs by minimizing resource input and waste, emissions, and energy leakage without jeopardizing growth and prosperity [4]. Sustainability enriches corporate value with relational meaning and dialogue by making the aims of the corporation more transparent and demonstrating mutual responsibility [6] for social, environmental, and economic development. The circular economy companies show increasing interest in investing in business intelligence and other practical data-based tools that enable them to make systematic planning for the future at both the strategic and operational level [7]. Business data also provide the companies with a basis for rapid and rational decision-making concerning their key operations, including business and product development. However, for SMEs, full utilization of data often presents challenges that may be related to a lack of competence and capabilities or not understanding the business potential of data utilization [8].

This paper studies the data-driven decision-making and management mechanisms and practices in innovative SMEs operating in the evolving circular-economy-related industries. The paper seeks to answer the following research question: How can SMEs operating in a circular economy utilize data in supporting their decision-making? We aim at finding answers to this question at both the strategic and operational level through a case study consisting of seven industrial cases. In the case analysis, we approach the main research question from three separate viewpoints (sub-questions): (1) What data is utilized in strategic decision-making? (2) How is data utilized in decision-making? (3) How much has Covid-19 affected data utilization in decision-making? The case data used in this paper was collected during two interview rounds, which enabled us to draw conclusions regarding the impact of the Covid-19 pandemic on data-driven decision-making and management in circular economy SMEs.

2 Data-Driven Decision Making in SMEs

Increasing digitalization and massive volumes of data provide new sources of value for companies [9]. Data-driven decision-making is an approach to managing big data throughout the entire decision-making cycle of the organization, where the role of the data-driven manager is to base business decisions on data-analytic thinking to make use of data in prescribing actions, predicting future developments and drive change [3]. The impact of data on the economy has also been referred to as "the new oil" [10]. Yet, many SMEs face challenges in making use of this 'new oil' [11]. Big data technologies per se do not allow the automatic attainment of innovation [12], competitive advantage [1] or increased stakeholder value. Previous research has identified several challenges in harnessing big data that is peculiar to SMEs: a low level of understanding of big data, classifying emerging developments such as big data analytics as hysteria and not as a viable business opportunity, lack of adequate infrastructure to analyze data, lack of in-house data-analytic experts, lack of representative case studies and success stories in big data analytics in SMEs, lack of expertise in selecting suitable solutions, effort needed in order to understand the available data, dirty data and other data quality issues, etc. [11, 13–15]

2.1 Types of Data

Another good question is what kind of data can be used in data analytics. Data at the disposal of SMEs can be machine-generated (e.g., data that comes from machines, sensors, mobile phone applications, computer networks, etc.), human-generated (data collected by people, e.g., name, address, telephone number, and data generated in technology-mediated interactions via documents, emails, and social media services), and business-generated, such as transaction data from point-of-sale or enterprise resource planning systems [16, 17]. Furthermore, data can originate from internal sources or external sources. External data sources include open data, acquired data, customer-provided data, and freely available data [18].

2.2 Data Analytics in Decision-Making

Data can be used in decision-making in various ways, and SMEs may not understand what analytical methods are available in the first place and which of these

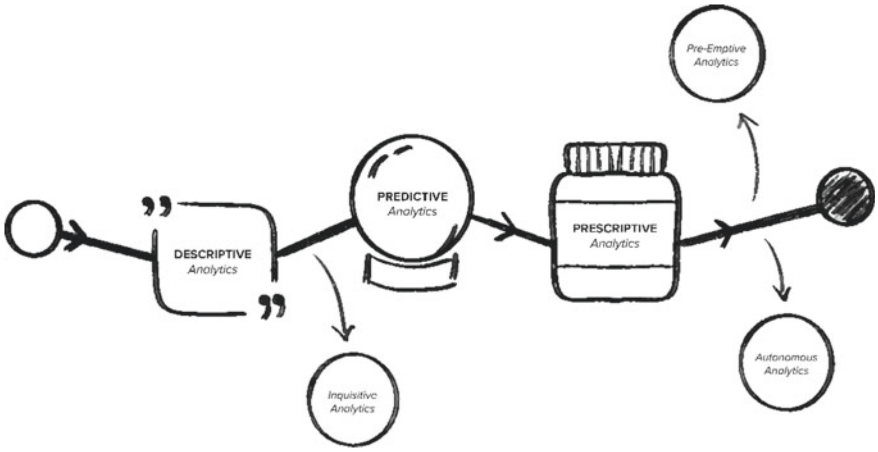

Fig. 1 Data analytics methods for improved decision making [19]

methods could be feasible in their context. Analytical methods that support improved decision-making are illustrated in Fig. 1.

Each of the data analytics methods can be used to answer various business questions. Next are outlined some typical business questions that can be addressed with these methods [19–21]:

- Descriptive analytics: Analytics that help in understanding, e.g., "What happened? How many, how often, where? What actions are needed?"
- Diagnostic or inquisitive analytics: Analytics that help in comprehending, e.g., "Why did something happen? Why is this happening?"
- Predictive analytics: Analytics that help in anticipating, e.g., "What if these trends continue? What will happen next? What is likely to happen in the future?"
- Prescriptive analytics: Analytics that help in responding to "Now what? What happens if we try this? What is the best that can happen? What actions should be taken?"
- Preemptive analytics: Analytics that help in recommending "What is required to do more?"
- Autonomous analytics: Analytics that help to understand the data without human hypotheses and minimal involvement of human analysts: "What can we learn from the data? What if we take action?"

For applying these analytic methods, several alternatives are available—from relatively simple statistical and optimization tools in traditional spreadsheet software packages, data visualization and analytics tools, and descriptive, predictive, and prescriptive analytics tools to open source programming environments [20]. While large corporations have specialist data scientists and the technology infrastructure in-house, SMEs may lack both the expertise and the tools to benefit from data analytics [13] or they may be unaware that they possess this capability.

2.3 Data Analytics in Circular Economy SMEs

Kristoffersen et al. [22] have explored the relationship between data science and the circular economy. Their focus is on how organizations can better structure their data understanding and preparation in order to align business objectives and circular-economy-related objectives. They propose that a suitable utilization of data and analytics can have major efficiency improvements supporting a sustainable and circular economy.

A supply chain requires information flows that enable sharing and optimizing material flows and can be supported by the key enabling technologies of Industry 4.0 [23]. The key challenge when reusing waste material is material quality, and the barrier is information exchange relating to the material flow supply and demand, transportation, and infrastructure [24]. SMEs are required to provide information on circular economy benefits to convince customers, and they find it challenging to get support from the supply-and-demand network [25]. Industrial networks provide opportunities to create value from waste by closing material loops among companies, but there are also various barriers, such as the lack of information management systems, technological and financial resources, qualified professionals, and managerial commitment [8].

3 Methodology

In this paper, we conduct a comparative qualitative case study of seven SMEs operating in the area of the circular economy. All of the case companies are located in Finland. The case companies provide services related to waste management, biogas production, material recycling, or the manufacturing of products based on waste materials. The empirical data used in this study was collected by interviewing company executives, mainly CEOs, in autumn 2019 and 2020. All the interviews were recorded and transcribed prior to analysis. The interview questions sought insight into how companies are utilizing data in strategic decision-making and what kinds of impacts the Covid-19 may have had on data utilization. Table 1 displays a summary of the case companies.

Table 1 Case descriptions

Case	Interviewed person	Number of employees	Industry	Core business area
A	COO	50	Combined facilities support activities	Waste management, recycling services and solutions for households and companies
B	Service Manager	60	The treatment and disposal of non-hazardous waste	Waste management and recycling services for households and companies
C	CEO	80	The treatment and disposal of non-hazardous waste	Waste management and recycling services for households and companies
D	Marketing and sales coordinator	20	Town and city planning	Environmental engineering design and delivering biowaste treatment solutions
E	CEO	40	The recovery of sorted materials	Recovering sorted materials
F	CEO	10	The dismantling of wrecks	Recycling services for wrecks
G	CEO	10	The manufacture of other food products	Recycling and processing of oil-based material into fuel and animal feed

4 Results

In this chapter, we summarize the results of the analysis made based on case-specific interviews. This chapter is divided into three sections, each of which presents the key results of the interviews from the viewpoint of our three research sub-questions. Some key results from the case data are also summarized in Table 2.

4.1 What Types of Data are Utilized in Strategic Decision-Making?

Based on the interview data, companies most often mentioned business-generated data. Data that companies are utilizing relates to their own finances, the efficiency of production and collection routes, material-specific and customer-specific volumes, and customer experience and satisfaction. These were the most often-used internal business-generated [18] data sources in the interviewed circular economy companies.

We are utilizing data too little. Our financial data is somewhat in use. (Case D)

We utilize data on the number of our client companies and the amount of waste generated by them. (Case B)

Companies mentioned that they use data describing competitors' development and financial condition, construction permits granted and forthcoming initiatives, price trends of material fractions, and country-specific data. These data sources represent external data sources [18]. One case company mentioned a partner company as an important data source to provide forecasts of forthcoming waste volumes.

In a competitive situation, we utilize as external data our competitors' financial data to monitor their situation. (Case D)

We utilize data on the price trends and seasonal variation of material fractions. (Case F)

Strand and Syberfeldt [26] stated that external data may be the key asset for organizations, but most organizations primarily utilize internal data. They found that valuable data for waste management companies can be found from the following external data sources: maps, orthophotos, and road data; property and civil data; and traffic & weather data. Compared to the companies we interviewed, none of them mentioned these external sources. This could be because SMEs may lack the expertise and tools to benefit from data analytics [13]. This requires more research in the future.

4.2 How is Data Utilized in Decision-Making?

Based on the interview data, all seven interviewed companies conduct descriptive analytics, and two of them conduct predictive analytics. These companies use data in production planning, process development, investment planning, competition, and internationalization. Data is utilized for making material-specific decisions on whether the company should process the material or source the processing as a service. Descriptive analytics shows the current state of a business, while predictive analytics allows forecasting and shows future possibilities [19].

The bottom line is that we have an adequate load, we can provide staff with work, we keep the work productive, and we make data-driven decisions about which direction to go. (Case A)

We've had to analyze more closely what we're doing, what works, and what doesn't. Changes in clients have required us to make operational changes. (Case A)

We are preparing to make investments and evaluate whether it is worth processing materials ourselves or sourcing as a service. (Case B)

You always must quantify things that where we are, where we're going, and what road we're going to take. Data itself is the big value for us, through which we justify our decisions. (Case E)

Predictive analytics allows forecasting and may indicate future opportunities [19]. This analysis type was mentioned as a data analysis method in two interviewed company cases. These companies utilize data to determine their stock size according to the price fluctuation or to predict forthcoming movements in the market.

> *We collect external data on the financial situation of our customers and competitors to conclude, what kind of movements it is possible for them to make. Combining this information with a view of the market, we know who would be able to build the facility and, on the other hand, who could order it. (Case D)*

> *In terms of the material fractions we sell, we aim to outline how large stocks we want or can hold, whether it's worth waiting for a price hike, and whether the variation is unpredictable. (Case F)*

According to Strand and Syberfeldt [26], descriptive analytics in a waste management company shows the annual waste volumes and number of bins, while predictive analytics predicts the required emptying fees for different bin types for the coming years, whereas prescriptive analytics optimize the number and configuration of vehicles as well as fuel consumption. Our interview results support these findings. For instance, the interviewees indicated that descriptive analytics methods help them to keep the work productive. As predictive analytics, they mentioned external data of the financial situation of their customers and competitors to anticipate what is likely to happen in the market. Another example relates to price fluctuation and defining the stock size.

4.3 How much has Covid-19 Affected Data Utilization in Decision-Making?

Based on our interview data, the Covid-19 pandemic has had only a minor impact on how data is utilized in our seven case companies Some companies found that data utilization should be further developed to allow forecasting and timely decision-making. During the Covid-19 pandemic, companies have had to analyze their own activities due to changes in their clients.

> *We realized the need and had an opportunity to develop data utilization. We found that processing information must be more real-time to be able to make the right decisions in the right moment. (Case A)*

> *We recognize that we need to develop data utilization in decision-making. We found during Covid-19 that if data utilization was better, we would be able to anticipate earlier. We learned the hard way that it should be done. (Case D)*

> *Not affected exactly. As regards the export of material fractions, we monitor shipping routes, restrictions and in which locations the transport fleet accumulates. The location of transport equipment affects export costs. (Case F)*

For the time being, Finland has coped better with Covid-19 than many other industrialized countries. There have not been wide restrictions or lockdowns in society, which might explain our interview results. The companies indicate that

Covid-19 has had only a minor, if any, impact on data utilization in decision-making. The companies we interviewed highlighted increased consumer waste as well as infectious waste from hospitals due to Covid-19. Thus, our interview results support the earlier findings of Ibn-Mohammed et al. [27] who reviewed the impacts of Covid-19 on the global economy and observed that the circular economy business relates to the increase in consumer waste caused by social distancing, online buying, and take-out food as well as increasing volumes of waste from the healthcare industry that can be infectious.

> *If the Covid-19 situation gets bad, then preparedness planning will start in waste facilities: what kind of waste flows we should be prepared for, for example, for the treatment of contaminated hospital waste from which diseases can spread. (Case B)*

Ibn-Mohammed et al. [27] also expect that the digitalization of the supply chain enables companies to attain resilience to the global pandemic. Digitalization enables intelligent assets to share location, condition, and availability, as well as prevent failures across the supply chain. They stated that another view for digitalization must keep this in mind: Even if digital technologies can provide great benefits, they harm the environment by increasing energy consumption and material consumption in the production of devices.

Table 2 summarizes the findings presented in this chapter.

As shown in Table 2, there was only a small impact by Covid-19 on the utilization of data in decision-making. Descriptive analysis was the main approach for data utilization in all the companies. The most often-used data source was business-generated data, while some companies also made use of machine-generated data and human-generated data.

Table 2 Summary of utilized data types, data analytics, and the effect of Covid-19 in each case

	A	B	C	D	E	F	G
1.What data is utilized in strategic decision making?							
machine-generated	x	x	x	x			
human-generated	x		x		x		x
business-generated	x		x	x	x	x	x
2.How data is utilized in decision making?							
descriptive	x	x	x	x	x	x	x
predictive				x		x	
prescriptive							
3. How much Covid-19 is affected to data utilization in decision making?							
not at all		x	x		x	x	x
only a little	x			x			
to some extent							
rather much							
very much							

5 Discussion

In this paper, we have studied data utilization in seven SMEs operating in the area of the circular economy by means of a qualitative case study. The main goal of the study was to improve understanding of how these companies utilize data in supporting their decision-making. In our analysis, we approached our main topic from three separate but interconnected viewpoints. The first viewpoint was related to the types of the utilized data. Our empirical data revealed that business-generated data, which most often came from a companies' internal processes, was the most utilized data type. However, external data related to competitors, material flows, and construction are growing in value in the companies' operational management and planning.

The second viewpoint focused on the data analysis methods used by the case companies. The results revealed that descriptive analysis was the mainstream type for data utilization in all the companies. This was not surprising, since the daily operational management in the SMEs obviously relies on descriptive analysis that analyzes the current state of the business. However, two of the case companies also utilized predictive analytics, which allows forecasting and exploring future opportunities. One possible explanation for the difference between those companies that utilize only descriptive analytics and those that utilize predictive analytics is that some of the circular economy SMEs are focused on business-to-citizen transactions [28], where there is limited competition in the markets. An example of such is the case mentioned by one of the interviewees, where a citizen has practically one alternative for where to bring their waste for recycling. Hence, there is no need to predict customer volumes as they are more or less stable. Also, there is no significant advantage in predicting customer churn, as it is minimal or non-existent in the case of the company. One other explanation mentioned by the interviewee was that municipal waste management organizations tend to be conservative with a long history of operations with low use of technology to drive change.

The interview data showed that those companies that are utilizing predictive analytics have clearly understood the meaning and value of data-driven decision-making in strategic planning and management. However, our analysis also shows that there is significant room for improvement in the utilization of data in the circular economy SMEs, who would clearly benefit from efficient predictive analysis methods.

As the third viewpoint, we inspected the impacts of the current Covid-19 pan-demic on data utilization in the circular economy SMEs. Whereas the societal impacts in Finland have been quite low in general, we also conclude that the pandemic has had a minor impact on the SMEs studied. However, digitalization and the development of advanced data utilization in the circular economy sector can clearly advance sustainable material usage and also contribute to the building of resilient businesses in this area.

The study was limited to seven circular economy SMEs in Finland. The cases were selected to represent typical circular economy companies in terms of size and years in operation. However, most of the companies were in the early stages of adopting data-driven decision-making. An interesting further research opportunity would be to also investigate circular economy SMEs that are more advanced in the adoption of data-driven decision-making and derive insights into what steps and actions the circular economy SMEs should take to improve their maturity in data-driven decision-making.

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Chapter 11

Barriers and Practical Challenges for Data-driven Decision-making in Circular Economy SMEs

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Abstract

The circular economy (CE) model is seen as an alternative model to the linear economy models, which seem to be reaching their physical limits. The CE business model aims to reuse materials and decrease the need for virgin materials. This requires the implementation of a reverse supply chain, close collaboration between actors, as well as well-organized logistics. For this reason, the CE companies have typically high demand for digitalized processes and the utilization of data on both operational and business development dimensions. Also the utilization of big data collected from the companies' business environment can provide new opportunities for business development in CE. Despite the fact that utilization of data collected from the business environment and operations enables data-driven approaches for various decision-making functions in companies, many companies still struggle to figure out how to use analytics to take advantage of their data. In the small- and medium-sized enterprises (SMEs), in particular, the managers are facing difficulties with ever-increasing amounts of data and sophisticated analytics. Indeed, prior research identified several kinds of barriers to the effective utilization of data in SMEs. Still, research on data-driven decision-making remains scarce in CE context. This chapter presents a case study consisting of seven cases, all representing SMEs operating in the field of CE in Finland. In the case study, the barriers and practical challenges for data-driven decision-making in CE SMEs are investigated. Based on the case study results, this chapter proposes that utilization of data, lack of resources, lack of capabilities, and regulation are the main barriers to data-driven decision-making in CE SMEs.

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1. Introduction

Whereas the current linear economic model based on "take–make–dispose" is reaching its physical limits not least due to the unbearable amounts of waste, CE-based economy system is emerging as an alternative to this model (Suchek et al., 2021). The CE incorporates a regenerative system that minimizes the entry and waste of resources, emissions, and expenditure of energy through slowing down, closing, and straightening the energy circuits (Geissdoerfer et al., 2017). CE is based on closed-loop production systems and material flows. It aims to reuse materials and decrease the need for virgin materials, which requires the implementation of a reverse supply chain and cooperation between actors (Urbinati et al., 2017). The principal logic of the CE is to convert waste into resources by applying technical or biological conversion. The outcome of the conversion can be re-used in an industrial process or returned to the biosphere (McDonough & Braungart, 2010). The business concepts related to the area of CE aim at addressing sustainable development needs by minimizing resource input and waste, emissions, and energy leakage without jeopardizing growth and prosperity (Urbinati et al., 2017). Sustainability enriches corporate value with relational meaning and dialogue by making the aims of the corporation more transparent and demonstrating mutual responsibility (Ciasullo & Troisi, 2013) for social, environmental, and economic development.

Technological advancements, especially in the past decade, have revolutionized the way that both every day activities are conducted (Mureddu et al., 2020). To be successful in the rapidly changing CE business environments, the companies operating in this area have typically high demand for utilization of data on both operational and business development dimensions. It is known that exploratory utilization of data collected from business processes, customers, competitors, and other sources enable data-driven approaches for various decision-making functions in companies. In addition to that, ever-increasing big data provides opportunities for innovative companies in new business and process development (Visvizi et al., 2021) in terms of, for example, material flows, customer behavior, or logistics planning. However, many companies still struggle to figure out how to use analytics to take advantage of their data. The managers are facing difficulties with ever-increasing amounts of data and sophisticated analytics (Ransbotham et al., 2016; Susha et al., 2017). This is particularly true for firms operating in the CE business environments, in which a firm may obtain significant competitive advantages by coming up with new innovations and customer solutions. On the other hand, operational requirements related to, for example, supply chain management, production, and material flows are significantly higher in CE business than in many other business areas. For the companies, data-driven decision-making can reduce costs, improve operations efficiency, increase stakeholder loyalty, and increase communication flows within the organization and ecosystem (Pulkkinen et al., 2019; Troisi et al., 2020). For this reason, it is natural that the CE companies show increasing interest in investing in business intelligence and other practical data-based tools that enable them to make systematic planning for the future at both the strategic and operational level (Järvenpää et al., 2020). Business data also provide the companies with a basis for rapid and rational decision-making concerning their key operations, including business and product development. However, due to their relatively small organizations with limited competences and resources, SMEs are often rather streamlined and limited in their financial resources and capabilities. For this reason, developing capabilities to utilize data in their business analytics and operations is particularly important for SMEs (Järvenpää et al., 2020).

This chapter considers the data-driven decision-making and management mechanisms and practices in innovative SMEs operating in the evolving CE-related industries. This study aims at answering the following research question: *What are the barriers and practical challenges in data-driven decision-making in circular economy SMEs?* This question is aimed to be answered at both the strategic and operational level through a qualitative comparative case study consisting of seven cases, each representing a SME operating in CE in Finland. Thus, this study presents a qualitative multiple case analysis using the case companies as a unit of analysis. For this reason, the study contributes to the existing research on data-driven decision-making and management by focusing on the SMEs. The study extends the existing literature concerning barriers to the use of data in a complex but increasingly important business area of CE. The findings of the study may also have significant managerial interest, given that managers, particularly in SMEs are facing difficulties with ever-increasing amounts of data and sophisticated analytics. This chapter is organized as follows. Section 2 outlines the theoretical background of the chapter, and focuses on four main barrier types. Section 3 presents the methodological choices of the chapter. Section 4 focuses on the results obtained from the analysis of the empirical data. Discussion and concluding remarks are presented in Section 5.

2. Challenges for Data-Driven Decision-Making in SMEs

The rapid progress in industrial digitalization has caused a massive increase in the amounts of data. This data, collected from the operational or business processes of the companies provide new sources of value (Ruohomaa, 2020). Data-driven decision-making is an approach to managing big data throughout the entire decision-making cycle of the organization, where the role of the data-driven management is to base business decisions on data analytic thinking to make use of data in prescribing actions, predicting future developments, and driving change (Troisi et al., 2020, p. 538). Thus, the impact of utilization of data on the economy has also been referred to as "the new oil" (Hilbert, 2016). However, large and multinational companies often have capabilities to fully deploy data in their business on both operational and strategic levels, many SMEs are still lacking competence and resources for data-driven decision-making (Iqbal et al., 2018). It has been shown that big data analysis tools and technologies as themselves do not allow the automatic attainment of innovation (Troisi et al., 2021), competitive advantage (Watson, 2016), or increased stakeholder value. This may be particularly problematic for SMEs that typically do not have capabilities or resources to allocate for full-scale deployment of these kinds of tools (Järvenpää et al., 2020).

2.1. Utilization of Data

Järvenpää et al. (2021) discussed what kinds of data is typically used in data analytics in SME context. The data can be (1) machine-generated – when it comes from, for example, machines, sensors, mobile phone applications, or computer networks; (2) human-generated – when it is collected by people, for example, personal information; and data generated in technology-mediated interactions via, for example, documents, emails, and social media services; and (3) business-generated – including transaction data from point-of-sale or enterprise resource planning systems (Olshannikova et al., 2017; Saggi & Jain, 2018). In addition, the data may also originate from company internal or external sources. The external data sources include open data, acquired data, customer-provided data, and freely available data (Hartmann et al., 2016).

Previous studies in the data-driven decision-making in SMEs (Iqbal et al., 2018; Kim et al., 2003; Parra et al., 2019; Ransbotham et al., 2016) have identified several types of obstacles and challenges in harnessing big data in the operations of SMEs. The challenges may include a low level of understanding of big data and classifying emerging developments such as big data analytics as hysteria and not as a viable business opportunity. Other challenges are lack of adequate infrastructure to analyze data, lack of in-house data analytic experts, lack of representative case studies, and success stories in big data analytics in SMEs. Lack of expertise in selecting suitable solutions and effort needed in order to understand the available data, as well as dirty data and other data quality issues may challenge the data-driven decision-making in SMEs. The SMEs operating in CE are likely to face these kinds of challenges in their business operations and planning. However, the CE SMEs also have their own, specific challenges that are related to their business area. Their key challenges are often related to materials that they are re-using. Material quality issues as well as the barriers related to the information exchange in material flow supply and demand, infrastructure, and transportation are found to be key obstacles for using data in decision-making (Winans et al., 2017). As stated by Strand and Syberfeldt (2020), external data may be the key asset for data-driven decision-making in organizations, but still most organizations primarily utilize internal data. In the field of CE companies, Strand and Syberfeldt (2020) found that valuable data for waste can be found external data sources: maps, orthophotos, and road data; property and civil data; and traffic and weather data.

2.2. Lack of Resources

Typical approaches to utilizing data analytic methods in companies vary from relatively simple statistical and optimization tools in traditional spreadsheet software packages to more sophisticated data visualization and analytics tools including descriptive, predictive, and prescriptive methods (Davenport & Harris, 2017). While large corporations can typically invest in specialist data scientists and in-house technology infrastructure, SMEs often lack both the expertise and the tools to benefit from data analytics (Parra et al., 2019). Ormazabal et al. (2018) and Rizos et al. (2016) have indicated that two main resource-based barriers for CE SMEs include lack of technical and financial resources. What comes to financial resources, it is natural that adopting data analytics tools and technologies require financial resources from the companies in terms of both investments in information managements tools and human resources operating these systems. In fact, inadequate information management systems have been recognized as one of the major barriers for CE activities in SME context (Rizos et al., 2016).

2.3. Lack of Capabilities

Rizos et al. (2016) indicate that the lack of internal technical skills is one of the key obstacles preventing SMEs from taking advantage of the opportunities provided by CE. The SMEs do not have the technical capacity to identify, assess, and implement more advanced technical opportunities that would enable them fully take advantage of CE-related business models. Consequently, these firms often prioritize technologies and tools which they are already operating. Furthermore, the SMEs may not have enough understanding on what kinds of technological solutions (such as analytical methods) are available in the first place and which of these methods could be feasible in their context (Järvenpää et al., 2021).

2.4. Regulation

Flash Eurobarometer Survey number 441 (*Flash Eurobarometer 441. European SMEs and the Circular Economy*, 2016) investigated what issues firms encountered when undertaking CE activities, and which of the following five barriers were significant: (1) lack of human resources; (2) lack of expertise to implement these activities; (3) complex administrative or legal procedures; (4) cost of meeting regulations or standards; and (5) difficulties in accessing finance (Garcés-Ayerbe et al., 2019). According to Garcés-Ayerbe et al. (2019), of those firms ($N = 7{,}843$) that had implemented or were implementing at least one of the CE measures the biggest barrier was complex administrative or legal procedures (perceived by 31% of the respondents) and the second was cost of meeting regulations or standards (28%). Despite the fact, this study was not focused on data-driven decision-making in CE firms, it can be inferred that regulation may also impact data-driven decision-making in CE SMEs. Regulatory barriers frequently mentioned in literature include, for instance, lack of consistent regulatory framework and obstructing laws and regulations (Hart et al., 2019).

3. Methodology

This chapter presents a comparative qualitative case study of seven CE SMEs, all located in Finland. The case companies provide services related to waste management, biogas production, material recycling, the manufacturing of products based on waste materials or consulting, as summarized in Table 11.1. The research data used in this study was collected by two rounds of interviews. First interview round was conducted by two of the authors that interviewed each company representative, mainly CEOs, in May 2021. The interviews lasted about 60 minutes each, and they were recorded and transcribed prior to analysis.

Table 11.1. Summary of the Case Companies Used in This Study.

Case	Interviewed Person	1st Interview Round	2nd Interview Round (Group Interview)	2nd Interview Round (Group Interview)	Industry	Core Business Area
A	COO	X	X	50	Combined facilities support activities	Waste management, recycling services, and solutions for households and companies
B	Service Manager	X	X	60	The treatment and disposal of non-hazardous waste	Waste management and recycling services for households and companies
C	CEO	X	X	80	The treatment and disposal of non-hazardous waste	Waste management and recycling services for households and companies
D	CEO	X	–	<5	Security services	Disposal of confidential material
E	Quality Manager	X	–	20	Hazardous waste management	Waste processing and disposal
F	CEO	X	–	10	The dismantling of wrecks	Recycling services for wrecks
G	CEO	–	X	<5	Management consulting	CE

Source: Authors.

In the interviews, the researchers used a semi-structured interview template that sought insight into how companies are utilizing data in strategic decision-making. Special attention was paid to the barriers and obstacles of data usage in the CE area. After the analysis of the first interview round, the second round was conducted by three of the authors as a group interview of the company representatives in November 2021.

The purpose of the second interview round was to validate preliminary conclusions, clarify some of the ambiguities and to gain a deeper understanding on the topic.

4. Results

In this section, we summarize the results of the analysis made based on the case-specific interviews. Following the research question, the analysis of results is divided into four sections, each of which presents the key results of the interviews in the four challenge categories identified from literature: utilization of data, lack of resources, and lack of capabilities, and regulation. Some key results from the case data are also summarized in Table 11.2.

Table 11.2. Key Results From the Case Data.

Challenge Category	Challenge in Cases
Utilization of data	Data is scattered in various information systems [F] Combining data from various sources is challenging and time-consuming [A] Pre-processing and cleaning of data is challenging and time-consuming [D] Manually inputting of data is needed because data does not automatically transfer between information systems [D]
Lack of resources	Inadequate information management systems [C] [D] [F] Current in-house information systems do not support ad hoc reporting and drilling of essential data [F]
Lack of capabilities	Insufficient competence in using existing information systems [A] [D] [F] Lack of capability in using and refining collected data [A] [D] [F] No in-house competence in developing reporting, automated queries [A] [B] [D] [F]
Regulation	The legislation must be followed, the data must be collected in the form required by legislation [G]

Source: Authors.

4.1. Utilization of Data

The reliability and data quality play a critical role in achieving the desired output. Challenges include missing data, wrong data, and unusable data (Kim et al., 2003), also referred to as "dirty data" and the cleaning of these (dirty) datasets (Iqbal et al., 2018). Many organizations suffer from data quality issues that may lead to bad decisions and a negative data-driven culture (Parra et al., 2019). Based on the interviews, data utilization challenges are mainly caused by various information systems, challenges in data processing, and manual data input.

> At the moment we are in the beginning in developing descriptive analytics, the challenge is that we are still cleaning data and there is a lot to do before we get descriptive analytics in sensible form. (Case E)

> We've never considered our business as data-driven, that we would collect and utilize the data. We have quite a few data collection points that provide fragmented data, which in turn brings challenges to the next steps, namely processing and analysis. Our key challenge is that data is not perceived as fuel for doing business analyses, our expertise has not evolved through data collection and processing. Our situation culminates through many reasons. (Case C)

For waste management company (case A) one critical challenge is that it is not possible to measure fulfillment rates for all waste containers. Therefore, there is missing data on waste container fulfillment rates. This is especially a challenge for optimizing routes of emptying waste containers because there is incomplete information for decision-making. Technologies for measuring waste container fulfillment are not perceived cost effective enough for the company to invest:

> Data is being collected from the fulfillment rates of the waste containers. However, we do not currently have a system that could process and analyze that data. (Case A)

The processing in that case requires real-time processing to be useful for the company. As has been recognized in the literature, the benefit for the company necessitates in addition to real-time data processing also relatively fast responses from the operational management (Watson, 2016):

> We found that processing information must be more real-time to be able to make the right decisions in the right moment. (Case A)

> We have the same system as other companies, and it doesn't meet today's demands. We collect a lot of data from everything, the

> biggest problem is how to put it together, automate processing and visualization. The resources allocated for doing this is scarce, as it has not been needed before. There will be more reporting requirements and the best solution would be reporting models. According to the provided models it would be possible to compile required reports from the data. (Case A)

The information systems used by the companies provide several challenges for the utilization of data. Many of the challenges that the companies face is not related to data analytics software or services by themselves, but to those information systems that generate or originate the data used for data analysis.

> We store information in several systems that do not discuss with each other. It is a challenge to make use of information from different systems. We partially lack data collection automation, some of the information is still stored manually. In general, the waste sector has a single ERP system in use. Software development has been a challenge, and it hasn't developed quite so quickly over the past few years. Knowledge management is not commonplace in any organization in this industry. We need basic knowledge and insight into how this is worth doing – and we need help with that. (Case B)

> Interoperability is a word I hope you write strongly down, it's a challenge in the big picture. It is not worth making solutions for just one company, region, or industry. Information must also serve statistics and reporting to the EU. This has been underthought from a waste management perspective – local and regional measures are made, and the connection is not open through interfaces forward. (Case G)

4.2. Lack of Resources

Based on the interview data, the main resource related challenges are lack of platform and lack of time. Rizos et al. (2016) has suggested that inadequate information management systems include one of the main barriers to CE activities in SME context.

> The challenge is that we have no data platform. (Case C)

> The main challenge is that we are not exploiting data to the extent that could be. We collect a lot of data, but we are a small company, and we do not have the resources (to exploit data). (Case D)

> There is no time to form essential (data) packages. (Case F)

> The same owner has several plants with same technology. There are weekly reports available that could be compared, but they are not used (because lack of time). (Case F)

Based on the interview data, it seems that the companies may possess remarkable amounts of data, but the problem is that there are no dedicated resources in the company that have skill, capabilities, and tools to collect, process, analyze, and interpret the relevant information to support managerial decision-making and operational management in the company.

> We have a lot of data, but compiling information into the necessary form and visualizing it is a stumbling block. For example, if I could get the information necessary for myself from the accounting, it would be relevant. (Case F)

According to the work of Ransbotham et al. (2016) despite the increased access to useful data, companies' ability has decreased to apply analytics insight into strategy and the challenge is to get useful insight for decision-making. They stated that companies are not effective to disseminate and use insight strategically.

4.3. Lack of Capabilities

When asked about the lack of capabilities as a potential barrier for data utilization in CE SMEs, the interviewed company representatives mentioned lack of expertise and infrastructure. Our interview data was quite coherent in this, and most of the interviews supported this finding:

> We don't understand analytics in a way we would be able to design a data platform. (Case C)

The interviewees' insights were in line with many studies. For example, Iqbal et al. (2018) stated that SMEs are still lacking competences and resources for data-driven decision-making and Rizos et al. (2016) indicated that lack of technical skills is one of the key obstacles preventing SMEs from taking advantage of the opportunities provided by CE. As SME's usually concentrate on their core business and competencies, they might miss opportunities to take advantage of data (Iqbal et al., 2018):

> We lead by emotion, not by information. (Case C)

Data utilization in SMEs is hindered by the fact that they are incapable to analyze data by themselves because of the shortage of data analytics expert and high set-up costs (Iqbal et al., 2018). Parra et al. (2019) found that the use of data depends on the senior management technological familiarity and that data analysis are mainly used rather at management level not operational. Nevertheless, managers data analysis expertise relates to tracking indicators, dashboards, and tailored spreadsheets (Parra et al., 2019).

> The biggest challenge is that the staff do not have sufficient competence to use systems. Activities focus on standardized programs and systems such as enterprise resource planning and customer management, staff do not have sufficient skills to exploit, and process collected data in Excel or PowerBI. (Case A)

> If the new system is easy to use, it will be easier to deploy it. Due to resistance to change, we need to invest in introducing a new system so that everyone adopts it, and no one is left to use the old one. (Case B)

Ransbotham et al. (2016) categorized companies at three levels of analytical maturity: analytical challenged, analytical practitioners, and analytical innovators. They suggested that analytical innovators are likely to have formal strategy for analytics focusing on skills development, data management, and cultural norms. To further clarify this topic within our case study companies, we specifically inquired about this on the second interview round (group interview) by asking the interviewees: "What kind of bottleneck is competence in utilizing data and what could help you to overcome the competence-based barriers?" Many of the company representatives named the lack of experience on data utilization as the main bottleneck. One central reason for that is the fact that the core business of the companies is not related to data, and the SMEs are reluctant to focus their limited resources outside of their core business area:

> Since we have not been engaged in data processing and utilization, our know-how has not evolved. (Case A)

> In the customer's experience and the end-user perspective, the challenge is to combine the substance into the digital field: to translate the hopes into digital so that an easy-to-use perspective could be made. Developing a customer perspective on the side of waste management companies is of interest to big firms. But it is often the case that is understood coding but there is no understanding of what it is in the field. (Case G)

> Waste management operators are looking too much inward. They should benchmark services from more advanced fields. In many areas, new services have emerged through the use of open data. (Case C)

The interview data also shows that the mindset and culture in the companies focuses on much on technologies and engineering thinking at the operational level. In this context, the considerations on data utilization or service-oriented business development may sound distant managerial topics:

> The waste industry is often focused on engineering thinking. We should emphasize the importance of customer experience, not just making smooth and efficient systems for ourselves, but that the customer could benefit and thus increase recycling activity. We could develop better service solutions for customers if we have a good understanding of customer experience and the ability to take advantage of service design. (Case B)

> It would be interesting to look at the exploitation of data across corporate boundaries. There are channels to which companies should export information, but we need solutions that go beyond companies and benefit the sector as a whole. (Case C)

In both interview rounds, the company representatives mentioned co-operation with students. Interviewees think that the students have better skills than their staff, and they think that co-operation with students provides valuable ideas for companies. As there is a shortage of data analytics experts in the labor market, co-operation with students could provide new opportunities for companies as well as missing case studies and examples of data analytics in SMEs. This could be one potential way of filling the capability in the companies.

> We can train staff, but we are getting ideas from students' projects that helps us significantly. (Case A)

> It seems like the student knows how to use these instruments (analytic tools) better than us. (Case B)

> A lot of competence comes along through students' work, but conversely, each company has its own systems for which students do not find competence. However, it is knowledge sharing and training, getting from students' know-how to the company and from company to students. I see cooperation with students as important. (Case A)

> Students are a potential resource; we have done several collaborative data analytics projects that have been surprisingly good. Students have such competence, e.g. the features of Excel, which we don't. (Case B)

4.4. Regulation

In the first round of interviews regulation and legislation was mentioned by several companies while discussing data-driven decision-making. Therefore, in the second interview round we directly inquired: Is the legislation barrier or challenge for data utilization? Based on the interviewees ´opinions, it seemed that regulation may cause barriers, but on the other hand, some of these barriers can be overcome by increasing knowledge and skills within the companies:

> Legislation generally speaking is a lagging force. (Case C)

> GDPR is often misunderstood (in companies) and the development might be stopped just in case. Legislation is important, you can take a great risk if you don't understand it. We need more understanding and a critical analysis of what the GDPR is and what are its requirements for data utilization. It hinders development because it is not exactly known what it actually prevents. (Case C)

We wanted to further understand, whether the industry is data-driven or "legislation driven" and to what degree does legislation impact at decision-making. Hence, we inquired in the group interview: Is the activity controlled by data or delivered under the coercion of legislation?

> The legislation must be followed, the data must be collected in the form required by legislation. For example, the EU Implementing Regulation defines that reporting of reusable building parts and materials must be done in tons, even if no such information can be found. What is asked can contradict what exists. (Case G)

> The idea in all legislation should be permissiveness for development, not to make a regulation that is locked up at this moment. Regulation should enable new innovations, new systems, and their exploitation. (Case G)

> If there is material, which is treated in tons, but the reporting requirement is cubic meters, measuring and monitoring may not go hand in hand. This will bring challenges and errors in the statistics. (Case A)

> Uncertainty where legislation is going to guide, meaning where we should focus on and allocate resources, or do we have any more interests in the first place – it is a legislative problem that cannot be influenced by ourselves, but to live with it. (Case A)

5. Discussion

The objective of this chapter was to increase understanding on the practical challenges and barriers to data-driven decision-making perceived by CE SMEs. In this manner, the chapter increases understanding of how data in its different forms influences the processes of decision-making, and management on operational and strategic levels. In this chapter, four major challenge themes were identified: utilization of data, lack of resources, lack of capabilities, and regulation. The CE SMEs had several data utilization challenges for decision-making. The data is fragmented in several information systems that do not communicate with each other. Operations rely to some extent on manually inputted data, and there are challenges in automated data collection and developing automated queries to support the discovery of essential information. Concerning lack of resources, the Finnish CE SMEs mostly highlighted lack of platforms and lack of time for hindering data-driven decision-making. The platforms that the CE SMEs use are mostly adequate for reporting but fall short on discovering and visualizing essential information.

Based on the interviews the lack of capabilities for data-driven decision-making in CE included some usual suspects. For example, lack of competence (Iqbal et al., 2018; Rizos et al., 2016) in data and performance management (Aho, 2012; Parra et al., 2019; Ransbotham et al., 2016). These results add to the previous studies on dynamic capabilities of CE firms (Khan et al., 2020a, 2020b) from the perspective of SMEs. Some novel insights pointed out by the managers include the need for a mindset shift from engineering thinking to design thinking: "not just making smooth and efficient systems for our selves, but that the customer could benefit and thus increase recycling activity." It was also pointed out that large firms are more customer oriented, whereas the CE SMEs customer perspective on the waste management is underdeveloped. This may indicate challenge the competitive advantage for CE SMEs if bigger national or international companies enter the same market. Interestingly, several of the SMEs noted that students, who they have collaborated with, have more advanced data analytics skills than they do and that the students can offer valuable help in capability development, and thus fill the competency gaps in the companies.

In CE and waste management industry the regulation and legislation enforce what companies must do, and regulation has been found as a barrier in earlier studies as well (Garcés-Ayerbe et al., 2019). It can be interpreted based on the interviews that in this sense the CE SMEs are more legislative-driven than data-driven. Reflecting on the MoSCoW method of what can be considered as "must have," "should have," "could have," and "won't have" for the design of data-driven decision-making (cf. Kollwitz et al., 2018), the regulation defines what must be done. "Should have" and "could have" in data-driven decision-making are something extra that most SMEs don't have dedicated resources or capabilities to perform.

The CE SMEs also recognized that they could benefit from open data, and application programming interfaces (APIs) for local and regional waste management data, which has been also recognized important in other industries (Jussila et al., 2019). One implication for policy-making in Smart Cities is that SMEs especially need support in terms of open data repositories and APIs to support their reporting and business development (see also Watson & Ryan, 2021). Most SMEs do not have resources themselves to develop needed interfaces for data flow and management. Instead, they need to rely on third-party information system providers that may not have the same incentives or need to meet the legislative requirements as the CE SMEs. Regional actors could pool together resources to develop information resources and systems to better support CE SMEs business. Increasing funding for CE SMEs development could significantly support meeting the European Union (European Commission, 2018) net-zero greenhouse emissions by 2050 and the national carbon neutrality goals.

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Developing data analytics capabilities for circular economy SMEs by Design Factory student projects

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Abstract: Circular economy (CE) is a key strategy for achieving corporate sustainability. However, it is still difficult for many firms to translate the concept of circular economy into their strategies, business models, and operations. Utilization of data and digital tools are among the key capabilities facilitating the transition to CE. Therefore, firms need to develop new dynamic capabilities for the utilization of data, as a part of circular economy implementation. In this paper, we investigate how data analysis capabilities in the CE SMEs are developing in the joint action between university and companies. We introduce a comparative multiple case study of three CE SMEs, all located in Finland, who have developed their data analysis capabilities by participating in a collaboration project with university. The main focus of the project was to conduct a data analytics course and related student projects in close collaboration with the CE SMEs. This development of the firms' data analytics capabilities in this collaboration are analysed in this study by employing a framework of relationship learning. As a result, this study presents recommended practices for knowledge sharing, joint sensemaking and knowledge implementation to support the development of SMEs' dynamic capabilities in data analytics through university-industry.

Keywords: Design Factory; Data analytics; Dynamic capabilities; Circular Economy; Small and medium-sized Enterprises; University-Industry Collaboration; Knowledge sharing; Sensemaking; Knowledge implementation

1 Introduction

The circular economy (CE)-based business models aim to reuse materials in effective and sustainable manner. Switching from the traditional linear models of economy to circular ones would not only bring remarkable economical savings, but also significantly reduce the negative impact on the natural environment (Lewandowski, 2016). Therefore, the CE has attracted increased attention as one of the most powerful and most recent moves towards sustainability. CE-based business models also require close collaboration and information transfer between the companies and other stakeholders in the value chain and other actors, as well as well-organized logistics (Järvenpää et al., 2021). Data and digitalization play a central role in this.

However, large part of the CE companies is still facing challenges figuring out how to utilize the opportunities of digitalization and ever-increasing amounts of data. Small and medium enterprises (SMEs) have a key role in implementing the CE, and they also are

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responsible for the majority of the jobs in these areas (Prieto-Sandoval et al., 2019). However, particularly in the SME sector, the managers are facing difficulties with ever-increasing amounts of data and finding appropriate analysis methods. Previous research has identified several types of obstacles and barriers to effective data utilization in SME sector (Järvenpää et al., 2021). The barriers and other challenges are emphasized in the SME sector since these companies have typically small organizations with limited competences and resources. CE SMEs tend also be rather streamlined and limited in their financial resources and capabilities (Järvenpää et al., 2020). In addition, whereas large and multinational companies usually have capabilities to fully deploy data in their business on both operational and strategic levels, many SMEs are still lacking competence and resources for data-driven decision-making (Iqbal et al., 2018).

In this study, we investigate how collaboration with universities, and in particular student projects can support CE SMEs to develop necessary capabilities for data utilization. Thus, the aim of this study is to understand how development of CE SMEs data analytics capability can be integrated into university-industry collaboration in a successful way. The research questions are the following: "*How the data analysis capabilities in the SMEs are developing in the joint action between university and companies?*" This research question is further divided into two sub-questions: 1) How does the university-industry collaboration correspond to the data analytics capability needs of the CE SMEs? 2) How did the capabilities of the CE SMEs develop during the collaboration?

We aim at answering the research question by using the theory of dynamic capabilities (Teece, 2018; Teece et al., 1997) as a theoretical lens. According to this theory, to successfully develop and sustain their competitiveness under rapidly changing environmental circumstances, firms need to develop dynamic capabilities that enable them to draw on, to extend and redirect their technological capabilities and R&D resources. We use this theoretical framework as a basis of a qualitative case study consisting of CE SMEs operating in Finland.

2 Developing dynamic capabilities in CE SMEs

Knowledge-intensive firms often operate in the dynamic environments characterized by strong competition, rapid changes, accelerating product life cycles, changing customer expectations and product discontinuities. To successfully develop and sustain their competitiveness under these environmental circumstances, firms need to develop dynamic capabilities that enable them to draw on, to extend and redirect their technological capabilities and R&D resources (Teece et al., 1997). Dynamic capabilities have been defined as: “The firms’ processes that use resources—specifically resources to integrate, reconfigure, gain, and release resources—to match and even create market change. Dynamic capabilities thus are the organizational and strategic routines by which firms achieve new resource configurations as markets emerge, collide, split, evolve, and die.” (Teece et al., 1997). An enterprise with strong dynamic capabilities will be able to profitably build and renew resources, assets, and ordinary capabilities, reconfiguring them as needed to innovate and respond to (or bring about) changes in the market (Teece, 2018).

3.1. Data and digitalization as a dynamic capability in CE SMEs

Circular economy is a key strategy for achieving corporate sustainability, and scholars have argued that firms need to develop new dynamic capabilities for circular economy implementation. The theory of dynamic capabilities provides a theoretical perspective to explore how firms can innovate in rapidly changing environments, and therefore it can be used as a theoretical lens in inspecting the firms' behaviour in the dynamic environments of CE. Moreover, in the research of (Sehnem et al., 2022) dynamic capabilities were found to be among the most investigated research topics in the intersection of CE and innovation. Dynamic capabilities are organizational and strategic routines by which firms achieve new resource configurations as markets emerge, collide, split, evolve, and die".

According to Parida & Wincent (2019), the transition to circular economy is widely driven by digitalization. This, in turn, has facilitated the development of new service-based business models. For this reason, the companies operating in CE have typically high demand for digitalized processes and the utilization of data on both operational and strategic levels, as well as in the business development dimension (Saleem et al., 2021) For these companies, the exploratory utilization of data collected from business processes, customers, competitors, and other sources enable data-driven approaches to various decision-making functions (Lacam, 2020). In addition to that, ever-increasing both business-specific and process-specific data provide opportunities for innovative companies in new business and process development in terms of e.g. material flows, customer behavior, or logistics planning (Lacam, 2020). On the other hand, the data management processes must be used well to benefit the firm (Ham et al., 2017). In addition, operational requirements related to e.g., supply chain management, production, and material flows are significantly higher in CE business than in many other business areas (Järvenpää et al., 2020). In addition, data-driven decision-making can provide the companies with several kinds of benefits, including reduced costs, improved operational efficiency, better stakeholder loyalty, as well as improved communication flows within the organization and ecosystem (Troisi et al., 2020).

3.2. Developing dynamic capabilities in university-industry collaboration

In this paper, we inspect how the CE SMEs can develop their dynamic capabilities in data utilization by intensive collaboration with universities. Previous research has shown that innovative research collaboration between universities and industrial firms may effectively facilitate shared knowledge creation, learning, and joint innovation (Kunttu & Neuvo, 2019; Perkmann et al., 2013). The role of university students and researchers may be significant in transferring the research-based knowledge into the industrial domain. In case of the dynamic environment of the CE SMEs, and in particular the topic of data utilization, the collaboration between the companies and universities may enhance the SMEs' dynamic capabilities in this area.

The concept of relationship learning (Selnes & Sallis, 2003, p. 80) has been applied to the collaborative learning process in the university-industry collaboration in (Kunttu & Neuvo, 2019). The process contains three phases. In the first phase, *knowledge sharing*, the partners share their previous knowledge and capabilities, whereas in the second phase, *joint sensemaking*, the partners work together to build new knowledge in joint action. The third phase, *knowledge integration* is a process of making concrete outcomes from the learnings. The outcomes on the industrial side may be prototype implementations, demonstrations, or proofs-of-concepts of the jointly developed

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technology. In this paper, we study the development of the dynamic capabilities related to data utilization in CE SMEs by using the framework of relationship learning.

3 Methodology

The research methodology in this paper is based on the qualitative interview data collected from the case companies. The interview data was collected from the participating CE SMEs in two separate interview rounds in 2020 and 2021. Based on this data, we formulated a comparative multiple case study of three CE SMEs, all located in Finland. The case companies provide services related to waste management, biogas production and material recycling. In addition to the company interview data, we used additional data from the student projects that include course reports, presentation and other outcomes created by the students.

Table 1 Descriptions of the case companies studied.

	Case A	Case B	Case C
Number of employees	100	50	90
Main products/services of the customer company	Waste management and recycling services	Waste management, recycling services and solutions, biogas production	Waste management and recycling services
Duration of collaboration with university	2 years	2 years	1 year
Area of the joint development projects(s) with university	Data Analytics Project 2020-2021	Data Analytics Project 2020-2021	Data Analytics Project 2021
Added value for the industry	Additional resource, outside perspective	Additional resource, outside perspective	Additional resource
Key academic results of the development project(s)	Scientific article	Scientific article	Scientific article
Company interviewees	CEO & marketing manager	CEO	Chief Development Officer

4 Results

Case study results describe university-industry collaboration that took place during 2020-2021. Collaboration started with companies participating as challenge owners and data providers for data analytics student projects in 2020. In 2021 data analytics student project was followed by student trainees for companies that continued the data analytics project in the company, and also planning thesis projects as continuum that could follow the data analytics project course.

Major results from the three case studies in 2020 data analytics student projects were that the data visualization created by the student teams helped companies to increase understanding about their business, generated new ideas for improvement and familiarized the companies with new data analytics tools. The companies were able to implement some of the student teams results in reporting and operations planning. In 2020, many of the case studies companies, however, found it difficult to apply the student project results in their company, due to lack of data analytics capabilities.

Based on the feedback received from the year 2020, special attention was placed in sharing the results and approach used by the students' teams for problem solving of the company challenge. As a result of the recognized gap of companies’ data analytics capabilities, a tailored data analytics tools course was developed for participating companies, so that the companies could benefit more from the solutions developed by the students and continue the development in-house. Another important finding was that in some of the cases, a short eight week long data analytics project is inadequate for solving the company challenge by itself but serves as good starting point for student trainees and thesis workers to complete the work.

As an outcome of the changes made in 20200, the following year companies benefited more from university-industry collaboration and were highly satisfied with the collaboration. Another finding was that those companies that participated for the second or third time in the similar projects, were able to better define the problem together with the university and also receive more useful results from the project. From the teachers’ and companies’ perspective it was recognized that university-industry collaboration is a multisided learning process and the more times you do it the more you can benefit from it.

4.1. Knowledge sharing

In the data analytics student projects, knowledge sharing from the student perspective included sharing the ideas, findings and visualizations created by the student teams and also information about modern data analytic tools and their possibilities in supporting and developing the operations of the company. The companies shared knowledge about their business environment, their products and services, processes, and current approaches in data analytics to the students. Knowledge sharing was done in weekly or bi-weekly meetings with the company, beginning from the first week by a presentation from a company representative. When feasible the students also visited the company to learn more about the target of their project. The knowledge level of data analytics in the studied companies was found to be relatively low in the beginning, and for that reason the students were able to provide valuable knowledge about data analytics tools and the possibilities for data analytics use in the company. For instance, case C representative described the starting situation as:

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"We must start with the basics, it is a big effort."

To address the identified gap in data analytics capability of the CE SMEs, a tailored data analytics tools online course was developed for companies that was provided after the student projects in 2020. Several of the company participants found the course helpful. Case A representative commented after participating in the tailored course for companies:

"We learned about the possibilities of Excel and Power BI. An online course in data analytics for SMEs is a good continuum for this project."

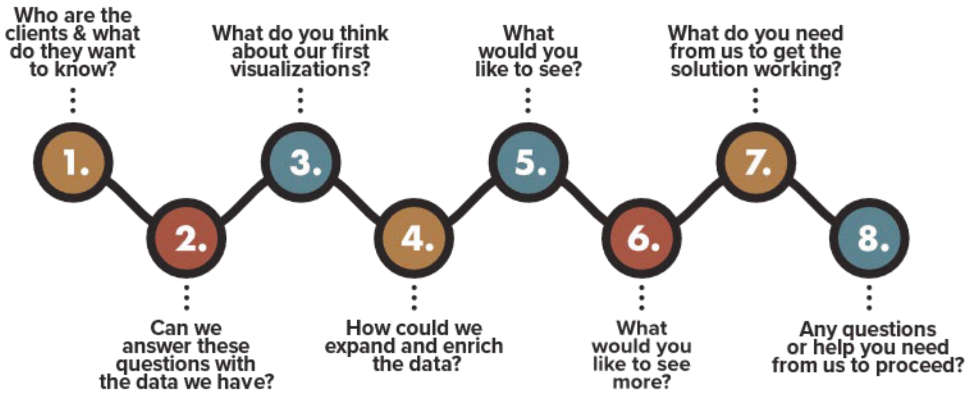

Figure 1. Joint sensemaking process in data analytics projects.

4.2. Joint sensemaking

Joint sensemaking took place mainly in interaction between the students and the case companies. Through discussions and questions every week, students tried to understand better the context of the project they are creating visualizations for. Companies on the other hand gained understanding about their data through the visualizations developed by the students, and got concrete development ideas. By the words of case company representatives:

"We got a better understanding about data through visualizations." Case A

"The benefits were data visualization and getting to know new tools (Power BI, Power Pivot)." Case B

"We got concrete development ideas. There was a better understanding about the issue through visualization." Case D

Based on the experience of the 2020 data analytics projects, the sensemaking process for the students was formalized as eight questions to ask from the case companies each week. These questions were aimed to guide the interaction between the student teams and the case company. Each week contained one key question to support joint sensemaking illustrated in Figure 1. Following this joint sensemaking process the companies can benefit from the students outside-in view of the company problem and solution space. Some of the questions rely on students creating ideas and prototype visualizations to demonstrate for the company and get feedback on the direction of the project. The companies described their experiences of the process in the following ways:

> "The students ask questions and give perspectives that we haven't noticed" Case A

> Students provide an additional resource, competence, outside vision, and fresh thinking" Case B

> "We're going to use the outputs, but I don't know exactly how yet. We are not very good from a reporting perspective." Case C

The feedback received from the companies about the joint sensemaking process uncovered also some challenges for knowledge implementation and ideas how this could be enhanced in university-industry collaboration.

4.3. Knowledge implementation

Companies were able to implement gained knowledge into the management, reporting and monitoring. In the first round of data analytics student projects, there were also major challenges related to knowledge implementation. While some companies were able to incorporate the developed solutions to their processes, others lacked the capability of making use of the students' solutions.

> "Visualization is incorporated as part of the reporting of our plant, we can monitor the flow of materials as well as the balance of the process." Case B

> "When CE SME already has data analytics capability and solutions used in-house, they can more easily make use of the results of the student teams. There were, also opposite examples."Data processing is a type of work that is not going to be undertaken and nobody can do it (currently), but it can give a significant impact on operations management. Visualizations can be used to plan work shifts." Case A

This highlights the challenge of knowledge implementation in instances, where the company does not have staff familiar with data analytics solutions and prior experience of doing data analytics themselves. As a result of these experiences from the year 2020 student data analytics projects, the guidance process of student projects was adjusted to better enable knowledge implementation. Specifically, one extra process phase, "Share results", was added to the process (Jussila et al., 2020; Lahdenperä et al., 2022) that the students followed to create the solution for the company, illustrated in Figure 2.

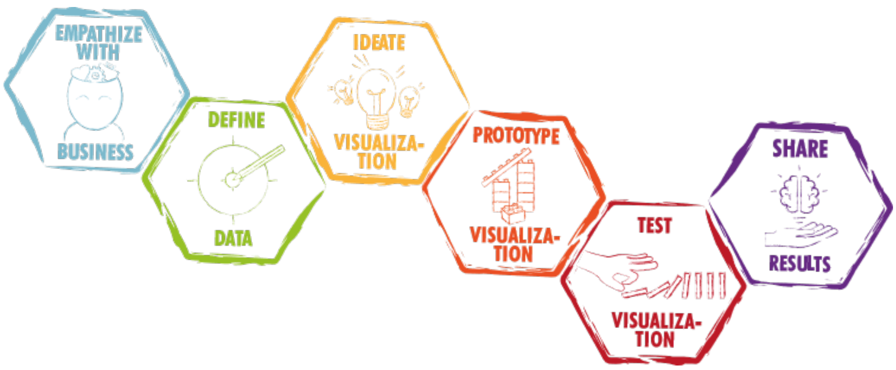

Figure 2. Six step design thinking process for data analytics.

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The five steps in design thinking process, namely empathize, define, ideate, prototype and test, were found to work well in student data analytics projects, however, companies lacked capability in making use of the results. Therefore, the “Share results” was added as a sixth step in the design thinking process for data analytics. This required the students to create a short guidebook or instruction manual for the company on how to use the data analytics solution developed by the students. In addition, the guidebook or manual included instructions on how to update and add new data to the data analytics solution in order that the solution could be used also in the future inside the company when new data is collected or acquired. As one company representative noted:

> "This was an exceptional project as we received instructions that help us to getting familiar with PowerBI." Case A
>
> "By updating the data, we can obtain an advanced prediction of how packaging waste should be collected." Case A

Overall, the companies gained models and functioning data analytics solutions that they can utilize independently of the students inside the company. The data analytics solutions were prepared in such a way that the company can keep using them and following the instructions prepared by the students. As each company had two student teams working for them, they were able to get either two different views on the same topic or solution to two different focus areas related to the problem.

> “It was very interesting to see the different perspectives of two teams. We received concrete material to be used in customer communications and marketing as well as a model of how data can be processed and utilized in our own use." Case B

5 Discussion

This study contributes by introducing solutions to developing dynamic capabilities that answer challenges identified in previous research, for instance, the CE SMEs difficulties with ever-increasing amounts of data and finding appropriate analysis methods and the common SME sector limitation of having limited competences and resources for data analysis. Companies can develop their dynamic capabilities in university-industry collaboration by working with students to solve business problems and simultaneously developing their own data analytics capabilities in interaction with students and the university.

Table 2 A summary of the main findings of this study on university-industry collaboration in developing data analytics capabilities of CE SMEsrelationships

	Knowledge sharing	*Joint sensemaking*	*Knowledge integration*
Co-created student project course	Methods for data analysis are shared between university and companies, university learns about company needs	Weekly or biweekly meetings between students and company create shared understanding on problem and solution space	Student created data analytics solution instruction manual help companies to adopt the results
Tailored course for companies	Company learns about university data analytics methods and tools, university about industry needs and problems	Discussions in tailored data analytics course for the company increase understanding of match between needs and tools used	Companies' data analytics capability is enhanced by tailored course
Student trainees for companies	University gains knowledge about company information systems and problem space and company about data analytics tools and methods	Trainee interaction with company and university increase domain specific understanding on data analytics problem and solution space	Student trainee contributes to development of data analytics solution and absorptive capacity of the company
Thesis projects for companies	Data analytics focused thesis disseminates learnings to company and future student projects	Thesis meetings and work increase domain specific understanding on data analytics problem and solution space	Thesis project provides extended opportunity to integrate knowledge to the company knowledge base

In this paper, we have studied how the dynamic capabilities of the CE SMEs in the area of data utilization can be developed by means of university student projects. In our analysis, we have employed the framework of relationship learning, where the mutual learning process is analyzed in three phases: knowledge sharing, joint sensemaking and knowledge implementation. The results of this study, summarized in Table 2, reveal practices that facilitate learning and new knowledge development in all of these three phases. Thus, this study contributes to the existing research on data-driven decision-making and management by focusing on the SMEs. The study provides also new insights into university-industry collaboration in Design Factory context (Lahdenperä et al., 2022), thus elaborating what different actors benefit from knowledge sharing, joint sensemaking and knowledge implementation in university-industry relationships.

6 Practical implications

As a practical implication, higher education institutions need to pay more attention how the results and approaches for solving the problems are transferred to the industry.

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Merely giving the data analysis results or source documents and presenting the solution for the company is not enough. A recommended practice based on the experience of the case studies is to create instructions for companies how to use the results, and how the company can add more data, metrics and dashboards independently from the students and original designers of the solution. Student trainees are effective ways to improve the absorptive capacity (Cohen & Levinthal, 1990) of the company and further develop student data analytics project results into working solutions for the company. In the case of CE SMEs in particular, more attention should be paid to the joint implementation of the results related to the research-based collaboration. One example of this may be the building of prototypes for industrial use. Also, recruiting the students and newly graduated engineers is an excellent way of transferring the newest knowledge from the university to industrial domain.

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